INSTITUTE OF TRANSPORT STUDIES, MONASH UNIVERSITY

EXPLORING NEW METHODOLOGIES AND PERSPECTIVES ON THE ROAD SAFETY IMPACTS OF BUS PRIORITY

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B.Eng.(Hons), DIC, MSc(Transport)

Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

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May 2014

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ERRATA

Page 11: "Bus consolidation" should be omitted in Table 2.1

Page 14 Line 13: Replace "…displayed with…" with "…displayed when…"

Page 16 Line 14: Delete "require" and read "…would involve a paradigm shift…"

Page 20 Line 17: Insert "of" between "knowledge" and "crash"

Page 21 Note in Table 2.5: Replace "before" with "after" and "after" with "before"

Page 22 Table 2.6 Line 3: Replace "certainly" with "certainty"

Page 27 Line 7: Delete "been" and read "…statistics have also been commonly used…"

Page 28 Line 6: Replace "useful" with "usefulness"

Page 29 last sentence: Replace "…none of SSMs were…" with "…none of the SSMs was…"

Page 30 Line 9: Insert "of" between "development" and "accident"

Page 31 Line 21: Replace "It was also interested…" with "It was also interesting…"

Page 34 Line 6: Delete "that" and read "Results showed that apart from driving exposure…"

Page 36 Line 26: Insert "of" between "effects" and "traffic"

Chapter 3: The title for this chapter should read "Research Framework, Context and Data"

Page 40 Line 3: Delete "as" and read "This is presented in the form of…"

Page 45 Line 6: Replace "significant" with "significance"

Page 53 Line 2: Insert "are" between "they" and "the"

Page 62 Line 25: Delete "context" and read "…with bus priority in other contexts arises."

Page 65 Line 29: Insert "on" between "based" and "a"

Page 67 Line 2: Replace "…poor accident records." with "…poor safety records."

Page 69 Table 5.1 Line 3: Replace "certainly" with "certainty"

Page 72 Line 3: Insert "in the" between "doubts" and "reliability"

Page 72: Equations (5.5) and (5.6) should read:

$$Var(\theta_{EB-CG}) = w^2 Var(\theta_{EB}) + (1-w^2)Var(\theta_{CG}) + 2w(1-w)p_{1,2}SD(\theta_{EB})SD(\theta_{CG}) \quad (5.5)$$

$$Var(\theta_{EB-CG}) = w^2 Var(\theta_{EB}) + (1-w^2)Var(\theta_{CG}) \quad (5.6)$$

where

where	w	=	Weight determined from equation (5.4)
	$p_{1,2}$	=	Correlation between EB and CG estimate
	$SD(\theta_{EB})$	=	Standard deviation of EB estimate
	$SD(\theta_{CG})$	=	Standard deviation of CG estimate

Page 88 Line 7: Replace "…while that in the chapter…" with "…while that in this chapter…"

Page 106 Line 4: Delete "being" and read"…influence the probability of bus drivers being at-fault…"

Page 133: Last paragraph should start as "~~Table 9.3~~**Table 9.3**"

ADDENDUM

Page 11: Comment: The priority measures investigated in this thesis do not fall under the "bus-way" category in Table 2.1, given that this term is typically associated with high quality facilities reserved exclusively for bus use.

Page 14 Paragraph 3: Comment: Priority at rail crossings is now more commonly categorized as "signal pre-emption".

Page 52 Last Paragraph: Comment: The CMF values used to account for bicycle lanes and narrower lane widths in this research are 1.20 and 1.14, respectively.

Page 53 Paragraph 3: Comment: The safety assessment in Appendix B, which was developed by the author, closely follows the approach adopted in the U.S and Australia.

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Kelvin Chun Keong GOH

May 2014

ACKNOWLEDGEMENT

I would like to thank Professor Graham Currie, Associate Professor Majid Sarvi and Dr David Logan for their immense patience and guidance throughout this research. Their close supervisions and encouragement have provided me the strength to explore new research opportunities and have certainly made a significant difference in this research.

I would also like to express my sincere appreciation to the Land Transport Authority (LTA) of Singapore for the invaluable opportunity given to me to pursue this PhD. It would have been financially impossible for me to further my knowledge at Monash University without LTA's support.

Heartfelt gratitude is expressed to Group Director (Engineering) Paul Fok, Director (Design) Neo Bian Hong and Deputy Director (Design Development, Road) Ho Pui Ming for their guidance and endorsement given for my pursuit of this PhD.

I am also most grateful to the Australian Research Council for supporting this research through the Industry Linkage Program project LP100100159, 'Optimising the Design and Implementation of Public Transport Priority Initiatives'. This project is administered by the Institute of Transport Studies, Monash University and done in association with the Transport Research Group, University of Southampton, UK, with Professor Graham Currie as the Principal Chief Investigator, Associate Professor Majid Sarvi as the Chief Investigator and Professor Nick Hounsell as Partner Investigator. The Industry Sponsors include VicRoads and Public Transport Victoria.

My sincere thanks go to Roger Lau, Nick Sitoriou, Robin Marston from VicRoads, Andrew Cornwall, Cheryle Colbron, Shawn Slawson from Ventura Bus and Ivan Pitcher (formerly with Grenda Transit) for their assistance in obtaining the relevant data needed for this research.

Lastly, my personal appreciations to my family, especially my parents and my wife Soo Wee for the enduring support and care rendered to our children Victoria and Troy throughout this trying period.

LIST OF ASSOCIATED PUBLICATIONS

The following publications have arisen from the research reported in this thesis:

Goh K., Currie, G., Sarvi, M. & Logan, D. (In Press) Investigating Road Safety Impacts of Bus Priority Using Experimental Micro-simulation Modelling. *Transportation Research Record - Journal of the Transportation Research Board.* (Accepted 9th February 2014)

Goh K., Currie, G., Sarvi, M. & Logan, D. (2014) Bus Accident Analysis of Routes With / Without Bus Priority. *Accident Analysis & Prevention*, 65, 18-27.

Goh K., Currie, G., Sarvi, M. & Logan, D. (2014) Factors Affecting the Probability of Bus Drivers Being At-Fault in Bus-Involved Accidents. *Accident Analysis & Prevention*, 66, 20-26.

Goh K., Currie, G., Sarvi, M. & Logan, D. (2013) Road Safety Benefits from Bus Priority - An Empirical Study. *Transportation Research Record - Journal of the Transportation Research Board*, 2351, 41-49.

Goh K, Currie G, Sarvi M and Logan D (2013) 'Investigating the Road Safety Impacts of Bus Rapid Transit Priority Measures' Transportation Research Board 92nd Annual Meeting, 2013 Washington DC USA

Goh K., Currie, G., Sarvi, M. & Logan, D. (2013) Understanding the Road Safety Implications of Bus Priority Measures in Melbourne. World Conference on Transportation Research, 15-18 July 2013, Rio de Janeiro, Brazil.

Goh K., Currie, G., Sarvi, M. & Logan, D. (2013) Exploring Bus Lane Safety Impacts Using Micro-Simulation, 36th Australasian Transportation Research Forum, 2-4 October 2013, Brisbane, Australia.

Goh K., Currie, G., Sarvi, M. & Logan, D. (2012) An Improved Methodology to Compute Crash Modification Factors: A Case Study of Bus Priority in Melbourne. 25th ARRB Conference, 23 - 26 September 2012, Perth, Australia.

EXECUTIVE SUMMARY

Road accidents have and will remain a major concern as cities around the world continue to grow. The safety problem is likely to worsen as population growth is accompanied by increased travel. For many cities, these trends have led to a greater provision of public transport as private vehicles become a less viable mode of transport. With the rise in public transport travel, it comes as no surprise that road management agencies are turning to an increased application of priority measures to improve the travel experience for commuters. For buses, the provision of priority measures has typically been justified based on travel time savings and operational benefits. Although recent years have seen the advances in research valuing the wider ridership, mode shift and environmental benefits of bus priority schemes, including the network wide benefits, a major issue that has yet to be considered in bus priority planning is the road safety impacts of providing priority schemes.

This thesis therefore aims to develop an in-depth understanding of the road safety implications of implementing bus priority through an investigation of accident records and conflicts in Metropolitan Melbourne. It is structured around six approaches that had been established to fill the knowledge in the area of bus priority safety effects. Each approach is the focus of a thesis chapter where the research context is discussed before the research methodology is presented. Results and key findings that emerged from subsequent analyses were used as a basis to understand the implications of implementing bus priority in the context of bus priority planning and research.

The first approach concerns an exploration of the safety effects of bus priority at the aggregate level. Here, a before-after safety evaluation of both “space based” and “time based” bus priority was carried out to understand its effects at the network and bus route levels. A before-after accident type analysis was done to examine whether accident counts or nature of accidents had changed following the implementation of bus priority. Results of the safety evaluation based on the Empirical Bayes approach showed that the implementation of bus priority treatments led to a 14% reduction in accidents. “Space based” treatments (mainly bus lanes) yielded a stronger positive safety effect (18.2%) compared to “time based” ones (11.1%). In terms of fatal and serious injury accidents, a drop of 42 to 29 per annum was recorded.

Given that different design types are available in before-after safety evaluation, the second approach focuses on understanding how the choice of comparison group type affected the bus priority safety estimate. Using the Empirical Bayes (EB) and

Comparison Group (CG) approaches, it was found that the effect of using different comparison group types led to discrepancies in the final safety estimates. It is likely that these differences were due to the (necessary) omission of sites with zero accident history and effect of matching treatment sites with similar sites in the CG approach. A new approach that combined both EB and CG results showed promise as a more precise safety estimate was obtained.

The third approach relates to an investigation of bus accidents at the route level. Using two mainstream modelling methodologies (MENB - Mixed Effects Negative Binomial and BPNN – Back Propagation Neural Network modelling), risks factors in bus accidents were explored with particular attention paid to the safety effect of bus priority. Results showed that bus priority led to lower occurrence for certain accidents types. The MENB and BPNN model results showed that bus priority had the effect of reducing route section level accident frequency by about 53.5%. The MENB model recorded better performance which pointed to benefits in adopting the MENB approach to account for time- and location-specific effects in accident count modelling.

The fourth approach concerns the analysis of bus accidents in terms of vehicle, driver, roadway and environmental factors. This was done to identify the significant risk factors in a bus company database of accidents where bus drivers were deemed to be at-fault. Similar to the third approach, the aim was to understand the effect of bus priority on drivers' at-fault probability in bus-involved accidents. Results from mixed logit modelling showed that bus length / age, driver's gender / age / experience / accident record, road type, speed limit, traffic / daylight conditions, and the presence of bus priority affect the likelihood of bus drivers being at-fault in bus-involved accidents. For bus priority, the effect was found to be random as bus priority only reduced the at-fault likelihood for some 57.8% of drivers.

The fifth approach centres on an investigation of the bus priority effect (bus lanes) at a corridor-level through micro-simulation. The focus was on conflicts at intersections and bus stops as the introduction of bus lanes was expected to have most impact on traffic movements at these locations. Results showed that the provision of bus lanes, regardless of whether they are created through space reallocation or creation, lead to a reduction in conflicts at intersections and bus stop locations. These pointed to lower rear-end and lane change accident risks for vehicles when bus lanes are in place.

The sixth approach concerns an estimation of crash risk for vehicles that are behind a slowing or stationary bus at a bus stop in a mixed traffic configuration. This was done to quantify the safety benefit delivered by bus priority schemes that segregate buses from mainstream traffic. Using recorded travel behaviour and accident history of a representative road corridor, the average crash risk of vehicles that were in conflict with buses was found to be 0.0154% (with a standard error of 0.0063%). Based on the assumption of an average of thirty such conflicts occurring daily, it works out that there is an approximate 80% chance of one or more accidents taking place annually as a result of buses slowing down or being stationary at bus stops.

Overall the thesis presents a range of advances in knowledge in the area of bus priority. Through the six approaches, new light has been shed on the safety effects of bus priority. The thesis concludes with a synthesis of the findings, in which its implications in the context of bus priority research and planning as well as opportunities for future research are presented.

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LIST OF ABBREVIATIONS

AADT	Annual Average Daily Traffic
BPNN	Back-Propagation Neural Network
BRT	Bus Rapid Transit
CG	Comparison Group
CMF	Crash Modification Factor
CPI	Crash Potential Index
DRAC	Deceleration Rate to Avoid a Collision
EB	Empirical Bayes
HOV	High Occupancy Vehicle
MADR	Maximum Available Deceleration Rate
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
MENB	Mixed Effects Negative Binomial
NB	Negative Binomial
PET	Post-Encroachment Time
RTM	Regression to the Mean
SCATS	Sydney Coordinated Adaptive Traffic System
SPF	Safety Performance Function
SSM	Surrogate Safety Measure
Transit	North American term for public transport
TTC	Time to Collision
TIMS	Traffic Incident Management System
TSP	Traffic Signal Priority

PART I:
BACKGROUND AND APPROACH

CHAPTER 1 INTRODUCTION

1.1 Introduction

This thesis explores the road safety effects of bus priority, with a focus on schemes implemented in Metropolitan Melbourne, Australia. This chapter starts with a discussion of the background and motivation for the focus of the research, followed by a presentation of the research aim and approach. It concludes with an outline of the thesis structure.

1.2 Background

1.2.1 Accidents in Cities – A Worldwide Issue

Traffic related accidents will remain as a key issue in all economies as cities around the world continue to grow. For the case of Australia, the number of people killed was 1,303 in 2012, equating to a fatality rate of 5.7 road deaths per 100,000 persons (Bureau of Infrastructure Transport and Regional Economics (BITRE), 2014, Australian Bureau of Statistics, 2013a). In 2003, the Bureau of Economics estimates that the costs for a fatality, serious injury and minor injury are \$1.832m, \$397,000 and \$14,183 (in Australian dollar values), respectively. This works out to be \$17.3b in terms of total cost of road traffic crashes or roughly 2.3% of Australia's GDP in 2003 (Connelly and Supangan, 2006), which clearly is a source of concern for the government and the community. If worldwide historical trends were to continue, the global road death toll will grow by approximately 66% from 2005 to 2025; predictions by the World Health Organization are that traffic fatalities will be the sixth leading cause of death worldwide and the second leading cause of disability-adjusted life-years lost in developing countries by the year 2020 (Kopits and Cropper, 2005).

This safety problem comes about because of increasing travel and population growth. The Australian vehicle population and corresponding total kilometres travelled in 2004 and 2012 increased from 13.49M to 16.6M and 199,055M to 232,453M kilometres respectively, which represents a growth of 16.7% and 23.1% respectively in just 8 years (Australian Bureau of Statistics, 2013c)

1.2.2 Increased Travel by Public Transport

The densification of cities has also inevitably resulted in space pressures, which has in turn led to an increased reliance on public transport. A recent Australian national survey revealed that the proportion of adults using public transport for work and study trips have increased from 11.9% in 1996 to 16% in 2012 (Australian Bureau of Statistics, 2013b). In terms of motor vehicle use, a separate survey found that the total kilometres travelled by buses in 2005 and 2012 in Australia (**Figure 1.1**) has increased by about 70.4% as compared to 24.4% for the general motor car (Australian Bureau of Statistics, 2013c).

The growth of public transport travel has seen road management agencies turning to an increased application of priority measures to improve the reliability of transit operations, travel time and overall travel experience for commuters. Since its introduction in the late 1980s in the form of bus lanes, bus priority has evolved to take on many different forms along road corridors and particularly at intersections (Gardner et al., 2009). These priorities, which essentially exist as “space based” or “time based” priorities and feature prominently in Bus Rapid Transit (BRT) Systems in various cities. Recent years have seen worldwide growth in the development of BRT schemes including high quality bus systems operating in mixed traffic (Levinson et al., 2003a, Hinebaugh, 2009).

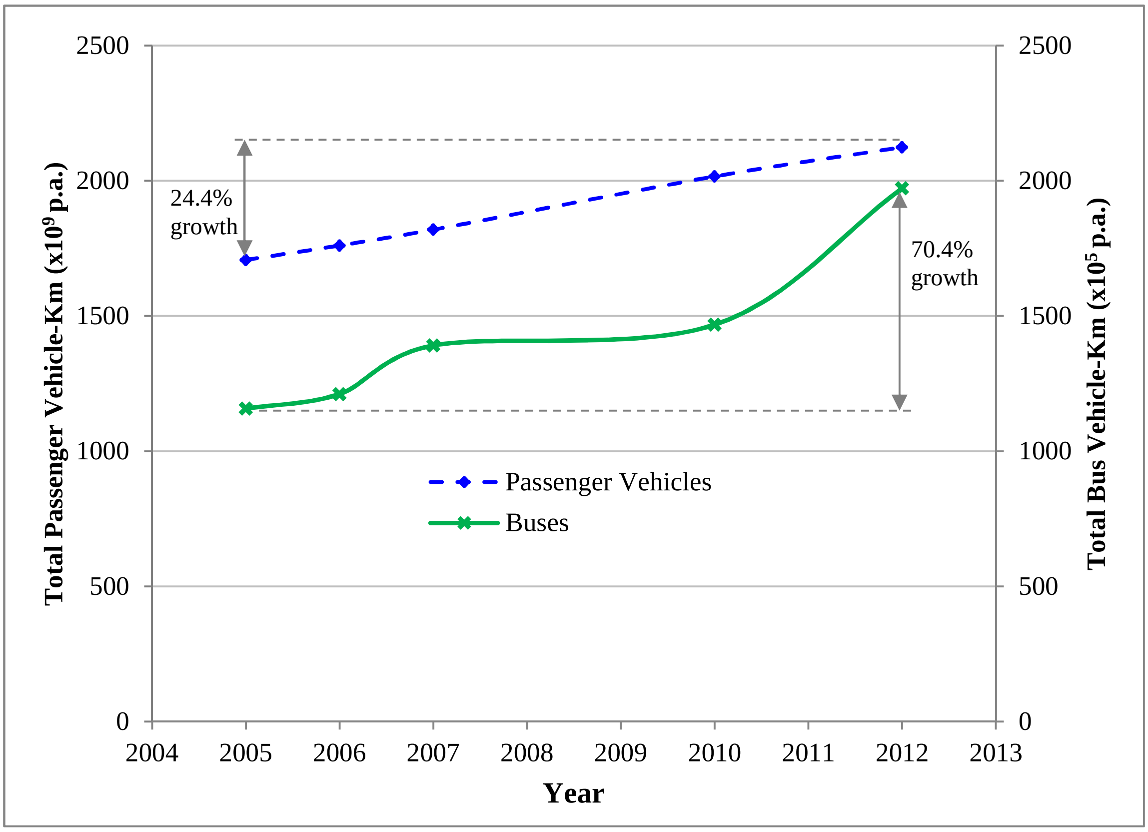


Figure 1.1: Total Distance Travelled for Passenger Vehicles and Buses in Australia (Source: Australian Bureau of Statistics, 2013c)

The provision of bus priority measures is challenging to justify in practice in the North American and Australian contexts where the majority of road travel is in private vehicles and compromises are required between road space and road time uses for private traffic and bus priority (Black et al., 1992), with private vehicles often being favoured. This could be partly attributed to weak methodologies for the justification of bus priority measures in identifying the wider benefits of priority schemes (University of

Southampton, 2002). Although there have been recent advances in research valuing the wider ridership, mode shift and environmental benefits of bus priority schemes (Currie et al., 2007), advances in examining the network wide benefits of schemes compared to corridor evaluations (Mesbah et al., 2008) and more recently advice on using cost benefit analysis for evaluating BRT schemes (Chisholm-Smith, 2011), a major issue that has yet to be considered in bus priority planning is the road safety impacts of providing priority schemes.

1.2.3 Importance of Bus Safety

Public transport is one of the safest forms of transportation (Chimba et al., 2010) with the risk of being killed or seriously injured in a bus, in particular, found to be several times lower than in cars (Albertsson and Falkmer, 2005, Yang et al., 2009). This holds much promise for policies aiming to improve modal split and mitigate traffic congestion in cities. However, knowledge regarding bus safety, especially in terms of the effects of the various bus priority measures, remains unclear. This could partly be attributed to previous road safety research that placed greater focus on passenger vehicles rather than buses (Wåhlberg, 2002). Recent years have however seen increasing recognition of the need to account for transit related collisions in transport planning and transit safety research with the development of safety evaluation tools and prediction models for transit planning at the route-level (Cheung et al., 2008, Quintero et al., 2013) . Given that these have mainly been confined to applications in North America (Jovanis et al., 1991, Cheung et al., 2008, Quintero et al., 2013), there is a clear need to explore crash related characteristics that influence route-level bus collisions in other locations around the world where public transport is gaining importance, such as in Metropolitan Melbourne, Australia.

At the accident-level, little research has been carried out examining the role of driver, vehicle and environmental factors in bus crashes, as well as understanding these accidents in terms of culpability (or crash responsibility). The dearth of such studies is not surprising, as accident data are rare, let alone those with culpability assigned to drivers. What makes this harder is the fact that culpability itself is often hard to determine (Wåhlberg, 2003). Studies that examined culpability have also typically relied on police records or self-reported data, which is often plagued with response bias, due mainly to under-reporting. Clearly, there is a need to gain further understanding of culpability in bus accidents, with detailed knowledge of the risk factors (including the influence of priority measures) to help design better bus priority systems.

1.2.4 State of Play in Safety Evaluation and Collision Prediction

In the field of safety evaluation, observational before-after studies are most commonly employed in evaluating safety effectiveness and establishing Crash Modification Factors (CMF) for specific road / traffic management measures (or treatments). Various study designs exist in mainstream research with the Empirical Bayes (EB) and Comparison Group (CG) methods being the more commonly adopted approaches by researchers (Persaud et al., 2001, Garber et al., 2006, Fayish and Gross, 2010) . Unfortunately, each method comes with its own limitations and unless properly accounted for, they can lead on to erroneous results and conclusions. With the limitations in current methodologies, there is a clear need to explore an alternative approach to evaluate the safety implications of bus priority schemes.

There exist various approaches to modelling collision predictions too. Generalized linear modelling is one of the more widely used approach (Lord and Mannering, 2010). More recently, there is an emergence in the use of neural network modelling, as recent studies have pointed to excellent function approximation abilities of these models (Li et al., 2008, Vlahogianni et al., 2012, Xie et al., 2007). Hence, there are significant insights to be gained from the use of both generalized linear and neural network modelling using accident data, with a focus not only on an understanding of bus crashes, but also with the secondary aim of assessing and comparing model performance.

In summary, with bus use continuing to increase and more cities implementing various traffic management measures to favour buses, there is a need to develop an understanding on the implications that such measures have on buses and overall road safety. The importance of bus safety has been outlined in preceding sections, and this is primarily driven by trends in:

- ✓ Growing population in cities and travel;
- ✓ Increasing reliance on public transport;
- ✓ Increasing wealth and corresponding rising cost of fatality, injuries and property damage; and
- ✓ Greater application of bus priority measures

1.3 Research Aim and Approach

With the trends identified above, this research aims to develop an in-depth understanding on the road safety implications of bus priority in Metropolitan Melbourne. To achieve this aim, five broad approaches are established as follows:

1. To assess the overall road safety impact of bus priority measures implemented in Melbourne;
2. To understand the implications of using different study design types in road safety evaluation;
3. To explore the safety impact of bus priority at the bus route level and its influence in relation to other risk factors in bus driver related accidents;
4. To investigate the disaggregate road safety impact of different bus priority schemes; and
5. To estimate the safety benefits of bus priority schemes that segregate buses from mainstream traffic

1.4 Thesis Structure

This thesis is structured around the five broad approaches as established in the preceding section. The overall structure is split into four parts as follows and shown in **Figure 1.2**.

Part 1:	Background and Approach	Chapters 1-3
Part 2:	Aggregate-Level Analysis	Chapters 4-6
Part 3:	Disaggregate-Level Analysis	Chapters 7-9
Part 4:	Synthesis and Conclusions	Chapter 10

Part 1: Background and Approach is dedicated to providing the background and proposed methodology to investigate the safety effects of bus priority. It begins in Chapter 1 - “Introduction” where the context is laid out and an explanation on the value of investigating the effect of bus priority from a safety perspective presented. In addition, an account of the key motivation behind this research is provided. Chapter 2 - “Literature Review” begins with a review of the literature before key findings and learning points are presented from previous research on public transport safety, safety evaluation techniques, safety analysis of buses at the route and incident level as well as safety evaluation using micro-simulation tools or empirical vehicle trajectory data. Most importantly, it concludes with the identification of knowledge gaps from the literature review. In Chapter 3 - “Research Methodology, Context and Data”, the research methodology is presented and through a study framework, the proposed key tasks and activities are laid out to achieve the research objectives. A description of the research context and data used for this research is also provided.

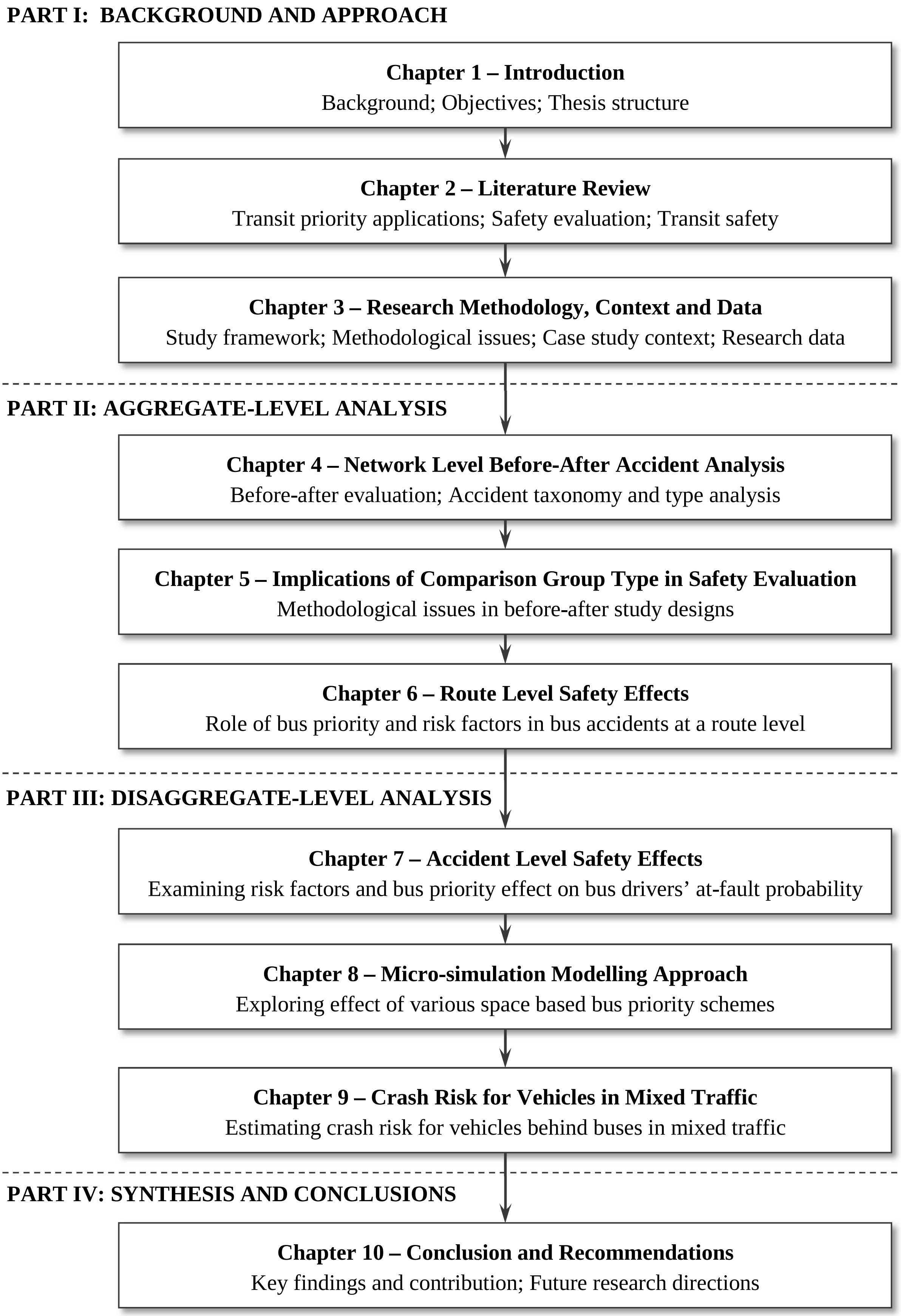


Figure 1.2: Thesis Structure

Part 2: Aggregate-Level Analysis focuses on the exploration of bus priority safety effects at the network and route levels. It starts in Chapter 4 - “Network Level Before-After Accident Analysis” where an overall before-after safety evaluation of both “space based” and “time based” bus priority is carried out. This includes a before-after accident type analysis to examine whether there had been changes in the accident counts or nature of accidents following the implementation of bus priority. Various before-after safety evaluation approaches exist in mainstream research, and it is expected that the approach choice will have an effect on the final bus priority safety estimate. As such, Chapter 5 - “Implications of Comparison Group Type in Safety Evaluation” begins with a review of the state of practice in safety evaluation and exploration of how the choice of comparison group type affects bus priority safety estimates. In Chapter 6 - “Route Level Safety Effects”, the focus will be on investigating bus accidents at the bus route level. Here, the risks factors of bus accidents will be explored and particular attention paid to the safety effect of bus priority. For analytical rigour, two mainstream modelling methodologies will be adopted, thus allowing for a comparison of model performance and a more meaningful interpretation of results.

In Part 3: Disaggregate-Level Analysis, the attention will turn to uncovering the safety effects at a finer level. It begins with Chapter 7 - “Accident Level Safety Effects” where bus accidents will be analysed in terms of vehicle, driver, roadway and environmental factors to identify the significant risk factors in a bus company database of accidents where bus drivers were deemed to be at-fault. Similar to the accident analysis at the route level, the focus will be on an understanding whether the presence of bus priority has any effect on drivers’ at-fault probability in bus-involved accidents. In Chapter 8 - “Micro-simulation Modelling Approach”, an investigation of the bus priority effect (bus lanes) at a corridor-level through micro-simulation will be presented. Given that the introduction of bus lanes changes the nature of traffic movements at intersection and bus stop locations, a detailed investigation of conflicts was undertaken at these two locations. Finally, Chapter 9 - “Crash Risk for Vehicles in Mixed Traffic” encapsulates the effort to estimate the crash risk of vehicles (in a mixed traffic configuration) that are behind a slowing or stationary bus at a bus stop. The final risk estimate will provide a sense of the safety benefit provided by bus priority schemes in which buses are segregated from mainstream traffic.

The thesis will conclude and make a number of recommendations in Part 4: Synthesis and Conclusions with Chapter 10 - “Conclusion and Recommendations” providing a synthesis of the key findings, summary of the contributions of the research, implications for bus priority research and planning as well as commentary on limitations and future directions for this research.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter aims to provide a review of the literature that concerns the safety effects of bus priority. The existing knowledge gaps are then identified, followed by a discussion on opportunities that they present for further research.

Investigating the safety effects of bus priority measures requires a good understanding of two major fields - (1) Bus priority, which itself is a subset of the public transport domain, and (2) Road safety (**Figure 2.1**).

Public transport (or transit) is a broad term that refers to any form of transportation service that is available for use by the general public. What differentiates public transport from other transport modes is that it provides for a shared form of transportation. It is meant to cater to all groups of people, regardless of their race, culture, physical ability, etc. and includes all modes of transport available to the public (with the exception of taxis and coaches), irrespective of ownership (White, 2001).

A widely accepted definition of bus priority is that it refers to the use of traffic management schemes or measures to improve bus operations through reduced travel time and enhanced reliability. Often, bus priority forms part of an overall urban transport strategy with the objective of improving bus operation, restraining use of car for commuting as well as enhancing the environment for residents, workers and visitors (Slinn et al., 2005).

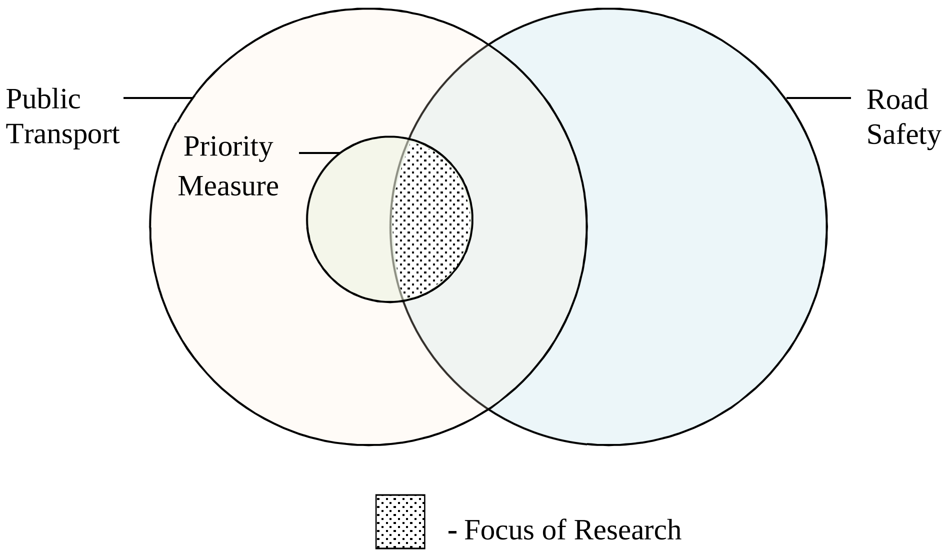


Figure 2.1: Research Area and Focus

Road safety, on the other hand, concerns the well-being of all road users travelling on or interacting with the road system. It usually entails developing strategies to minimise death and injuries, themselves a by-product of the road transport system, the operation of which is essential for the efficient functioning of modern cities (AustRoads, 2009a).

Given the focus of this thesis is on the safety effects of bus priority as well as research aim and approach identified in section 1.3, a review of the literature was undertaken with the objective of understanding the:

- ✓ Latest developments in bus priority (section 2.2);
- ✓ Principles and key concepts in road safety research (section 2.3);
- ✓ Leading methodologies in road safety research and evaluation (section 2.4);
- ✓ Previous research findings on bus safety (section 2.5); and
- ✓ Previous research findings on the safety effects of bus priority (section 2.6)

In line with the above objective, a review of the current state of practice in bus priority is first presented, covering the types of priority treatments in existence. Following this, an account of the key research in the field of road safety is provided. Given the large body of research work in developing various means to evaluate road safety, a section is dedicated to both mainstream methodology and emerging techniques used in measuring road safety outcomes. This is followed by a review of findings on bus safety and the safety impacts of bus priority from previous studies. Finally, the chapter concludes with the identification of gaps in existing knowledge of bus priority safety and a discussion on opportunities available to advance knowledge in the areas identified.

2.2 State of Practice in Bus Priority

Bus priority is typically provided with the aim of improving the travel time and reliability of bus operations, travel experience for passengers at stops and interchanges and altering traffic balance in favour of public transport use. Achieving all these objectives at the same time often involves compromises between improving transit operation and the needs of private vehicle and other road users (Slinn et al., 2005).

The provision of priority for buses is not a straight-forward task for road management authorities, especially in countries where car dependency is high, as it involves finding the right balance between competing demands between public and private transport users for limited road space and time (Black et al., 1992). This is in addition to the challenging need to give due consideration to the wider environmental, safety and efficiency impacts.

Notwithstanding the challenges that road management authorities face today, there have been a number of priority measures implemented for buses in recent times. The types of bus priority initiatives vary from city to city (Gardner et al., 2009, Hounsell et al., 2004), but their differences lie essentially in the amount of road space or time allocated for buses. Spatially, priority measures can also be categorised into (1) road corridors or (2) intersections.

2.2.1 Priority Measures on Road Corridors

Priority treatments on road corridors generally involve giving the right of way (or space) to buses along their travel route. Typically, traffic management measures are taken to accord this right of way to buses, with the use of traffic warning or advisory signs and physical line demarcation, for example, to indicate dedicated bus lanes. The allocation of road space to buses can either be done by reallocating existing lanes or creating a new lane on a road carriageway. The various forms of priority treatments are summarized in **Table 2.1**, and their key features are described briefly in the following paragraphs.

Table 2.1: Types of Transit Priority Measures along Road Corridors

Priority Measures along Road Corridors	Types of Design Based On	
	Space Management	Traffic Management
Bus-way	Median transit lane	With-flow
	Kerbside transit lane	Contra-flow
		Bi-directional Flow
		Intermittent
Traffic Management	Prohibited parking	Full or part time
	Stop consolidation	-

The bus-way is a form of treatment where road space is allocated for bus use. When the highest level of priority is to be accorded, bus-ways are to be used by buses only, with general traffic not permitted to use this road space. Bus-ways can be grade-separated or physically segregated to ensure buses enjoy exclusivity to this road space. Bus-ways can also be located next to the centre median or on the slowest lane of a carriageway. The former is termed a median bus lane while the latter is called a kerbside bus lane. Depending on the level of priority to be accorded to buses, bus-ways can either be shared with other road users or reserved exclusively for use by buses.

There are different types of traffic management techniques to provide priority to buses. The most common ones are with-flow, contra-flow, bi-directional and intermittent bus lanes. The with-flow lane configuration is most common, where the transit vehicle moves in the same direction as the general traffic. In contrast, the contra-flow lane is designed to allow for transit vehicles to move in an opposite direction to the general traffic. The bi-directional lane, which is a hybrid of the previous two types, permits transit vehicles to travel on it regardless of whether it is moving with or against the flow. Compared to the abovementioned, the intermittent bus lane is dynamic in nature as it only becomes operational when the transit vehicle is in the vicinity, i.e. general traffic would be allowed to use this lane at other times. Guidelines are available on the suitability of each type of transit lane in the planning context, but the final choice typically depends on the traffic management and transit operation objectives (Levinson et al., 2003b).

Around the world, various forms of bus priority have been used. **Table 2.2** summarizes the different types of bus priority measures adopted in different cities around the world.

Table 2.2: Types of Bus Priority Measures along Road Corridors

Location	Roadway		Vehicles allowed			Right of way		Unique Features
	Highway	Arterial	Taxi	HOV	Bicycle	Segregated	Mixed	
Trondheim, Norway		✓	✓		✓		✓	Transit lane
Brussels, Belgium		✓		✓			✓	-
Assen, Holland		✓	✓	✓			✓	Residents use allowed
London, UK		✓	✓				✓	With bicycle lanes
Minneapolis, US	✓			✓			✓	Typically median lanes
New Jersey, US	✓						✓	Contra-flow lane
New York City, US		✓					✓	With offset lane
Toronto, Canada		✓	✓	✓	✓		✓	-
Essen, Germany		✓				✓		New road space created
Bogota, Columbia		✓				✓		-
Jakarta, Indonesia		✓				✓	✓	Centre of roadway
Melbourne, Australia		✓					✓	New lane created

In Europe, bus lanes are pre-dominantly found along arterial roads with some having the unique feature of allowing for shared use with other vehicles like taxis, High Occupancy Vehicles (HOV) and bicycles. In the US, it is not uncommon for bus lanes to be present on freeways. Often, they double up as HOV lanes and are located between the centre median and fast lane. In Essen, Bogota and Jakarta, buses travel on segregated bus-ways, allowing them to travel relatively unimpeded along their route. Melbourne's case is somewhat similar to those in Europe. Apart from a stretch along the Eastern freeway, all bus lanes are located on arterial roads. Another difference is that taxis, HOV and bicycles are generally not permitted to travel in the bus lanes.

Prohibited parking and stop consolidation are two other forms of bus priority treatments. In Melbourne, prohibited parking comes in the form of "clearways" in which private vehicles are not allowed to park in the slow lane. Similar to bus stop consolidation, the idea is to reduce roadside friction for the buses and improve travel time for commuters.

2.2.2 Priority at Intersections

The predominant form of bus intersection priority is transit signal priority (TSP), which by definition, means the adjustment of signal timing at junctions to "give transit vehicles a little extra green time or a little less red time at traffic signals to reduce the time they are slowed down by traffic signals." (Smith et al., 2005). **Table 2.3** summarizes the state of practice in TSP application based on signal control and time management strategies at intersections.

Table 2.3: Types of Transit Priority Measures at Road Intersections

Priority Measures at Road Intersections	Different Strategy Types Based On	
	Signal Control	**Time Management**
Traffic Signal Priority	Active / Passive	Green extension
	Conditional / Unconditional	Early green or red truncation
	Direct / Indirect	Actuated transit phase
	Differential	Phase insertion
		Phase rotation
		Rolling horizon
Queue Jump Lane	Typically active and conditional	Typically actuated transit phase

In terms of signal control, TSP can be implemented in several ways - the most common of which are active or passive control. In the passive method, TSP operates without taking into account the presence of the transit vehicle. Since it does not require any transit detection to trigger the priority request, passive priority operates continuously. With the knowledge of bus routes and ridership patterns, passive priority strategies can operate efficiently as the traffic signal system can be tuned based on travel speeds of buses so that they stay "in sync" with signals when travelling along the route. It also works well in situations where one approach has a significantly higher number of transit vehicles than the other approaches.

Active priority, on the other hand, operates by activating a priority request at the intersection following the detection of the approaching transit vehicle. It involves the real time sensing of vehicles and adjustment of signals to facilitate their movement across the junction. Sensing of vehicles can be either point-based or continuous. The most common point-based vehicle sensing equipment are road loops and vehicle tags (University of Southampton, 2002), which interact with each other to make priority requests for the transit vehicle. For continuous sensing of vehicles, Global Positioning Satellite (GPS) based systems are growing in popularity and are often used. Various types of active priority strategies exist and a brief description of each is provided in the following paragraphs.

One of the more effective forms of active priority is the green extension or early green (or red truncation) strategy, where the green phase is extended or introduced early for the approaching TSP-equipped transit vehicle. In both methods, the intent is to have the green signal provided for the transit vehicle when it reaches the intersection. The only slight difference between the two variations is that the green extension is applied when the signal is green, whereas the early green is implemented when the signal is red for the approaching vehicle.

An actuated transit phase is a third strategy, which works by displaying a traffic signal in favour of the transit vehicle only when it is detected. An example would be the “B” signal, which is only displayed with the bus is detected in the approaching lane. Other forms of the actuated transit phase include phase insertion or rotation, in which a special priority phase is inserted or the order of the original signal phases is adjusted to provide priority to the transit vehicle. The rolling horizon strategy is a variant whereby the signal phasing is being delayed or brought forward so that the green phase is provided when the transit vehicle reaches the intersection. Compared to the “B” signal strategy, the rolling horizon, phase insertion and rotation strategies accord a higher level of priority to the transit vehicle as they modify the existing phasing sequence to one that favours the transit vehicle in the following phase.

TSP can also be operated in a real-time or adaptive mode. In adaptive signal control systems, the traffic condition is monitored and signal control strategies adjusted continuously to not only provide priority to transit vehicles but also optimise the overall traffic performance of the intersection. Two other types of TSP signal control strategy defined by Chada and Newland (2002) are (1) conditional priority and (2) unconditional priority. Conditional priority works by providing priority to transit vehicles only when a certain criterion is met, such as when the transit vehicle’s approach has a volume to capacity ratio not exceeding a certain threshold. These constraints act to balance the need for priority of public transport vehicles against those of other road users. Unconditional priority is where priority at the signal is provided immediately to ensure the public transport vehicle can pass through the intersection without having to fulfil any condition (signal priority given to trains at level crossings is the most common example of unconditional priority).

Chada and Newland (2002) provided two further groups of (active) TSP strategies (1) Direct priority and (2) Indirect priority. Direct priority works by adjusting traffic signals at the next intersection where the public transport vehicle is approaching, while indirect priority does the adjustment way ahead of the public transport vehicle to clear traffic downstream so that the bus can proceed with greater ease through the intersections. Indirect priority is typically used in areas which experience higher traffic volumes as it creates less disruption to the traffic in the network.

The more advanced form of TSP at traffic intersections involves the provision of differential priority, where different levels of priority can be provided to transit vehicles at traffic signals according to specified criteria, e.g. on-time performance. The application of such a strategy requires a traffic signal control system that has the ability to utilize advanced ITS-based technology (University of Southampton, 2002).

The queue jump bus lane is a unique treatment found mainly in bus rapid transit (BRT) systems (e.g. 98 B-line BRT route in Vancouver and Smartbus routes in Melbourne) that involves the allocation of both space and time to the transit vehicle at road intersections. **Table 2.4** captures the various forms of transit priority measures in terms of space and time allocation, i.e. "space based" or "time based" priority.

Table 2.4: Summary of Transit Priority Measures

Location	**Types of Priority**	**Form of Priority**	
		Space based	**Time based**
Along road corridors	Transit Lanes	Median transit lane	Full Time
		Kerbside transit lane	Part Time
	Traffic Management	Prohibited parking	
		Stop consolidation	
At road intersections	Traffic Signal Priority		Green Extension
			Early Green
			Actuated Transit Phase
			Phase Insertion
			Phase Rotation
			Rolling Horizon
	Short Transit Lane Priority	Queue jump lane	Actuated Transit Phase

2.2.3 Measuring the Effectiveness of Priority Measures

The effectiveness of transit priority measures has typically been evaluated based on improvements in running time, on-time performance and wait time for passengers. In the study by Kimpel et al. (2004), an empirical analysis of bus data from TriMet's Bus Dispatch System in Portland, Oregon was done to evaluate the bus operational performance based on the changes in mean and variance of running times, scheduled running time, passenger wait time and in-vehicle times. Following a regression analysis to determine the factors that influence running time, it was found that the primary benefits of TSP on mean running time were limited to the afternoon peak period in the primary direction of travel. Although potential overall savings were found with respect to scheduled running times, recovery-layover times and excess wait time, the results were mixed when individual routes were considered by direction and time of day. Interestingly, the mean and variance of headways as well as the on-time performance decreased overall which was primarily due to buses shifting from either on time or late towards being early. In terms of wait time for passengers, Hounsell and Shrestha (2012) demonstrated through theoretical analysis and simulation modelling that the best strategy involves giving priority to buses based on their headway relative to the bus behind. In this rather radical idea, buses would only be given priority at intersections when their headways were found to be greater than that of the bus behind. Accepting this strategy would involve require a paradigm shift for bus planners and operators who, from a scheduling and timetabling perspective, will typically reason that priority should be accorded to buses with headway greater than the scheduled headway. Arguably, this strategy would only be suitable for high-frequency bus services, where regularity of bus arrival would be more important than adherence to timetables.

There exist other studies on the operational performance of on-road public transport and priority initiatives based on traffic micro-simulation studies (Tétreault and El-Geneidy, 2010, Lee et al., 2005, Currie et al., 2007, Robertson, 1985, Jepson and Ferreira, 1999).

These studies shed much light on how transit priority initiatives affect the operational performance of transit. However, none had considered the safety implications of providing transit initiatives. Section 2.6 provides further details on this.

2.3 The Road Traffic System and Road Safety

Road traffic can be considered as a system, in which various components interact with each other. This system is often described as comprising three components – driver, vehicle and road environment, in which any these elements can contribute to the occurrence of an accident (Ogden, 1996). The importance of the driver, vehicle and road environment as key elements in a road system is recognised by some 30 OECD member countries (OECD/ITF, 2008). This also showed up in Sweden's Vision Zero program, which incorporated a mechanism to allow for error-tolerance in the road system and new design principles for road- and street design strategies (Johansson, 2009), as well as Western Australia's Towards Zero strategy, which was focused on promoting safe roads and roadsides, safe speed, safe vehicles and safe road use (Corben et al., 2010).

Road (and similarly bus) safety, on the other hand, is commonly defined and evaluated in terms of the recorded number of traffic accidents, killed or injured road users as well as consequences of these accidents in terms of their severity of outcome. Hydén (1987) proposed a severity dimension that is common for all the events in traffic by defining a model that relates the events' severity outcome (represented by the vertical position in the pyramid) and their frequency (represented by the volume of the pyramid slice). Based on this model (**Figure 2.2**), events with higher frequency are associated with lower severity outcome and vice versa.

In terms of accident analysis, it is widely accepted that the number of accidents or injured road users during a certain time period is a result of a complex process (Elvik et al., 2009). To understand how different factors contribute to accident risks, researchers have employed various methodologies to relate accident accidents to vehicle, driver and environmental factors. These factors are termed as contributory factors by some researchers (Hamed et al., 1998, Jovanis et al., 1991, Evans and Courtney, 1985).

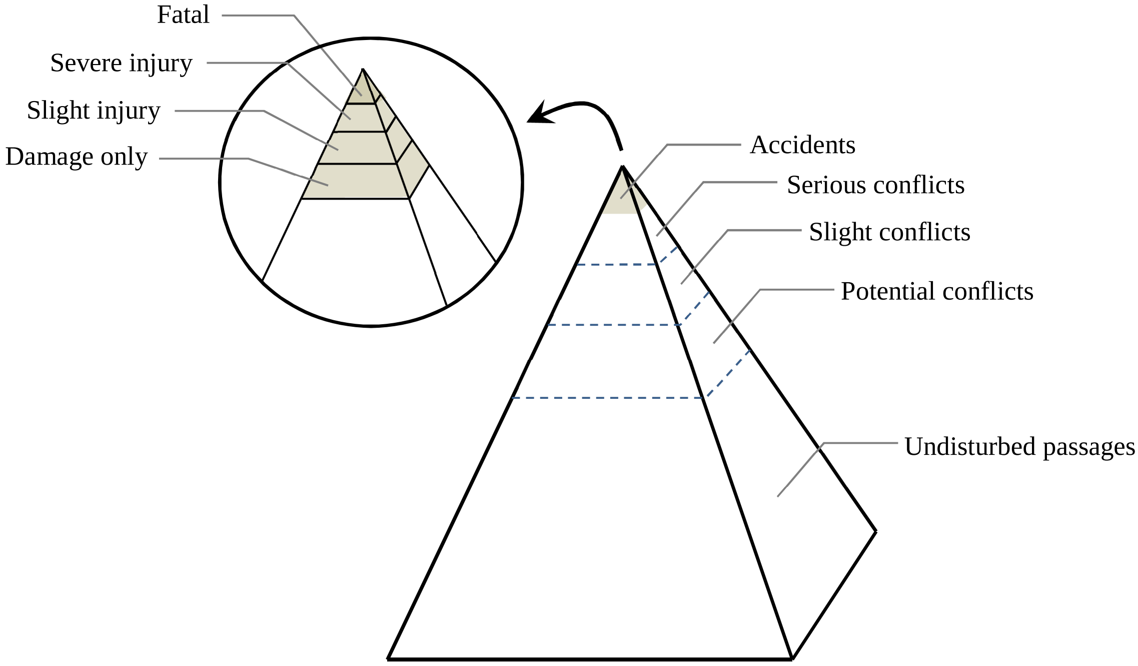


Figure 2.2: Safety Pyramid (Hydén, 1987)

The role of various contributory factors in accident occurrence had been studied in-depth by Sabey and Taylor (1980). In this UK-based study, over 2000 accident records were examined and it was found that road user factors predominate, followed by road environment factors, with vehicle factors playing the smallest role numerically. In a separate study, Rumar (1982) emphasised that the human component is the most difficult one to change or modify, therefore humans have several basic limitations which must be recognised and taken care of in the technical design of road geometry and surface, signs, signals, lighting, vehicles, etc. In other words, man-made things are easier to change than individual behaviour. For this reason, despite the predominance of road user factors, it is acknowledged that changes in the road environment by road safety engineering and improvements in vehicle safety are the ones that can make disproportionate contributions to accident reduction (Transport and Road Research Laboratory, 1991).

To this end, it is worth making the distinction between contributory factors and the cause-effect relationship in accidents. For the lay person, it is of natural tendency to think in terms of cause-effect relationship in accidents. Hauer (1997) however argued that this concept does not apply to road accidents and that it "only has meaning only if we think of something which, had it been done differently, would have affected the outcome." He added that changing any one of the contributory factors, e.g. altering road and traffic engineering features or traffic control, rarely makes an accident certain or impossible. Instead, the "change merely makes the accident somewhat more or less likely to occur. Therefore, there is no useful distinction between road or human factors as a cause and that there is just a causal chain in which the road, its environment, markings and signs affect what road users do".

2.4 Assessing and Measuring Road Safety

Various methodologies have been employed by safety researchers to better understand the relationship between accident occurrence and key factors that relate to the three components of the traffic system – driver, vehicle and road environment. From the literature, there appears to be four approaches to analyse accidents in road safety research:

1. Descriptive statistics – typically used to identify accident characteristics that contribute or relate to a crash counts or a certain crash type;
2. Before-after evaluation – typically employed to evaluate the effectiveness of a new on-road treatment;
3. Predictive modelling – typically used to identify factors that affect crash counts or crash type at a particular location over a period of time; and
4. Other emerging or advanced methodologies – typically used to allow for flexibility in the dataset assumptions in modelling and use of proximal safety indictors to measure road safety performance

2.4.1 Use of Descriptive Statistics

The work of Rowden et al. (2008) is an example of a study using descriptive statistics to analyse accidents. In this study, the authors analysed all animal-vehicle collisions in

Australia to ascertain driver, vehicular and environmental factors leading to such crashes. Through the use of statistical chi-squared tests, night-time travel, motorcyclists and kangaroos / wallabies were identified as risks factors. The analysis also revealed a high proportion of swerve and avoidance crashes, which led the authors to conclude that such crashes should not be overlooked by crash reporting agencies. Romano et al. (2008) undertook a similar approach by analysing empirical crash data to better understand female drivers' involvement in fatal crashes. The authors employed a crash incidence ratio benchmarked against a base year to evaluate crash risks for female drivers with various characteristics. Using a trend analysis approach, the authors were able to confirm that the observed increase in female involvement in fatal crashes is largely due to a parallel increase in female driving exposure. Another conclusion drawn was that young women were more vulnerable to risk-taking driving behaviour than others. Wang et al. (2008) adopted a similar approach by examining crash data to identify typical circumstances in which car crashes occur and investigate the association between crashes and speed regulation / road characteristics. By employing data-reduction techniques, the authors were able to identify crash attributes and patterns for various accident severity levels. One finding was that side-impact crashes were pre-dominantly found to be occurring in the Central Business District (CBD). A high proportion of accidents in the CBD were also found to occur in autumn and on main roads.

In all the above studies, the common approach was to analyse empirical crash data to sieve out details regarding a specific crash type under study.

2.4.2 Before-And-After Evaluation

The second approach, involving before-after evaluations is commonly adopted by researchers to evaluate the safety effectiveness of a new traffic facility, scheme, policy change, traffic regulation or treatment. Essentially, it revolves around the identification of cause and effect of the treatment implemented.

Before-and-after analyses are employed across a wide variety of fields to examine the effects of treatments in general. In medicine, it is a particularly useful tool in clinical studies to evaluate the effectiveness of a treatment or medical devices (Shayne, 2001). In psychology, before-and-after analyses are used frequently to better understand the effectiveness of certain psychotherapy treatments (Bootzin and McKnight, 2006). Often, these clinical studies include a placebo treatment group to allow for adequate control and ensure construct validity (of the cause), i.e. the proper understanding of the true meaning of the treatment, as inappropriate inferences about the treatment effects could be due to confounding variables, inadequate theoretical formulation of the treatment and inadequate description of the treatment and control conditions (Bootzin and McKnight, 2006). In the transportation field, a similar approach has also been applied in evaluating the effectiveness of a specific measure or treatment. Examples include the evaluation of drivers' level of awareness of the road rules following a public education campaign to improve driver compliance with streetcar transit lanes (Currie, 2009) and traffic and bus performances following the implementation of bus priority lane (Sakamoto et al., 2007).

In road safety, before-and-after studies have been central (although most had been limited to the use of observational data) in the safety evaluation of a site/s with a certain safety related measure or treatment implemented (treated site). As specified in the Highway Safety Manual (2010), there are three key methodologies that could be employed to evaluate observational before-and-after accident counts after a treatment is applied.

The first methodology, aptly called the Empirical Bayes given its roots in Bayesian theory, involves the use of a Safety Performance Function (SPF) to represent the safety performance of roadway segments or intersections that are similar to the ones under study. These SPFs are used to compute the predicted number of accidents at each treated location (assuming the treatment had not been implemented). The expected crash frequencies for each treated site in the before period is then determined by using the combined knowledge crash frequencies from the reference sites and study sites. Following this, the corresponding figure in the after period can be established based on the ratio of the predicted accident counts between the before and after periods. Finally, the odds ratio is computed by taking the division of the observed and expected crash frequencies in the after period. The safety effect is then determined by correcting the bias in the odds ratio that arises from using the estimated expected crash frequency.

The second approach is to use the Comparison Group (CG) method. Central to this method is the selection of appropriate reference sites that are comparable to the treated sites in terms of traffic volume, geometry and other site characteristics with the exception of the treatment of interest. The steps are largely similar to EB; the key is to compute the predicted number of accidents in the after period based on the safety performance of the reference sites. Following this, the safety effectiveness of the treatment can be determined in a similar manner to the EB procedure.

The third approach is based on a Cross-Section (CS) evaluation, where sites with and without a particular treatment are selected. The theory is largely similar to the CG approach in that comparable reference sites are selected to account for all other possible factors that have an influence on the safety effectiveness. The difference lies in that, while before data are required for the CG method, they are not required for the CS approach. The core of the CS method is the development of a model that accounts for the crash records of sites with and without the treatment in question. The difference in the number of crashes is then taken to be attributed to the presence of the treatment itself. **Table 2.5** summarizes the key steps involved in using either one of the three above approaches, while **Table 2.6** captures the key strengths and weaknesses associated with the use of each approach.

Table 2.5: Key Steps in Empirical Bayes, Comparison Group and Cross-Section Before-After Studies

Step		**Methodology**		
		Empirical Bayes	**Comparison Group**	**Cross Section**
1 - Data Preparation				
Treated Sites	Before	✓	✓	
	After	✓	✓	✓
Reference Sites	Before		✓	✓
	After		✓	
2 - Establish the safety performance of reference sites		A = f(*Length*, *AADT*)	$r = C_{OA}/C_{OB}$ x $1/(1+1/C_{OB})$	
3 - Predict number of accidents in before and after periods, T_{PB} & T_{PA}		T_{PB}, T_{PA} = f(*Length*, *AADT*) x CMF_X where CMF_X = correction for site-specific attribute	T_{PB} = f(average accident frequency at reference sites)	Methodology revolves around the development of a single accident model with a variable to indicate the presence or absence of the treatment in question
4 - Compute expected number of accidents, T_{EB} based on predicted (T_{PB}) and observed counts in the before period (T_{OB})		$T_{EB} = wT_{PB} + (1\text{-}w)T_{OB}$ where w = weightage derived from model's over-dispersion parameter in step 2	$T_{EB} = \alpha T_{PB} + (1\text{-}\alpha)T_{OB}$ where α = based on mean and variance of sample of reference sites	
5 - Compute expected number of accidents in the after period, T_{EA}		$T_{EA} = T_{PA}/T_{PB}$ x T_{EB}	$T_{EA} = r$ x T_{OB}	A=f(*AADT*,*T*) where T = indicates presence of treatment
6 - Compute odds ratio, *OR*, i.e. doing something over ding nothing		Odds Ratio, $OR = T_{OA}/T_{EA}$	Odds Ratio, $OR = T_{OA}/T_{EA}$	
7 - Correcting for bias in final result, *CMF*		$CMF = OR / (1+\text{Var}(T_{EA})/(T_{EA})^2)$	$CMF = OR / (1+\text{Var}(T_{EA})/(T_{EA})^2)$	

Note: Author's summary of key steps involved in the EB, CG and CS approaches

AADT refers to Annual Average Daily Traffic of the intersection approach or road corridor. C_{OA} *and* C_{OB} *represent the observed crash counts in the reference site/s in the before and after period respectively*

Table 2.6: Benefits and Disadvantages of Methodologies in Before-After Studies

Methodology	Pros	Cons
Empirical Bayes	- Regression to the mean effects could be addressed in a straightforward manner - Existing Safety Performance Functions (SPFs), if any had been developed earlier, could be used	- Confounding variables can be accounted for only if CMF values are known and with certainly that they are applicable in study context - Large numbers of reference sites are required for the development of a SPF - SPFs are likely to vary across different geographical areas
Comparison Group	- Sites can be matched such that confounding variables are accounted for	- Regression to the mean effects usually not accounted for - Unable to evaluate sites with zero accident history - Need for matching and comparability when selecting reference sites
Cross Section	- Data requirements are less onerous	- Regression to the mean effects cannot be accounted for - Cause and effect may be unclear, i.e. observed differences between the treated and reference sites could be due to unexplained factors

Note: Author's summary of the key pros and cons associated with EB, CG and CS approaches

On the whole, the EB method is preferred as it requires less computational effort and can account for sites with no accident history. The main appeal in using the EB methodology is its ability to account for secular trend and unrelated effects (that cannot be measured) as well as the widely accepted phenomenon of regression to the mean effects. It does this by combining accident counts with knowledge about the safety of similar entities (Hauer et al., 2002). However, the drawback is that confounding variables have to be accounted for with the use of appropriate Crash Modification Factors (CMF). In practice, obtaining a reliable CMF value is difficult. The CG method can overcome this limitation as sites can be chosen such that confounding variables are accounted for. However, its main disadvantage is that it is incapable of assessing sites with zero accident history. Also, data collection is onerous as historical crash data for reference sites in addition to those for the treated sites are needed. The CS method has the advantage of requiring lesser data. However, this method is not ideal given that regression to the mean effect cannot be properly accounted. More importantly, establishing a clear and effect is tricky given that any observed differences in accidents between the treated and reference sites could be due to unknown variables that have not been captured by the accident model.

From the literature, it appears that the choice of the methodology is largely dictated by the availability of data on hand (Step 1 in **Table 2.5**) given that accident data from reference sites or treated site in the before period may not be readily available, etc. The literature however has provided little knowledge on the implication of the choice of before-after study design on the final safety effect estimate. As such Chapter 5 is dedicated to understanding the implications of choosing different before-after study design in road safety evaluations.

2.4.3 Predictive Modelling

The third approach in accident analysis centres on predictive modelling, which can be considered to be an alternative to the establishment of cause-and-effect in road safety. Researchers using this approach typically employ regression methods to relate all possible risk factors with the number of crashes or crash type at a particular location over a specified time period. Poisson regression was one of the first modelling approaches adopted by researchers as a means to overcome the inappropriateness of using traditional ordinary least-square regression to analyse crash count, which is an integer that is often low and non-negative in value (Lord et al., 2005). Based on the probability of a certain number of accidents occurring in a given time period, it is expressed as:

$$P(x) = \frac{e^{-\lambda}\lambda}{x!} \tag{2.1}$$

where *P(x)* is the probability of a road entity (usually in terms of road intersections or corridors) having *x* number of accidents per time period and λ is the Poisson parameter that is taken to be equal to the expected number of crashes for the roadway entity. λ is then often expressed in terms of a group of explanatory variables, Y_i selected by the modeller:

$$\lambda = f(\beta Y_i) \tag{2.2}$$

Because crash counts are non-negative, typically low and plagued by under-reporting, this approach gives rise to problems relating to small sample size and over- or under-dispersion. The key drawback in using the Poisson regression model is that it is unable to handle crash data that are over-dispersed (Miaou, 1994). Using crash data with such a characteristic, which is common when sample size is small or accident counts are low, would mean a violation of a key assumption in the Poisson model, that being when the variance is equal to the mean of the crash count. To overcome this, safety researchers have resorted to the use of Negative Binomial (or Poisson-Gamma) models (Joshua and Garber, 1990). The structure of the Negative Binomial model is similar to the Poisson model, except that it assumes that the Poisson parameter follow a gamma probability distribution:

$$\lambda = e^{(\beta Y_i + \varepsilon_i)} \tag{2.3}$$

where $e^{\varepsilon i}$ is the gamma-distributed error term with mean of 1 and variance, α. The introduction of this function allows the relaxation of the Poisson's property of variance being equal to the mean.

Zero-Inflated Poisson (ZIP) and Zero-Inflated Negative Binomial (ZINB) models emerged in the 1990s to handle another common characteristic of crash counts – excessive zeroes in the dataset (Carson and Mannering, 2001, Shankar et al., 1997). The principle behind the ZIP or ZINB approach is to have modelling done in two parts – the first is binary logit or probit modelling to handle excess zeroes while the other is the usual Poisson or Negative Binomial modelling.

While the Negative Binomial model is designed to cope with over-dispersed data, the Conway-Maxwell-Poisson model emerged in the 2000s mainly because of its ability to also handle under-dispersed data. Allowing the model error structure to take on many of the common probability density functions also added to its flexibility in handling different types of crash data (Lord et al., 2008). Gamma models also came about around the turn of the century to handle crash data that are under-dispersed. It is similar to the ZIP and ZINB models in that it comprises two states to handle excessive zeroes in the crash counts (Oh et al., 2006b).

The use of regression techniques results in additional problems with endogenous variables, omitted-variables bias, temporal / spatial / crash-type correlation (Lord and Mannering, 2010). To overcome such data and methodological issues, researchers have formulated a wide variety of methods. The early 21st century saw the emergence of other models like the generalized additive and random / fixed effect models (Xie and Zhang, 2008, Guo et al., 2010). The former offers greater flexibility than Poisson and Negative Binomial models as its inherent smoothing function allows the explanatory variables to take on other forms of relationship and not be limited to the traditional linear or logarithmic ones. The latter became popular when the need to account for spatial and temporal correlation in the data began to be recognised. The model structure allowed common unobserved effects to be distributed over the spatial / temporal units or be accounted for by indicator variables. This form of modelling paved the way for the appreciation of spatial and temporal effects on accident occurrence (Chin and Quddus, 2003).

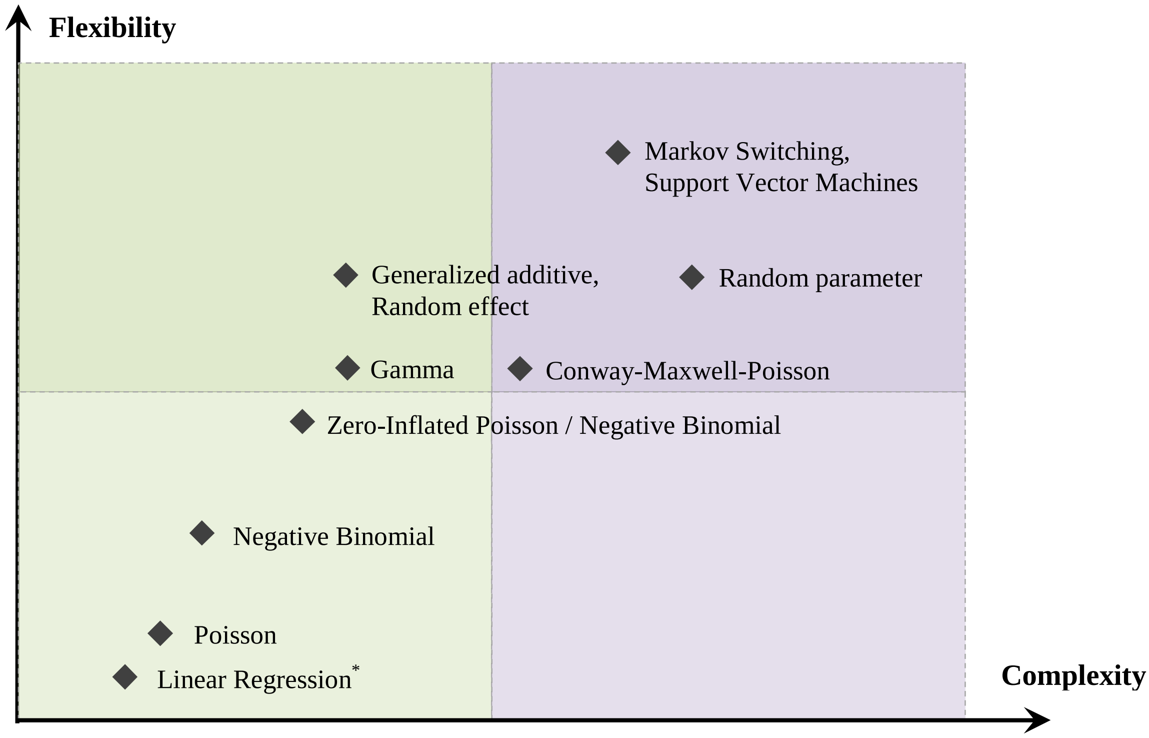
Recent studies have adopted random-parameter modelling, which is similar to random-effect modelling in that a parameter is introduced to allow for possible correlation between grouped observations (Gkritza and Mannering, 2008, Milton et al., 2008). This approach offers the additional flexibility of allowing the model parameters to vary and therefore accounting for site specific characteristics. This increased flexibility however comes at the expense of greater complexity as model estimation becomes harder.

2.4.4 Other Emerging and Advanced Methodologies

New types of models have emerged in recent years. This is driven primarily by criticisms of existing models such as the ZIP, ZNB and Gamma models for the problems associated with the assumption that the long-term mean will equal to zero (Malyshkina et al., 2009). Another reason has been the rapid advancement in computing power. The latter is likely to be the main driver for the emergence of the Markov Switching model, which allows for heterogeneous data to be analysed. With increased flexibility in allowing the dataset to take on different underlying distributions, it paves the way for a wide variety of crash data to be analysed at the same time, resulting in findings that previous models were not able to yield.

Greater computing power has also led to the advancement of statistical learning theory, which in turn gave rise to models such as neural network and support vector machine models (Li et al., 2008). The mechanisms in these models differ but essentially centre on learning algorithms that are based on optimization, statistics and information theory. Although such models generate better approximations compared to Poisson and Negative Binomial models, they cannot be generalised to other data sets (Xie et al., 2007).

In summary, various models have been developed by safety researchers to overcome issues inherent in crash data and provide greater insights into crash occurrence. **Figure 2.3** provides an assessment of the flexibility and complexity of the various models documented in the literature. Choosing a model that offers greater flexibility, e.g. to handle over-dispersed data, spatial correlation, etc. often comes at the expense of greater complexity. Models that are highly complex are however of limited use when they cannot be generalised to other datasets. In the case of neural network models, the main issue is that such models tend to behave like “black-boxes” that produce non-interpretable parameters (Lord and Mannering, 2010). For this reason, it makes sense to choose models that offer just enough flexibility to address specific issues relating to the dataset for research purpose. For instance, it would not be necessary go for a Conway-Maxwell-Poisson model (over a Poisson model) if the dataset do not have under-dispersion issues.



Note: (1) Author's assessment of flexibility is based on model's ability to account for data that are under-, over-dispersed, have excessive zeros, spatial / temporal correlation and allow for data to take on different underlying distributions

(2) Author's assessment of complexity is based on the models' transferability, ease in understanding the computation process and interpretation of final model results

*(3) *Not suitable for crash count analysis but included to reflect relative level of flexibility and complexity*

Figure 2.3: Flexibility and Complexity of Different Methods to Deal with Data and Methodological Issues in Accident Analysis

2.4.5 Use of Proximal Safety Indicators

The collection of crash data is difficult in practice (Giles, 2001). In Sweden, published research shows that accident data only covered about 40% of the lesser accidents (Statistics Sweden, 1995). Data provided by the police is also often inaccurate and may vary in quality and content, while those of hospitals only cover injury accidents. In France, it was found that only 37.7% of all road crash casualties are captured in police records. For New Zealand, less than two-thirds of all hospitalised vehicle occupant traffic crash victims were recorded by the police in 1995 (Alsop and Langley, 2001). Self-reported or self-recorded accident data is also considered to be imprecise, due to lack of experience of those involved, possible memory lapses and the tendency to provide socially desirable response by drivers (Wåhlberg et al., 2010, Wåhlberg, 2009a).

As highlighted in the preceding section, it is also extremely difficult to predict the actual number of crashes accurately given that accidents are rare occurrences. To overcome this limitation, researchers often resort to analysing crashes over an extended period of time or over a large spatial area, often at an aggregate level, e.g. county, state or country level.

The significant lack of accurate and reliable accident data has hindered efforts by transport analysts and researchers in measuring the true safety effects of existing or proposed safety measures. In practice, many of the models that have been developed and implemented for transportation planning purposes are very general in nature, and many are not equipped to allow for proper safety analyses for say a specific location where there might be important safety related factors that cannot be easily measureable. Traffic accident statistics have been also been commonly used to assess the safety performance and predict the effectiveness of new safety measures at specific locations such as junctions. The lack of quality accident data often leads to questionable estimates of accident reduction effect of measures.

Given this backdrop, the use of non-accident data or safety indicators as a measure for safety analysis and basis for statistical prediction modelling has been on the rise. This stem from research findings that suggest such measures are as equally effective as accident data per se in predicting the expected number of accidents at a particular traffic location (Archer, 2005).

One of the earliest and more widely used methods is the traffic conflict technique (Chin and Quek, 1997, Parker and Zegeer, 1989). In this technique, critical incidents that do not necessarily lead to collisions (or conflicts) are analysed to determine how safe a traffic facility or scheme is. The most appealing aspect of this technique is that conflict data can be collected over a much shorter time period, in contrast to accident data which typically requires a span of a few years (Migletz et al., 1985). This immediately overcomes the problem of having to gather sufficient accident history to ensure statistical inference can be made in analyses. The effectiveness of any safety program can therefore be assessed in a much shorter period of time.

Despite the voluminous research work done since the traffic conflict technique came to the fore, there still exist a number of issues that remain unresolved. The key issues, which are well summarized by Chin and Quek (1997), relate to (1) consistency in the definition of conflict, (2) validity of the traffic conflict technique and (3) reliability of conflict measurements.

The first issue relates to the variety of definitions that researchers have used to define conflict. From what was widely accepted of a traffic conflict in 1968 as being “any event involving swerving, braking or traffic violations” (Perkins and Harris, 1968), different research bodies have gone on to refine and develop their own version of what constitutes a traffic conflict (Transport and Road Research Laboratory, 1987, Gettman and Head, 2003). Comparison of results across studies thus becomes difficult when different conflict definitions and threshold levels are adopted, especially in deciphering between 'serious' and 'non-serious' ones (Grayson et al., 1984).

The second issue of validity has been the main point of argument for opponents to this approach. This arose after several conflict studies failed to show an acceptable level of statistical correlation between conflicts and accidents (Chin and Quek, 1997). Williams (1981) doubted the useful of the traffic conflict technique because "there would be a set of poor correlation for every other set of good correlation found between conflicts and accidents". Chin and Quek (1997) however argued that "such validation is only necessary if conflict studies are intended to predict accident occurrence", and hence, "validation of the traffic conflict technique would be unnecessary if it is used as a diagnostic and evaluative instrument and not for accident prediction".

The third issue of reliability relates to recordings made by the individual observer (intra-observer reliability) and interpretation of a given situation between observers (inter-observer reliability). At the observer level, inconsistent conflict detection can result because of fatigue and lack of training. Results from a full-scale conflict study involving safety officers from Europe and North America showed that there were considerable variations in the conflict recordings observed by the different groups of observers (Grayson et al., 1984).

To address methodological issues relating to the use of traffic conflict techniques Chin and Quek (1997) developed a framework that comprises three pre-requisites to ensure conflicts are robustly defined, objectively measured and suitably applied in traffic conflict studies. The first pre-requisite is that conflicts should be defined in simple, quantitative terms that can be easily appreciated by both drivers and conflict observers. Only by doing so will problems associated with philosophical definitions be adequately addressed. The use of "nearness to collision" in terms of space or time was cited as a good example of defining conflicts. Because unit time or space is used, it provides a simple and repeatable basis for comparison between different conflicts. The second pre-requisite is that observations should be easily observed and measured. One recommended approach is to define conflicts in terms of time proximity instead of space proximity. The reason for this is because distances between vehicles are often difficult to be judged by observers on the roadside. On the recording of conflicts, the authors argued that such tasks would become easier as video technology continue to advance. The final pre-requisite is that conflict measures should be selected such that they enable appropriate and meaningful inferences to be derived from subsequent analysis. For instance, using time or space proximity measures would be useful in studies focussing on the issue of speeding and skidding. It is also important to specify a threshold value of the conflict measure to distinguish critical from non-critical situations. This will facilitate safety evaluation through an analysis of the proportion of conflicts that are critical.

2.4.5.1 Surrogate Safety Measures in Micro-Simulation

The lack of good predictive accident models and difficulties in obtaining quality accident records was instrumental in driving the U.S Federal Highway Administration's (FHWA) efforts in exploring the use of microscopic traffic simulation to assess road safety. In the final FHWA report (Gettman et al., 2008) on Surrogate Safety Measures (SSM), it was highlighted that a potentially good alternative to traditional safety analysis is the use of SSMs in microscopic traffic simulation models to evaluate different traffic schemes in terms of safety. Compared to the approach of using historical accident data, this method has advantages similar to traffic conflict technique, in that:

- ✓ It is more resource effective given that a relatively shorter observation time period is needed;
- ✓ It is useful in before-after evaluations where the emphasis is on comparison or assessment of a new traffic facility or measure; and
- ✓ Carefully calibrated and validated models can provide a controlled and flexible "off-line" test platform that allows the user to experiment with alternative design solutions and different traffic parameter values in order to estimate the effect these will have on both safety and traffic performance.

It is clear that the use of SSMs in safety analysis has gained popularity in the recent years, especially in evaluation of intersection safety. Archer and Young (2009) used Post-Encroachment Time (PET) and the number of red light violations as SSMs to evaluate the safety and traffic system efficiency of five alternative signal treatments at a metropolitan highway intersection. Using micro-simulation software package VISSIM, it was shown that amber extension treatments yielded the greatest effect in terms of reducing red-light violations. In a similar vein, Saccomanno et al. (2008) utilized micro-simulation to compare the pattern of rear-end conflicts between roundabouts and signalized intersections. Through the use of three SSMs – Time to Collision (TTC), Deceleration Rate (DR) and Crash Potential Index (CPI), it was found that traffic volume and pavement surface conditions were significant factors. In another study, Ismail et al. (2009) used four SSMs – TTC, Post-Encroachment time (PET), Gap time and Deceleration to Safety time – to test the ability of an automated video analysis system in capturing important conflicts between pedestrians and vehicles automatically. Although results showed that none of SSMs were individually capable of detecting all dangerous conflicts, the combination of all four SSMs proved to be useful in identifying important traffic conflicts.

With regard to road corridors, there have only been a handful of studies that had used SSMs for safety evaluation. In a recent study by Meng and Weng (2011), the authors used Deceleration Rate (DR) as a SSM to develop a model relating rear-end crash risk and key risk factors in the merging area of a work zone. Crash Potential Index (CPI), another SSM developed based on DR, was used by Cunto et al. (2009) to evaluate the safety performance of a freeway segment. Results showed that the SSM was able to reflect the crash risk accurately.

2.5 Bus Safety

Previous research in bus safety have typically concerned (1) safety assessments of bus services and bus accident analyses or (2) the development accident prediction models to understand how vehicle, driver characteristics, environmental factors and human resource scheduling correlate with bus accident risk at the micro-level.

In the first group of studies, Evans (1994) provided a good overview of accidental fatality rates for buses and private transport in Europe. Statistics from the 10-year record in Great Britain showed that fatal accident rates between public transport and the private road modes are similar when exposure (per passenger-km) is allowed for. For bus-involved accidents, the bulk of fatalities typically involved unprotected road users. On the other hand, fatalities involving passengers were found to be low. An intriguing implication of this finding was that "door-to-door journeys by public transport would be riskier than the same journey by car, even though the former carries relatively low risk, because unprotected road users are exposed to relatively high risk while walking to and waiting for public transport". Notwithstanding this, it is acknowledged that bus accidents in Great Britain are relatively low, especially when compared to the 1970s, when total casualty figures were about two times higher at 50 to 106 per year (White et al., 1995). When compared to other European countries, the Netherlands and Britain displayed similar fatality rates, with West Germany having slightly lower rates in comparison with Britain. Tennyson (1998) focused on transit-involved accidents in North America by analysing fatality and injuries rates, including accident costs for all types of transit collisions over a 3-year period. Given that travel in North America is predominantly by automobile, the fatality rate is highest at 0.9 per 100 auto passenger km, compared to 0.37 and 0.43 per passenger km for light and rail rapid transit respectively. The fatality rate for transit buses is lowest at 0.12 per passenger km primarily because non-patron fatalities are reported separately. On the other hand, the injury rates for riders on transit buses are worse when compared to rail and automobile users. In acknowledging that that many less serious automobile accidents are likely to go unreported, Tennyson (1998) cautioned against a direct comparison of transit injury data with automobile injury data.

Certain bus accident types are known to be particularly common. Zegeer et al. (1993) found rear-end and sideswipe accidents to be most common in commercial bus crashes across five states in the U.S. A similar finding was obtained in the work by Jovanis et al. (1991), in which 89% of all accidents / incidents were collision events involving hitting another object or person, while the remaining 11% were non-collision events relating mainly to passenger injuries during boarding / alighting or moving about in the bus. Again, rear-end collisions were the most common, just as was found by Yang et al. (2009). Albertsson and Falkmer (2005) analysed bus and coach incidents in eight European countries and found that buses and coaches colliding with cars formed the majority of all crashes. Frontal impacts were most common, followed by side and rear impacts. As for non-collision incidents, emergency braking and boarding / alighting were the common causes. Wåhlberg (2002) developed a taxonomy of buses involved in low-speed accidents in Sweden with the aim of capturing common features of bus accidents and studying the causes of accidents from behavioural and environment perspectives. From the database of 2237 accident involvements, the most common accident types for buses were found to be shunts and side contact with another vehicle. In a follow-up study, Wåhlberg (2004a) developed a framework (star-diagram) of dependent and independent variables to examine the relationship between the various characteristics (17 in total) of bus accidents and found that a significant number of side contact accidents occurred at bus stops and involved parked cars. This suggested that the bus size was an issue for drivers when manoeuvring in tight spaces along streets. It was also interested to note that more than half of the injuries in buses happened independently of conflicts with other road users. Given that nearly half of single accidents occurred at bus stops, he reasoned that this outcome could be due to buses being stopped abruptly resulting in passenger falls.

Previous research into bus-involved accidents also suggests that buses may be indirectly involved in a larger number of accidents even though they did not participate in the collision and no one in the bus was injured (Brenac and Clabaux, 2005). By sieving through police reports on accidents in an urbanised area of France, Brenac and Clabaux (2005) discovered that accidents in which a bus was directly involved in accidents accounted for 1.4% of all traffic injury accidents recorded by the police. This percentage increased to 3.6% when indirect involvements of buses were also accounted for. Sight obstruction and hurried crossings by pedestrians were the main contributory factors when buses were indirectly involved in accidents. Typically, they involved vehicles hitting pedestrians who had crossed in front of buses or were crossing the street to catch the bus. These findings support the authors’ view that the indirect involvement of buses in accidents cannot be considered as insignificant.

Findings from the second group of studies have revealed interesting insights into the risk factors for buses. Albertsson and Falkmer (2005) found that the majority of bus and coach incidents in eight European countries took place on urban roads with speed limit of 50km/h and in dry conditions. In another study, the presence of on-street shoulder parking, lane in which bus was travelling in, posted speed limit, lane width, number of lanes and traffic volume were found to be associated with increases in accident and injury severity risks (Chimba et al., 2010). It was also interesting to note that the state of the road was reported to be a contributory factor in only a third of bus incident reports in Sweden (Wåhlberg, 2004b).

As for vehicle related factors, crashes involving older buses were found to be over-represented in commercial bus accidents across five states in the U.S. (Zegeer et al., 1993). Tseng (2012) also found that the use of automatic vehicle location systems in tour buses was associated with lower at-fault accident rates. In another study, Strathman et al. (2010) analysed factors contributing to bus operations safety incidents in the Portland Oregon metropolitan region in the U.S. using extensive data from an Automatic Vehicle Location system. It was found that a more varied daily work span, overtime shift hours and late-running are some of the more significant contributory factors in bus-related incidents. Buses with lift movements were also found to have higher incident risks, which the authors attributed to the likelihood of bus drivers running late (and thus increasing accident risks) as a result of using lift operations.

In terms of driver factors, the study by Wåhlberg (2002) found that bus drivers were responsible for as much as 40.2% of accidents. However, when single accidents (typically involving the hitting of stationary objects) were excluded, this figure dropped to 18.1%, which is comparable to the proportion of accidents where other parties were at fault. In other words, the number of bus drivers found to be at-fault is not significantly different to other motorists in multiple-vehicle accidents. In a subsequent study, Wåhlberg (2004b) tested acceleration behaviour along with other driver-related variables and found that the number of working hours and to a lesser extent age, are significantly associated with crashes. In this study, he argued that most accident prediction research had tested predictors that are far removed from the actual traffic behaviour. He further argued that accident data only requires basic tabulation and that the use of more advanced statistical techniques might yield misleading results. In particular, he made a case that prediction could only be made for culpable accidents, as those for which a person is not culpable in some way cannot be predicted by any variable from a behaviour point of view. Based on this principle, Wåhlberg (2008) tested the correlation between driving style, as measured by driver acceleration behaviour acceleration with other commonly used variables like age, gender, number of working hours and travel time. Although extensive on-board data collection was done, no definitive conclusion could be drawn from results of his analysis. Results from a later study however did reveal that bus driver accident risks vary by time of day when accounting for exposure (Wåhlberg, 2009b). In a separate study that involved an analysis of nearly 8,900 commercial bus crashes in the U.S., Zegeer et al. (1993) found that gender or age was not significant in accident involvement. Tseng (2012) also found age as well as education level to be insignificant in explaining at-fault accident rates of tour bus drivers. Driving experience and yearly mileage on the other hand, were found to be significant. In the work by Jovanis et al. (1991), age was found to be negatively correlated to accident occurrence when experience was accounted for. No statistical significance was found for gender but interestingly, experience with the transit agency was found to be strongly associated with accident occurrence, with drivers having 3 to 6 years of experience being over represented in accidents. As for the study by Strathman et al. (2010), results from the analysis of the extensive intelligent transportation system and operations data revealed that incident risks decreased until the age of 30 and length of service reached 33 years. The expected frequency of non-collision incidents for female operators was also found to be slightly higher than their male counterparts (14% more). In a separate study that examined bus drivers' self-assessed risk, it was found that their perception of accident risk increased with distance travelled and daily working hours (Hamed et al., 2000).

To summarize, **Table 2.7** provides a listing of the key accidents risks found in the above studies. While findings from these have provided valuable insights into crash characteristics and accident causation factors in bus accidents, <u>they appear to have generally fallen short of adequately representing all the traditional safety determinants, i.e. some studies have a good mix of driver related factors but lack vehicle and environmental factors or vice versa. The majority of these studies have also focussed on accident risks instead of probability of being at-fault in accidents, both of which appear similar but are distinct in form</u>. This is despite the recognition that addressing culpability when analysing accidents is important as earlier research has showed better correlation between driver characteristics and culpable accidents (Wåhlberg, 2008).

Table 2.7: Summary of Studies on Bus Accidents

Author	**Key Accident Risks Examined / Found**																			
	Driver related						**Vehicle related**						**Roadway related**							
	Age	Experience	Gender	Work hours	Temperament	Mileage	With lifts	With AVL System	Turning Bus	Side-swipe collision	Rear-end collision	Frontal Impacts	On-street parking	Lane bus was in	Posted speed limit	Lane width	Traffic volume	Sight Obstruction	Crossing Pedestrians	Time of Day
Yang et al. (2009)	✓								✓		✓									
Zegeer et al. (1993)										✓	✓									
Strathman et al. (2010)	✓	✓	✓	✓	✓		✓													
Jovanis et al. (1991)											✓									
Tseng (2012)	✓	✓																		
Chimba et al. (2010)		✓				✓		✓												
Wåhlberg (2009b)													✓	✓	✓	✓	✓			
Albertsson and Falkmer (2005)												✓			✓					
Brenac and Clabaux (2005)																		✓	✓	
Wåhlberg (2004b)	✓			✓																✓
Hamed et al. (2000)				✓		✓														

Note: Author's synthesis of existing knowledge on risk factors examined in bus accidents

2.6 Safety Impacts of Transit Priority and Service Features

As highlighted in section 2.2.3, operational (instead of safety) considerations are often central in evaluating the effectiveness of transit priority. Our understanding of the safety implications of transit and bus priority thus remains unclear, given that research in this area has been limited. In one of the studies that focused on transit cars (or trams) in Toronto, Canada, Cheung et al. (2008) developed zonal-level and arterial level collision prediction models using a generalized linear modelling approach. Results showed that that apart from driving exposure, the other variables that have significant associations with transit-involved collisions include stop density, transit frequency and presence of near-side stops and on-street parking. Shahla et al. (2009) also developed collision prediction models that incorporated transit characteristics but also focused on signalized intersections. The influence of geometric design and other road features on transit-involved collisions and all collisions were also examined in a bid to determine differences in safety between intersections with and without certain features such as TSP or exclusive lanes. Generalized linear modelling with a negative binomial error structure was carried out using 5-year records of bus- and streetcar-related collisions at signalized intersections in Toronto as well as data comprising public transit, general traffic and locations of public transit stops. Results from the best fit models showed that variables having significant associations with transit-related collisions at signalized junctions included annual average daily traffic, transit and pedestrian traffic volumes, turn movements and the presence of features. For the latter, it was interesting to note that the presence of traffic signal priority had a positive correlation with transit-related collisions at junctions. Another tram related study found that darkness and passengers under the influence of alcohol were key accident risk factors. Most injury events also happened at tram stops, on the tram tracks and pedestrian crossing locations (Hedelin et al., 1996).

For the case of BRTs, it was found that buses using Seattle's bus tunnel (with exclusive right-of-way for buses only) experienced 40% fewer accidents than in mixed traffic operations, while the introduction of the Bogota TransMilenio BRT system saw a 93% reduction of fatalities among transit users (Levinson et al., 2003c). With regard to other bus priority measures, Booz Allen Hamilton (2006) found that the introduction of bus lanes in London had resulted in a reduction of 12% in accidents involving buses. In evaluating the safety impacts of bus lanes and no-car lanes, Mulley (2010) examined personal injury accidents that occurred over a 3-year period on stretches of roads within 50m of a bus priority lane in Tyne and Wear, UK., and found that 5.3% of all personal accidents were due to priority measures along the corridor. However, whether priority measures actually resulted in more accidents overall was not stated. Sarna et al. (1985) studied the accident data on selected roads in New Delhi for a 2-year period before and after dedicated bus lanes were introduced. The results were unable to provide any definite evidence of safety impacts. LaPlante and Harrington (1984) studied contra-flow bus lanes in Chicago and concluded that they should be retained after determining that bus and pedestrian accidents decreased by 52% and 19% respectively in the "after" period. For the case of Hong Kong, Tse et al. (2014) examined the accident occurrence on seven sites where bus lanes were implemented, and found a reduction in fatal, serious and slight injury accidents involving buses. There was however an increase in fatal and serious accidents for other vehicle types. With two of the decreases and none of the increases found to be statistically significant, the authors concluded that the bus lanes appeared to have benefited buses only.

A number of studies have been carried out where transit priority had been applied in a context that is different to Melbourne, Australia (the focus of this thesis). In America, studies have focused on time-limited bus lanes (rush hour lanes) on highways, where share-a-ride schemes using private cars are permitted (Cooner and Ranft, 2006, Sullivan and Devadoss, 1993). The results from these studies showed that bus lanes appeared to lead to an increased number of accidents. The most likely explanation for this increase is that American-style bus lanes, also known as High Occupancy Vehicles (HOV), are constructed next to the central median and adjacent to the lane where traffic speed is highest. As a result, buses or vehicles wanting to use the HOV lanes have to make several lane changes to move in or out of them. In Dallas, Texas, this increased traffic weaving movement was deemed to be the key reason for the increase in accident rates following the implementation of HOV lanes (Skowronek et al., 2002). With bus speeds likely to be lower, there would also be major speed differences between the bus and other traffic lanes. The fact that light cars could also use the bus lane could also have contributed to the increase in traffic accidents.

In Norway, 2-wheelers are permitted to use bus lanes. This type of bus lane was found to increase the number of accidents (Elvik et al., 2009), possibly due to the fact that the heaviest (bus) and lightest (2-wheelers) vehicles use the same traffic lane. In addition, the differences in speed between a bus lane and other traffic lane would be relatively large, especially in heavy traffic, thus increasing the potential of more conflicts and accident occurrence.

Unlike Norway and America, the majority of bus lanes in Melbourne under this study are for exclusive bus use. These bus lanes are either created by introducing a new traffic lane or by reallocating existing traffic lanes for buses (e.g. clearways). From the literature, it was not clear whether bus priority schemes that were examined in previous studies had been implemented via reallocation of road space. In this regard, the closest comparison one can make is with the effects of "road diet" (Pawlovich et al., 2006), which a form of road space allocation for the benefit of other road users like pedestrian and cyclists. In this study, the authors found that the road diets in Iowa, America, resulted in a 25.2% reduction in crash frequency per mile and 18.7% reduction in crash rate. The key reason put forward was that road diets reduce traffic speed and vehicle interactions during lane changes, resulting in a reduction in frequency and severity of crashes.

Table 2.8 presents a synthesis of the safety research related to risk factors for transit and priority. The evidence shows that safety effect of priority measures is mixed:-

(a) Only one study on the road safety effects traffic signal priority that was found suggests an increase in accident occurrence; and

(b) Of the eight studies on bus lanes found, five suggest a decrease while the other three pointed to an increase in accident rates (although they all are in unusual or different contexts)

Table 2.8: Summary of Risk Factors in Safety Research on Transit and Priority Measures

Risk Factors	Author											
	Cheung et al. (2008)	Shahla et al. (2009)	Strathman et al. (2010)	Hedelin et al. (1996)	Levinson et al. (2003c)	Booz Allen Hamilton (2006)	Mulley (2010)	LaPlante and Harrington (1984)	Tse et al. (2014)	Cooner and Ranft (2006)	Skowronek et al. (2002)	Elvik et al. (2009)
(A) Transit Priority Features												
Traffic Signal Priority		+										
Bus Lanes					-	-	-	-	-[1]	+[2]	+[2]	+[3]
(B) Transit Service Features												
Bus Stop Density	+	+										
Transit Frequency	+											
Near Side Stops	+											
On Street Parking	+											
Traffic Volume		+										
Pedestrian Volume		+										
Turn Movements		+										
Overtime Shifts			+									
Late Running			+									
Tram Stops				+								
Tracks				+								
Pedestrian Crossings				+								
Darkness				+								
Alcohol				+								
Mixed Traffic					+	+	+					

Source: Author's assessment of the literature
Note: "+" indicates higher accident risk while "-" indicates otherwise

(1) Decrease in fatal, serious and slight injury bus accidents, but increases in fatal and serious accidents in other vehicles found
(2) HOV / Median bus lanes on freeways in the US
(3) Shared with 2-wheelers

2.7 Knowledge Advancement Opportunities

The provision of bus priority measures can be challenging to justify in practice, especially in the North American and Australian contexts where the majority of road travel is by private car and compromises are required between road space and road time uses for private traffic and buses (Black et al., 1992). Methodologies for the justification of bus priority measures have been shown to be weak in identifying the wider benefits of priority schemes (University of Southampton, 2002). Although recent research has started to examine wider impacts like ridership, mode shift, environmental benefits of bus priority schemes (Currie et al., 2007), network-wide benefits of schemes (Mesbah et al., 2008) and more recently cost benefit evaluations for BRT schemes (Chisholm-Smith, 2011), a major issue which has yet to be considered in bus priority planning is the road safety impacts of providing priority schemes.

Of the handful that have studied the safety effects of bus priority measures (listed in **Table 2.8**), only scant knowledge has been added to the field since none have discussed why the association between accident occurrence and the introduction of bus priority measures was found to exist. Clearly this is a field worthy of further research. From an industry perspective, further research in this area provides the opportunity for transit operators and road management authorities to gain a better understanding of the safety effects of bus priority measures on bus drivers and motorists. For the latter, findings from this research could pave the way for more objective decision-making on whether bus priority measures should be implemented.

The review of the safety assessment literature has also revealed that there exists a variety of methodologies to identify the risk factors or establish cause-effect relationships between the treatments applied and accident occurrence. For the latter, different before-after study designs are documented in the literature, with the choice often dictated by the nature of the available dataset. However, an understanding as to how the adoption of different study designs affects road safety effect estimates remains unclear.

Finally, the literature review shows much research has been done on bus safety. Whilst previous studies have provided significant insight into the risk factors for bus accidents, they appear to have fallen short of adequately representing all the traditional safety determinants (i.e. driver, vehicle, roadway and environment factors) when analysing accidents at the accident-level. It was noted that none of the studies have explored how bus priority influences bus drivers' probability of being at-fault in accidents. This is despite the recognition that addressing culpability when analysing accidents is important (Wåhlberg, 2008).

2.8 Summary

In this chapter, a review of the existing literature concerning the latest developments in bus priority, principles and key concepts in road safety research, leading methodologies in the assessment and measurement of road safety, bus safety and safety impacts of transit services and priority was done. The review identified important gaps in existing knowledge and accentuates the need for further research to be done in three areas, which are summarized in **Table 2.9**.

Table 2.9: Existing Knowledge Gaps that Provide Further Research Opportunities

Area	Knowledge Gaps	Research Opportunities
Safety Impacts of Bus Priority	Understanding of bus priority safety impacts is unclear given that previous findings have been mixed Previous studies focused on applications in Europe and America	Investigating the impact of implementing bus priority in Melbourne's context
Assessment and Measurement of Road Safety	Various before-after study designs exist, but the implication of the choice on the safety evaluation is unclear	Exploring the implication of using different before-after study designs in the bus priority safety evaluation
Bus Safety	Previous studies have generally fallen short of adequately representing all the traditional safety determinants (driver, vehicle, roadway and environment) at the accident level The impact of bus priority on bus driver's at-fault probability had not been examined	Examining the effect of bus priority (along with driver, vehicle, roadway and environment factors) on bus drivers' probability of being at-fault in an accident

Based on the research opportunities identified above, the following chapter presents the research objectives that are established to address the knowledge gaps. An outline of the research methodology and details of data used in this research will also be provided.

CHAPTER 3 RESEARCH METHODOLOGY, CONTEXT AND DATA

3.1 Introduction

This chapter lays out the research objectives to address knowledge gaps identified in the literature review. The research methodology adopted to achieve the research objectives are then put forward. This is presented as in the form of a framework as a means to guide research efforts in achieving the objectives. Finally, this chapter presents details of the research context and data before discussing limitations associated with the use of the data.

3.2 Research Objectives

Following the research aim and approach established in section 1.3, five specific objectives were established as follows:

1. Determine the safety effect of bus priority measures in Metropolitan Melbourne on the nature of accidents and crash occurrence;
2. Examine the impact of using different comparison group types in before-after study design on the final road safety estimate;
3. Identify the impact of bus priority in relation to other key risk factors on bus accident frequency at the route-section level and at-fault probability for bus drivers in bus-involved accidents;
4. Investigate the road safety effect of adopting different "space based" bus priority measures on conflicts at selected locations along a road corridor; and
5. Estimate the rear-end crash risk of vehicles that are behind a slowing or stationary bus in mixed traffic as a means to quantify a component of the safety benefit in bus priority schemes that segregate buses from mainstream traffic

3.3 Research Framework

As the research objectives cover different areas in relation to the safety impact of bus priority, a framework was developed to guide research efforts. As shown in **Figure 3.1**, six research components (or tasks) were defined to achieve the objectives as presented in the previous section.

The research context, details of the data source, methodology, key findings that follow for each task will be presented in accordance to this framework on a chapter-by-chapter basis. The following paragraphs provide a brief account of each the six tasks.

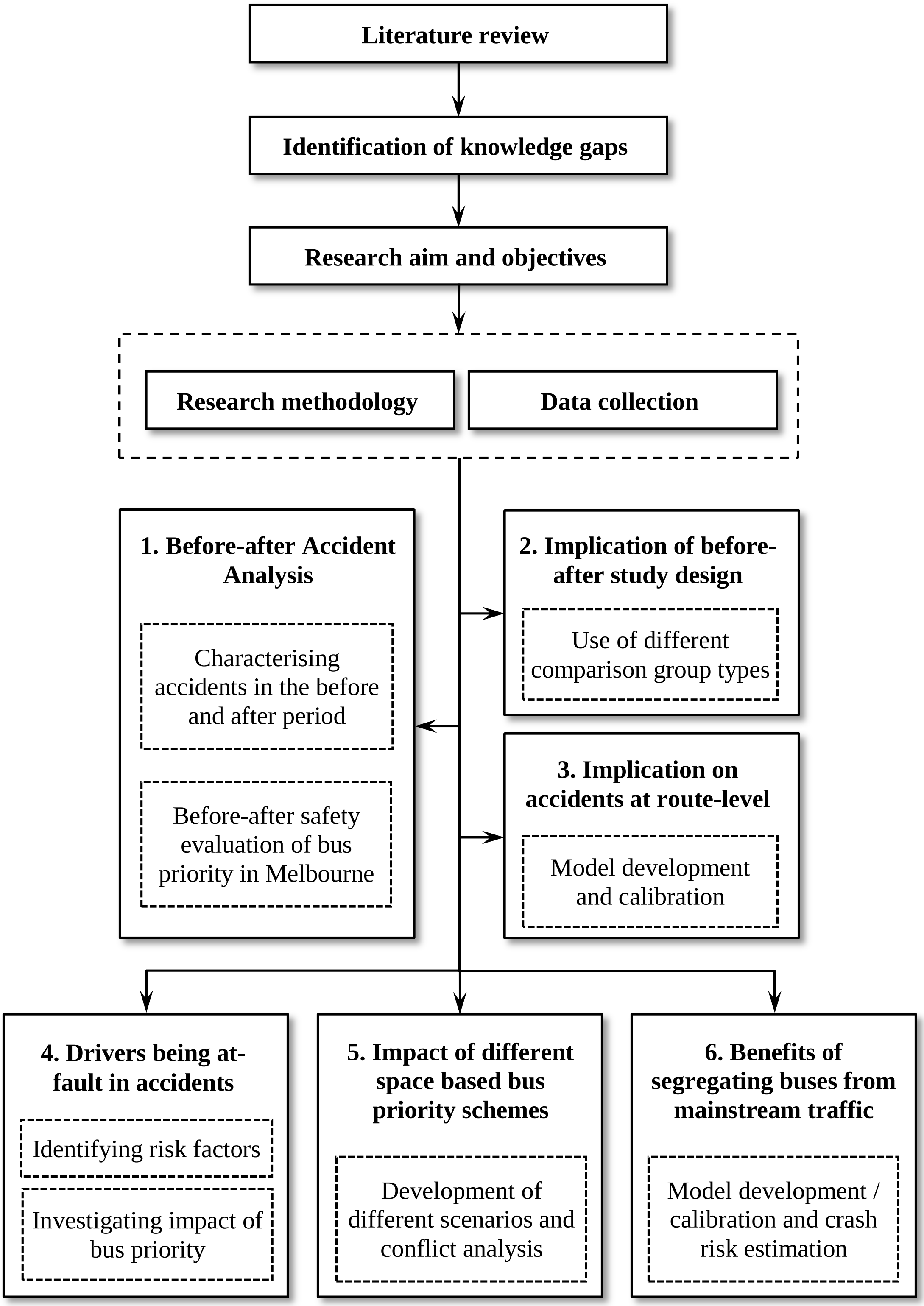


Figure 3.1: Research Framework

The first task of determining the safety effect of bus priority in the Melbourne context was accomplished using a robust before-after analysis based on latest research practice, with the results used to provide a sense of the safety effect of implementing bus priority at the network level. Noting the various before-after study design types in use for road safety evaluation, the second task sought to examine the extent to which the choice of comparison group types affected the safety effect estimate obtained earlier.

To further the understanding of the safety effect of bus priority, the third task focused on accident modelling to identify the risk factors involved in bus-involved accidents and more importantly, determine the effect of bus priority on bus accident frequency. For analytical rigour, different modelling approaches were adopted to allow for a comparison of model performance and results of bus priority effect.

Given that bus priority can be a significant factor in affecting the probability of bus drivers being at-fault in bus-involved accidents, the fourth task aimed to explore its impact in relation to other key risk factors at the accident-level. A model that captured driver, vehicle, roadway and environmental factors that were likely to influence bus drivers' at-fault probability was established and results on the bus priority effect, discussed.

The next (fifth) task focused on understanding the safety effects of different bus priority schemes. Through a case study of a road corridor in Melbourne, the implication of implementing a new bus lane via road space reallocation and space creation was explored using micro-simulation tools. Subsequent analysis was done using the conflict technique and the results comprised a comparison of conflicts across the different schemes.

An obvious benefit in bus priority schemes that segregate buses from mainstream traffic is that rear-end collisions between buses and following vehicles are largely eliminated when slowing down or stopping at bus stops. The goal of the final (sixth) task was to quantify this benefit by estimating the crash risk of vehicles that are behind a slowing or stationary bus at bus stop locations in a mixed traffic configuration. Implications of the findings will be discussed in the context of bus priority planning.

3.4 Research Context – Bus Priority in Melbourne

The focus of this research is on bus priority measures that had been implemented as part of the SmartBus Program in Metropolitan Melbourne, Australia. In Chapters 4 and 5, the aggregate-level analysis and safety evaluation using different before-after study designs were carried out using crash related data from routes in the SmartBus Program.

3.4.1 The Melbourne SmartBus Program

SmartBus was introduced in phases from 2006 to primarily uplift the status of bus routes in metropolitan Melbourne to a level equivalent to metropolitan heavy rail and tram routes in terms of service frequency, hours of operation and quality of passenger information. It has been promoted as a premium bus service that offers more frequent and reliable service for passengers. Part of its service offering includes the provision of real time bus arrival information at selected bus stops (Currie and Delbosc, 2010). The focus in the before-after analysis is on SmartBus routes 900 to 903, where various bus priority treatments had been implemented since 2006 (**Figure 3.2**).

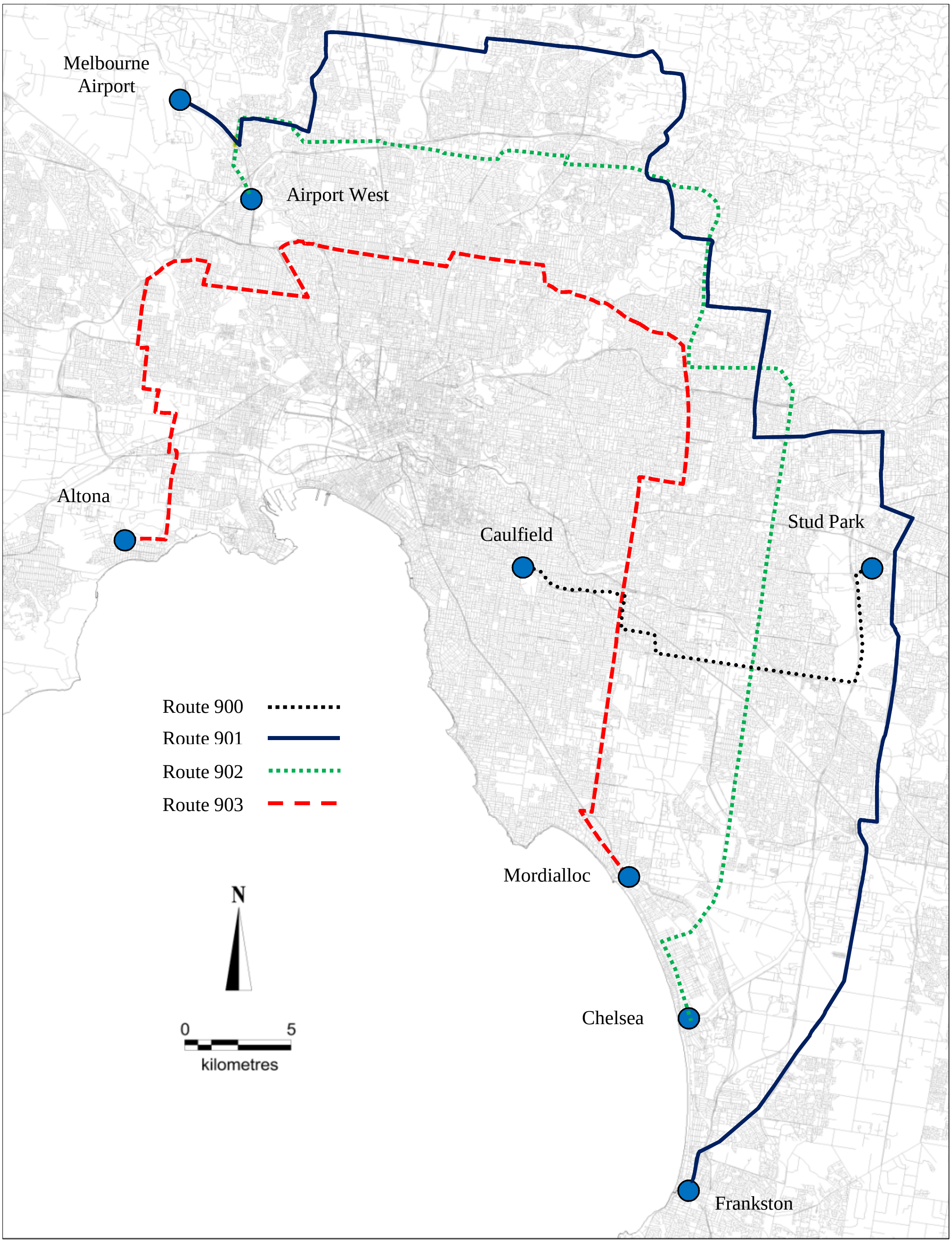


Figure 3.2: SmartBus Routes in Metropolitan Melbourne

As highlighted in section 2.2, there exist various forms of priority measures. The type of priority measures in the SmartBus program falls under one of the two general categories: Traffic Signal Priority (TSP) and non-TSP. TSP treatments for SmartBus involve the use of existing signal control system (Lowrie, 1992), vehicle detection technology and its infrastructure. Active TSP strategies are adopted (Smith et al., 2005), mainly for late-running buses, which involve the use of actuated transit phase ("B" signal) and phase insertion / rotation when the presence of SmartBus is being detected near an intersection.

Non-TSP treatments include clearways and full-time or part-time bus lanes. A potentially important part of the implementation of SmartBus bus lanes is that many have involved adding a new lane to existing roads rather than reallocating existing road space. This includes queue jump lanes at intersections, where an additional lane at the kerbside is carved out for buses' use only, to give buses first priority in clearing the intersection when the lights are in their favour. Also, unlike bus priority systems in Europe, goods vehicles, taxis or 2-wheelers are not permitted in bus lanes in Melbourne. The only exception to this rule is when at signalised intersections and side streets locations, where the Victorian legislation allows for a driver to use up to 100m of the bus lanes to make turns (Australian Transport Council, 2009). **Table 3.1** summarizes details of the bus priority measures implemented in the SmartBus program, while **Figure 3.3** shows an example of a full-time bus lane and queue jump lane in Melbourne.

Table 3.1: Details of Bus Priority Implemented in the SmartBus Program

Form of Treatment	No. of Locations	Types of Measure
Time based (at intersections)	25	Green extension, Red truncation, Phase insertion / deletion, "B" phase
Space based (along road corridors)	31	Bus lanes, clearways, curb extension

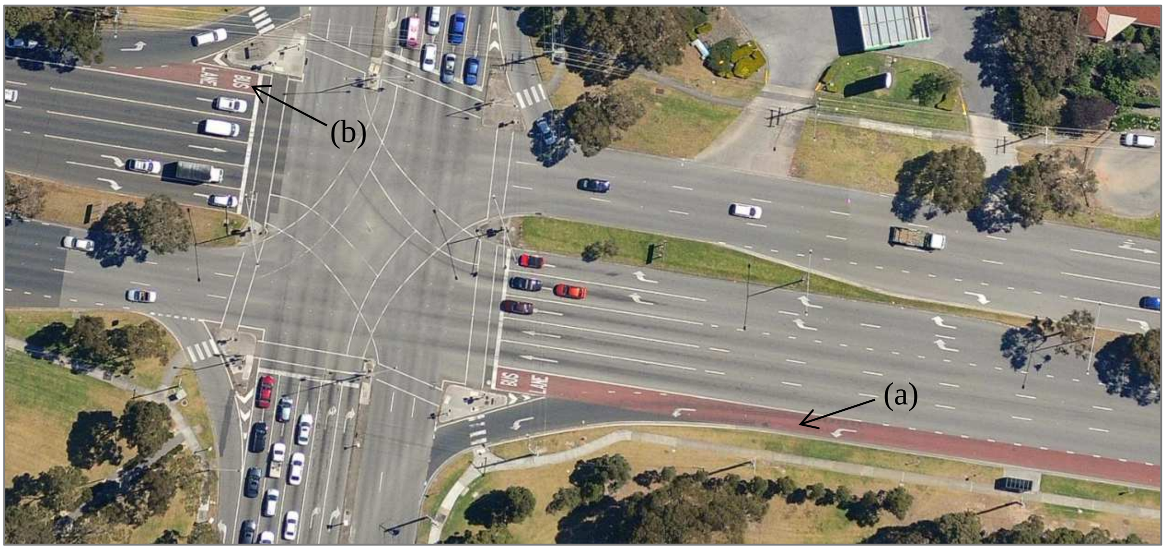


Figure 3.3: (a) Full-Time Bus Lane; (b) Queue Jump Lane in Melbourne **(Source:Nearmap)**

3.5 Research Data

A key challenge that researchers face in road safety research is obtaining quality accident data (challenges and data related issues are discussed further in section 3.6). Because the Victoria Police in Australia frequently do not attend to accidents if no person was injured in the accident and all involved parties have exchanged name and address details (Victoria Police), details of non-injury property damage accidents are not available. Such information though is of significance importance in the context of this research. Given this, data from three other sources (two providing primary data and the final, supplementary data) were obtained for this research:

1. Police records from the Victorian government data directory;
2. Bus accident records from Melbourne's largest bus operator;
3. Video recording of a road corridor; and
4. Traffic Volume from VicRoads (local Road Management Authority in Victoria)

3.5.1 Accident Data from Police records

The first set of data (police records) was obtained from CrashStats (VicRoads, 2012b), which is a crash reporting system developed by VicRoads (the local Road Management Authority in Victoria) and Victoria Police that contains all accidents on roads that involve injury or death but not those where no person was injured or those that involve property damage only. With the aim of assessing the overall road safety impact of bus priority, the focus was therefore on understanding how injury accidents patterns have changed along the SmartBus routes in Melbourne (**Figure 3.2**) where a spate of bus priority measures was implemented since 2006.

In total, there are 56 locations along the SmartBus routes where bus priority measures were implemented. At each location, 3 years' worth of "before" data and at least one year or up to the equivalent 3 years' of "after" data were extracted for the analysis, depending on when the priority measure was implemented. Estimates of Annual Average Daily Traffic (AADT) along the roadway segments and from major and minor approaches of the intersections under study were also extracted for this research. These data were computed based on the traffic volume data collected from the signal control (or SCATS) system (Lowrie, 1992) and records provided by the information system that is maintained by the Traffic Operations Unit of VicRoads, Australia (VicRoads, 2012a). Details on how the AADT is computed are provided in section 3.5.4.

3.5.2 Bus Accident Records

The second set of data comprised bus accident records that were obtained from the Traffic Incident Management System (TIMS) in Ventura Bus and Grenda Transit (both now part of Ventura Group), which were the two largest bus companies in Melbourne at the time of this research. The data from TIMS contained all incidents which occurred between the year 2000 and 2011 that were captured for the purpose of insurance claims settlement. In the event of an incident that results in damages, bus drivers from both companies have the responsibility of filling out and submitting an incident report to the incident management team. This not only includes traffic accidents, but also any event that results in injury to commuters, road users, damage to buses, road furniture, physical objects and arguments with passengers, for example. Each incident report is reviewed by officers from the bus company's incident management team and adjusters from the insurance company. Often, these reports are supplemented with pictures of the damage the buses sustained. An assessment on whether the driver is at-fault, that is assigned to hold primary responsibility for the incident occurrence, is typically made with the aid of pictures and video recordings captured from CCTV installed in buses.

In this research, additional information relating to the driver, vehicle, roadway and environment at the time of the accident was also obtained from Ventura Bus and Grenda Transit's human resource database. These include the driver's length of service / gender, age / accident record, bus length / age and road / traffic conditions.

3.5.3 Traffic data along a Road Corridor

The third set of data came from video recording of a road corridor segment in Melbourne for a case study in this research. The road segment of interest (Blackburn Road) was selected as it was deemed to be representative of a major arterial (three-lane divided road) in Melbourne. At a length of 1.6km, it comprises four intersections, operates in a mixed traffic configuration with a speed limit of 70kph and do not have priority measures for buses.

The video equipment needed for the recording (**Figure 3.4**) comprise a purpose-built steel frame and video surveillance camera (mounted at the top level of a thirteen storey building) and a computer server for video data storage. The camera was set up to capture traffic movements along a segment of Blackburn Road (3-lane carriageway) from Normanby to Ferntree Gully Road. Section 8.4 provides further details of Blackburn Road.

Figure 3.4: Equipment for Video Recording of Traffic on Blackburn Road

3.5.4 Traffic Volume Data

Traffic volume in the form of Annual Average Daily Traffic (AADT) was collected with the aim of developing micro-simulation models and accident models that are based on traffic volume. These data were obtained from the SCATS and information systems maintained by VicRoads. The month from which the data was extracted was chosen to be at the mid-point of the 1-year period. For instance, if the 1 year period spans from January to December, then traffic volume for the month of June would be obtained for the purpose of computing the AADT for that 1-year period.

Due to faulty loop detectors on site or road works on certain days, a small proportion of traffic volume data captured by SCATS were incomplete for the month of interest. To overcome this issue of missing data, relevant conversion factors provided in the *Transfund New Zealand Research Report 2005 – Guide to Estimation and Monitoring of Traffic Counting and Traffic Growth* (Traffic Design Group, 2001) were used to estimate the AADT. **Table 3.2** presents the approach in obtaining and computing the AADT for this research.

Table 3.2: Approach in Computing Annual Average Daily Traffic (AADT)

Scenario	Data Availability	Computation of AADT
1	Complete with no missing data	Average daily traffic for a selected week multiplied by the relevant week factor
2	Incomplete with missing data on certain days	Average daily traffic volume for a selected day (with complete data) multiplied by the relevant day factor

3.6 Data Limitations

It is widely accepted that data from accident records provide a good indicator of the safety performance or problems for the road under study. However, there exist limitations and drawbacks in the use of such data.

According to Elvik et al. (2009), the two main problems associated with the use of recorded number of accidents to estimate safety is under-reporting of accidents and random variation in the recorded accident numbers. Results from one study found that reporting of injuries in official accident statistics is incomplete at all levels of injury severity (Elvik and Mysen, 1999). Reporting levels were found to vary substantially among countries, ranging from 21 to 88 percent for hospital-treated injuries. Reporting was also highest for car occupants and lowest for cyclists. Single-vehicle bicycle accidents in particular were also found to be very rarely reported in official road accident statistics (Elvik and Mysen, 1999).

For bus accidents, White et al. (1995) and Brenac and Clabaux (2005) observed that under-reporting could be more pronounced with a greater proportion of single-vehicle non-collision accidents, involving injury sustained to occupants on-board a bus. In France, it was found that bus occupant injury accounted for 0.76% of hospital outpatients and inpatients injured in road traffic accidents, whereas police data showed that bus occupants accounted for only 0.58% of the injured (Brenac and Clabaux, 2005). James (1991) found that accidents involving children, pedal cyclists, pedestrians and minor injury were all substantially under-reported.

The second issue raised by Elvik et al. (2009) relates to biases in reporting and arising from missing or incomplete data. The former can be attributed to the regulation covering the reporting of accidents, as the reporting criteria are likely to vary between jurisdictions. The Victoria Police in Australia, for instance, do not record accidents in their database if no person was injured in the accident and all involved parties have exchanged name and address details. Details of such accidents and those involving property damage are therefore not available in the official database. With property damage accidents typically constituting the bulk of all accidents, the accident picture is incomplete and this means a comparison of accident experience across countries or jurisdiction is often not possible.

In using the at-fault data provided by Ventura Bus and Grenda Transit, it is acknowledged that the at-fault assessment might not have considered the fact that crashes are multi-causal and interaction between the driver and other of the road system. It is likely that the occurrence of a crash might not be due solely to the ‘failure’ of the driver, but rather the inability of the rest of the system to provide a suitable operating environment within which the driver should reasonably be expected to operate. The road system could have also presented an inappropriately complicated situation to the driver. Such "system deficiencies" might not be obvious when being judged by an insurance adjuster or bus company manager.

Missing or incomplete data, which is not uncommon in accident records, could result when a police officer did not record a particular factor in an accident because he/she was not aware of its presence, not been able to find out if it was present or did not think it was important. Police officers who complete the accident forms are also often general duties police and have little or no training in accident analysis or causation. These factors contribute to the likelihood that important information are being left out and subsequent analysis results could therefore be biased (Ogden, 1996).

3.7 Summary

In this chapter, the research objectives to fill the existing knowledge gaps identified in the previous chapter were presented. The research methodology that had been proposed to achieve the research objectives encompassed a wide range of areas related to bus priority. As such, a framework that sets out the key tasks needed to address the objectives was established to ensure a structured approach was adopted for the research.

The first task focused on assessing the overall road safety impact of bus priority measures implemented in Metropolitan Melbourne. In so doing, a secondary aim was to understand how the selection of different before-after study designs affected the safety estimate for bus priority. The next tasks aimed to explore whether bus priority had an impact on accidents at the route level and probability of bus drivers being at-fault in bus-involved accidents. Following this, the road safety impact of adopting different space based bus priority was investigated using micro-simulation tools. The final task entailed an estimation of crash risk for vehicles behind a slowing or stationary bus in mixed traffic, which provided a sense of the extent of safety benefit in bus priority schemes that segregate buses from mainstream traffic.

The data used in this research came from three key sources: (1) Police records from the Victorian government data directory; (2) Bus accident records from Melbourne's largest bus operators and (3) Video recording of a case study road corridor. Using bus accident and actual traffic flow movement data allowed limitations associated with the use of crash data alone to be overcome and impact of bus priority to be studied from different perspectives. The fourth source (from SCATS and information system maintained by VicRoads) provided traffic volume data which allowed for the computation of AADT. This data was important in the before-after safety evaluation where a comparison group was needed (Chapter 4) and development of a micro-simulation model to assess the safety impacts of different space based bus priority (Chapter 8).

PART II:
AGGREGATE-LEVEL ANALYSIS

CHAPTER 4 NETWORK LEVEL BEFORE-AFTER ACCIDENT ANALYSIS

4.1 Introduction

This chapter aims to further an understanding of the safety implication of bus priority with focus on those the system implemented in the Melbourne SmartBus Program (refer to section 3.4.1 for details).

As highlighted in section 2.6, an understanding of the safety implications of transit and bus priority remains unclear given that research in this area has been limited and that more importantly, results from previous studies have been mixed. Given that these studies covered bus priority from a variety of cities / countries, it is likely the mixed results were due to differences in driving behaviour and bus priority designs.

The chapter starts with an exploration of general trends in accident changes using a robust before-after crash count analysis. This is followed by a safety review and accident type analysis where the occurrence frequency of different accident and safety impacts of road configuration changes on road safety performance are investigated. It concludes with a discussion on implications of findings.

The bulk of the work presented in this chapter originated in the research paper Goh, K., Currie, G., Sarvi, M. & Logan, D (2013). Road Safety Benefits from Bus Priority. *Transportation Research Record - Journal of the Transportation Research Board*, 2352, 41-49.

4.2 Before-After Analysis Approach

There exist several before-after methodologies available for safety evaluation involving crash count analysis (section 2.4.2). This chapter focuses on an examination of accident statistics and use of the Empirical Bayes (EB) method for the before-after analysis, as the latter addresses many of the short-comings of the traditional before-after method. Its methodology is considered rigorous and its key strength lies primarily in its ability to account for regression to the mean (RTM) effects. RTM is considered to be minimal in this study as the selection of sites was unlikely to be based on their accident records, however it was still adopted to achieve better accuracy in the final results (Hauer, 1997).

The key element in the EB method is the development of a safety performance function (SPF), which acts to predict how well the treated sites would perform in terms of crash counts had the priority measures not been implemented. The SPF is used along with the observed crash counts at treatment sites to predict the expected crash number and in so doing, RTM effects are accounted for. Previous studies have demonstrated that traffic volume is an important casual factor in crash count prediction (Hadayeghi et al., 2003, Miaou and Lum, 1993, Sawalha and Sayed, 2001). In this study, the SPFs were developed as follows:

For intersections:

$$E(A) = \alpha_0 \times Q_1^{\beta_1} \times Q_2^{\beta_2} \tag{4.1}$$

For roadway segments:

$$E(A) = \alpha_0 \times Q_0^{\beta_1} \times L^{\beta_2} \tag{4.2}$$

where $E(A)$ = Predicted crash count per year;

$\alpha_0, \beta_1, \beta_2$ = Model parameters estimated in STATA;

Q_0 = Annual Average Daily Traffic (AADT) along the roadway segment;

Q_1 = AADT from the major approach of an intersection;

Q_2 = AADT from the minor approach of an intersection;

L = Length of roadway segment

The models were assumed to take on a negative binomial structure, which is a common practice adopted by most researchers to account for crash counts which are non-negative, random, infrequent and thus prone to over-dispersion. The variable coefficients and over-dispersion parameter were estimated using maximum likelihood techniques in the STATA statistical software (STATA, 2005). The R_α^2 as proposed by Miaou et al. (1996) was used to assess the model's goodness-of-fit given that the R^2 value found in OLS regression is not a good measure for negative binomial regression models:

$$R_\alpha^2 = 1 - \frac{\kappa}{1 + \kappa_{\max}} \tag{4.3}$$

where κ = Over-dispersion parameter in the final model; and

κ_{max} = Over-dispersion parameter in the base model with only a constant term

A likelihood ratio test that the over-dispersion is equal to zero was carried as a means to check the suitability of using the negative binomial model. A high chi-squared value would indicate that the negative binomial model is more appropriate than the Poisson model. As part of the procedure, Crash Modification Factors (CMFs) from previous studies in the U.S. and Europe (Gross and Jovanis, 2007, Elvik et al., 2009) were used to account for sites that had unique road characteristics, e.g. significantly narrower lane widths were implemented along with the bus priority measures along one of the road corridors, bicycle lanes were incorporated at a number of intersections. Arguably, these factors might not have been appropriate for use in Melbourne's context, but they were used nonetheless as they the only reliable source available.

The remaining steps were taken in accordance to the procedure outlined in the Highway Safety Manual (2010), with the eventual safety effect of implementing bus priority measures computed as:

$$\text{Safety Effect, } \theta = 100 \times (1 - OR) \tag{4.4}$$

where OR (odds ratio) represents the unbiased safety effect of bus priority measure. A detailed description of the EB methodology is provided in **Appendix A**.

4.3 Safety Review and Accident Type Analysis

Safety review or audits are widely recognised to be an important component of the overall project planning and delivery process. Kar and Blankenship (2010) have demonstrated that proper safety risk assessments or audits can help identify safety issues before a crash occurs. In this chapter, a safety review was carried out with the aim of identifying safety impacts of road configuration changes associated with the implementation of bus priority measures. The process involved an examination of construction plans and site visits to better understand the prevailing road and traffic conditions. Following the identification of each potential safety hazard, an assessment of the risk level was carried out. This was done by establishing the likelihood of an accident based on the anticipated frequency and level of severity. This risk assessment approach, detailed in **Appendix B**, is largely similar to that adopted in Australia and U.S. (AustRoads, 2009b, Synectics Transportation Consultants Inc. et al., 2006).

In the accident type analysis, an individual assessment of each accident record was first undertaken to determine whether it could have been related to bus priority. An attempt was then made to hypothesize positive and negative safety effects of implementing bus priority measures based on this analysis. To avoid subjectivity in the analysis, only factual information from the police reports was used with those relating to fault apportionment disregarded. This analysis also examined changes in accident records by type of accident class to provide more in depth consideration of how accidents were changing.

4.4 Results of Before-After Analyses

4.4.1 Accident Statistics

Table 4.1 shows the breakdown of accident statistics for a one year period before and after bus priority measures were implemented. Overall, accident numbers fell from 116 in the before period to 95 in the after period (an 18% reduction). The number of Fatal and Serious Accidents dropped from 42 to 29, a decline of 31%. This reduction was found to be statistically significant at the 20% level when the Wilcoxon Signed Rank Test (WSRT) was employed, a noteworthy result as the WSRT is known to be conservative.

Table 4.1: Severity, Type of and Vehicles Involved in Accidents (CrashStats, Melbourne)

Period	Severity			Accident Type			Vehicle Type		
	Fatal	Serious	Other[a]	Vehicle	Pedestrian	Other[b]	Cars	M/C[c]	HGV[d]
Before	3	39	74	100	6	10	223	16	13
		Total = 116			Total = 116			Total = 252	
After	0	29	66	78	9	8	165	8	10
		Total = 95			Total = 95			Total = 183	
Change	-3	-10	-8	-22	3	-2	-58	-8	-3
%Change	-100%	-26%	-11%	-22%	50%	-20%	-26%	-50%	-23%

Just as noteworthy was the observation that no fatal accidents had occurred in the “after” period, compared to an average of 3 in the “before” period. In general accident type (vehicle, pedestrian, other) and vehicle type (cars, motor cycle and heavy goods vehicle) associated with accidents remained relatively constant in the before and after period.

4.4.2 Results of Empirical Bayes Analysis

Table 4.2 presents the parameter estimates for the crash count models at intersections and roadway segments. The base model served to provide a means for measuring the goodness-of-fit for the final model, which performed the role of safety performance functions that are central in the EB procedure. Results of the likelihood ratio test showed that values of the over-dispersion parameter for the final models are non-zero and therefore, the negative binomial model was more appropriate than the Poisson model.

Table 4.3 shows the before-after results when the EB method was applied to estimate the overall safety effect of implementing TSP and non-TSP treatments at intersections and road corridors respectively.

At sites where only TSP measures were implemented, the odds ratio of 0.889 with a standard error (S.E.) of 0.11 was recorded. On the other hand, the value worked out to be 0.818 (with a S.E. of 0.12) at sites where only non-TSP measures were applied. Introducing non-TSP priority measures yielded a positive safety effect which is in line with findings from previous safety research (LaPlante and Harrington, 1984). A possible reason for this is that the introduction of bus priority had caused a reduction in space

[a] Light or no injury
[b] All other accidents including striking animals or objects
[c] M/C – Motorcycles including moped vehicle and bicycles
[d] *HGV – Heavy Goods Vehicle, including utility, vans, semi-trailers, trucks, buses and coaches*

available for the other modes of transport. Given this, it implies that the frequency of lane changing, travelling speed and hence the risk of collisions should drop. The finding that accident severity levels had reduced appears to support this point. When all locations were considered, an odds ratio of 0.86 with a S.E. of 0.08 was recorded. With the application of a t-test, this was found to be statistically significant at the 10% level. Assuming all other causal effects had been accounted for, it implied that the introduction of bus priority measures had resulted in an overall reduction of about 14% in accident counts.

Table 4.2: Results of Crash Count Models

Parameter	Final Model		Base Model	
	Estimate	P-Value	Estimate	P-Value
Intersections: $E(A) = \alpha_0 \times Q_1^{\beta_1} \times Q_2^{\beta_2}$				
4-Legged Intersection				
$\ln(\alpha_0)$	-8.347	0.000	0.920	0.000
β_1	0.355	0.019	-	-
β_2	0.578	0.000	-	-
Dispersion parameter, α	0.111		0.285	
Chi-squared value, χ^2	6.39		28.49	
Probability > χ^2	0.006		0.000	
R_α^2	0.611		-	
3-Legged Intersection				
$\ln(\alpha_0)$	-11.267	0.006	-0.135	0.000
β_1	0.622	0.084	-	
β_2	0.558	0.001	-	
Dispersion parameter, α	0.177		0.417	
Chi-squared value, χ^2	0.92		3.69	
Probability > χ^2	0.169		0.027	
R_α^2	0.576		-	
Road Corridors: $E(A) = \alpha_0 \times Q_0^{\beta_1} \times L^{\beta_2}$				
$\ln(\alpha_0)$	-15.29	0.000	0.564	0.000
β_1	0.868	0.000	-	-
β_2	0.988	0.000	-	-
Dispersion parameter, α	0.236		0.980	
Chi-squared value, χ^2	8.97		55.7	
Probability > χ^2	0.001		0.000	
R_α^2	0.759		-	

Table 4.3: Results of EB Before-After Analysis

Parameter	Types of Treatments		
	Non-TSP	TSP	Overall
Number of Locations	25	31	56
Total observed crash counts in the “after” period	66	94	160
Expected crash counts in the “after” period	80.29	105.38	185.7
OR’	0.822	0.892	0.862
OR	0.818	0.889	0.860
SE(OR)	0.12	0.11	0.08
Safety Effect, θ	18.2%	11.1%	14.0%*

Note: OR’ is the biased odds ratio (due to taking the ratio of random variables)
** denotes significance at 10% level*

A noteworthy finding is that non-TSP treatments had yielded a stronger positive safety effect compared to TSP treatments (18.2% compared to 11.1%). Although no scientific explanation can be offered at this stage, one plausible reason is that non-TSP measures involving road space reallocation along road corridors had produced a greater effect on reducing travelling speed for the general traffic compared to non-TSP measures at intersections.

It is interesting to note that findings on TSP measures in this study are opposite to those by Shahla et al. (2009), who examined transit safety at intersections in Toronto, Canada. The lower bus frequency and pedestrian volume in Melbourne, especially along routes 901 to 903, could be reasons why the introduction of TSP had not led to an increase in accident occurrence.

4.5 Safety Review Findings

Table 4.4 presents the safety review findings for the road corridors and junctions pre- and post-implementation of bus priority measures (risk category assignments are provided in **Appendix B**), while **Table 4.5** captures the findings summary in terms of the risk categories and implementation stage. For the latter, results show that more safety hazards were identified in the post-implementation as compared to the pre-implementation stage (6 vs. 4). However, the number of intolerable hazards was fewer (2 vs. 3).

Table 4.4: Safety Review Findings

No.	Safety Hazard	Risk Category
Pre-Implementation		
1	At locations without bus bays, the risk of rear end collision increases when buses slows down or make sudden stops for commuters at bus stops	Intolerable
2	Inadequate intersection sight distance raises the risk of side collisions as motorists from a side street would not have a good field of vision to check for traffic	Intolerable
3	At locations where bus bays are provided, buses run the risk of side-swipe collisions when attempting to merge with the main traffic	Undesirable
4	Any inadequate clear zones on the side-table raise the risk of motorists colliding into roadside objects if they veer off-path	Intolerable
Post-Implementation		
5	The introduction of an additional lane for buses would mean pedestrians need extra time to cross the road	Intolerable
6	Motorists may resort to illegal use of bus lanes to beat the heavy traffic during peak hours	Undesirable
7	The operational hours and use of red pavements for bus lanes are not consistent across sites, which could lead to confusion for motorists	Tolerable
8	At locations where bus lanes end, buses run the risk of side-swipe collision if there is insufficient length for merging	Undesirable
9	The introduction of bus lanes raises the risk of side-impact collisions involving buses at locations where vehicles enter or exit side streets	Intolerable
10	At large intersections, buses may not be able to clear the intersection in time if the length of the “B” phase duration is insufficient	Undesirable

Table 4.5: Summary of Safety Review Findings

Risk Category	Number of Hazards Identified	
	Pre-Implementation	Post-Implementation
Intolerable	3	2
Undesirable	1	3
Tolerable	0	1
Acceptable	0	0
TOTAL	4	6

In the pre-implementation stage, the key intolerable safety hazards identified were mainly at bus stop locations as buses run the risk of being hit in the rear when slowing down at bus stops. Where bus bays are provided, there is risk of side-collisions when buses attempt to merge with the main traffic stream. Locations with inadequate clear zones on the side-table were another safety concern as motorists risk colliding with road side objects when they veer off-path. Two intolerable hazards were identified in the post-implementation stage. The first relates to pedestrians, as the addition of a new lane for buses would mean pedestrians would require a longer time to cross the road. The other hazard is due to the increased interaction between buses and other vehicles at the locations of side streets. This is because motorists would have to weave through bus lanes when entering and exiting side streets.

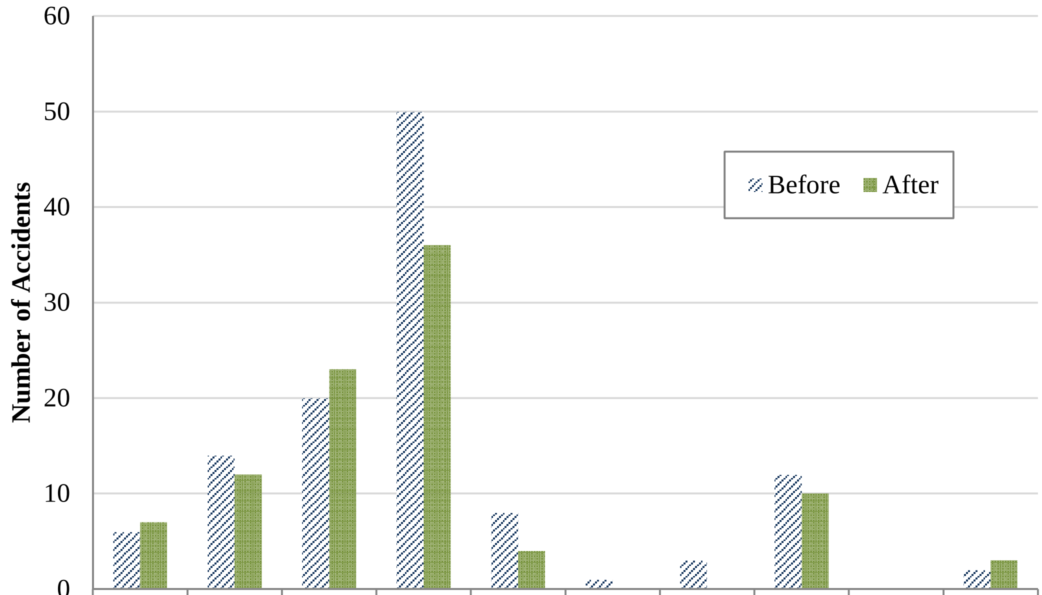
4.6 Accident Type Analysis

Figure 4.1 presents a breakdown of all accidents by type and FSI accidents respectively according to Definition of Coding Accidents (AustRoads, 2009b) classification in the year before and after implementation of bus priority measures. The top figure shows all accidents while the bottom shows only the fatal and serious accidents (the major priority concern for research of this type).

The key observations recorded are:

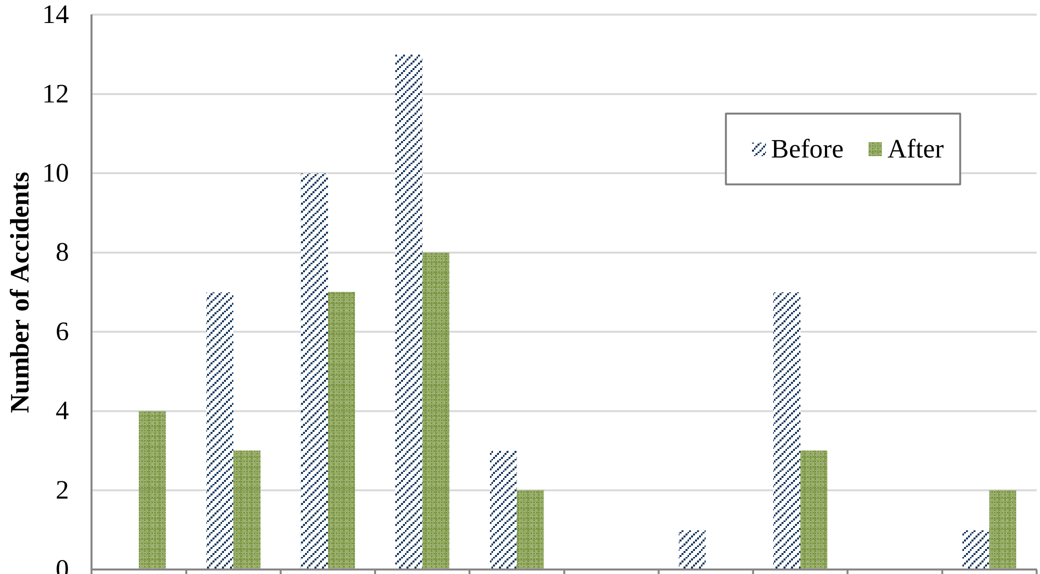
- ✓ Overall accidents numbers fell across the board, except for pedestrian related (types 10x and 19x) and those involving vehicles from opposing directions. A similar pattern was recorded for FSI accidents, i.e. numbers in all accident types registered a fall except for pedestrian related ones;
- ✓ The number of pedestrian-related accidents (in types 10x and 19x) rose from 6 to 9 (50% increase). No bus-related accidents were recorded pre-implementation. However, there were 3 post-implementation of which 2 involved passengers being hurt when the buses braked hard to avoid colliding with another vehicle;
- ✓ Rear end collisions, which formed the bulk of type 13x accidents, registered a 23% drop (from 35 to 27). A noteworthy pre-implementation case was that of a car running into the rear of a bus that had slowed down for passengers at a bus stop;
- ✓ The number of accidents at locations of side streets, which accounts for half of type 14x accidents, fell from 4 to 2 (50% reduction). On closer inspection, the 2 post-implementation accidents took place just prior to the start of bus lanes. As such, one could state that no such accidents took place at locations with bus lanes in the post-implementation period;

(A) All Accidents



	10x	11x	12x	13x	14x	15x	16x	17x	18x	19x
Before	6	14	20	50	8	1	3	12	0	2
After	7	12	23	36	4	0	0	10	0	3

(B) Fatal and Serious Accidents Only



	10x	11x	12x	13x	14x	15x	16x	17x	18x	19x
Before	0	7	10	13	3	0	1	7	0	1
After	4	3	7	8	2*	0	0*	3	0	2

Note: 11x: Types 110 to 119 - Vehicles from adjacent directions
12x: Types 120 to 129 - Vehicles from opposing directions
13x: Types 130 to 139 - Vehicles from same directions
14x: Types 140 to 149 – Vehicle/s manoeuvring
16x: Types 160 to 169 – On path
17x: Types 170 to 179 – Off path on straight
18x: Types 180 to 189 – Off path on curve
19x: Types 190 to 199 – Passengers and Miscellaneous
** indicates significance at 10% level (when referenced against group of 69 sites)*

Figure 4.1: Accident Occurrence by Type (Before and After Priority on p.a. basis)

- ✓ The number of type 16x accidents, all of which involved vehicles in the kerbside lane, dropped from 3 to 0 (100% reduction); and
- ✓ The number of off-paths accidents that involved drivers veering off the slow lane, mounting the roadside kerb and hitting road furniture or trees on the side-table (types 17x and 18x), fell from 6 to 2 (66% reduction).

The analysis suggests that the outcomes of four pre-implementation accidents could have been different had there been bus priority:

- ✓ The first was a collision between a right-turning vehicle and an on-coming bus at an intersection. This may have been mitigated had there been a bus-only phase (present in the after case);
- ✓ The second took place at a merging point of 2 kerbside lanes located just prior to a road intersection, where a truck ran into the rear of a car that had just merged and slowed to stop at the intersection. This could have been avoided had there been bus priority in the form of queue jump lane (available in the after case) as its presence would mean the merging point would be further upstream, allowing drivers to react better to merging and stopping vehicles;
- ✓ The third was a case of a car hitting the rear of a bus when the latter slowed down to call at a bus stop. This may not have occurred had there been an exclusive bus lane (available in the after case); and
- ✓ The fourth involved a car hitting a motorcyclist when entering from a side street. A bus lane (available in the after case) may have mitigated this accident as it would provide the driver better intersection sight distance and longer manoeuvre distance to avoid a collision.

The outcomes of 3 post-implementation accidents could also have been related to the presence of bus priority measures:

- ✓ In the first accident, a right-turning car collided with a taxi that was travelling in an operational bus lane; and
- ✓ Similarly, the second and third accidents were cases of vehicles colliding with cars travelling in the bus lane.

Arguably, these post-implementation accidents should not have happened as private vehicles or taxis are not permitted in operational bus lanes. However, the background as to why these vehicles were present was not available in the police report and hence no judgement can be made on whether any traffic violation had taken place.

4.7 Implications of Findings

Findings from the before-after accident analyses indicated that there is an overall positive road safety impact of bus priority. Results showed that there are major reductions in accidents that are associated with reduced on-path and off-path incidents. It appeared that bus lanes act as an additional clear zone reducing vehicle collisions with roadside objects while improving vehicle interactions with vehicles leaving and emerging from side roads. Given that decelerating or stationary buses can cause rear end accidents, the provision of bus lanes would bring positive safety benefits as such traffic interactions (and thus risk of rear end crashes) are largely eliminated. Bus lanes also appeared to be acting to improve sight distances for traffic at un-signalised intersections resulting in a reduction in the number of side collisions. A third possible positive effect, although not evident in the results, is that traffic speeds had dropped on stretches where road space allocation was implemented. This can act to lower accident risk since speed is known to be major accident risk factor.

The results also showed that there were some negative impacts. The main concern was at side street locations in the after case. Here motorists entering / exiting side streets tend to expect only buses to use bus lanes but can be caught unawares when other vehicles use bus lanes. Weaving movements were also a potential hazard issue; buses have to contend with cars filtering in and out of the bus lanes to enter or exit side streets. This may also be a potential cause for concern. There was also a small rise in pedestrian related incidents in the after case. It is unclear why this was so from the available records. These types of incidents tend to be more serious so are worthy of closer examination in future research.

4.8 Conclusion

In this chapter, an exploration of the safety impacts of bus priority schemes in Melbourne was undertaken. Previous research is limited in this area and suggests mixed outcomes. Before-after analyses were carried out based on accident statistics and use of the Empirical Bayes before-after approach (to account for statistical effects). A safety review of road design changes and detailed investigation of the impacts of priority on accident type records were also carried out in this chapter.

The Empirical Bayes results showed that the implementation of bus priority treatments led to a 14% reduction in accidents (after taking into regression to the mean effects). Non-Traffic Signal Priority treatments (mainly bus lanes) yielded a stronger positive safety effect (18.2%) compared to TSP treatments (11.1%). Importantly the number of Fatal and Serious Incidents dropped considerably from 42p.a. to 29p.a. (significant at the 80% using the rigorous WSRT test).

The safety review findings revealed a reduction in intolerable accidents risks and some concerns in the 'after' situation for interaction of buses and traffic at bus lane setbacks as well as increasing pedestrian road crossing distances due to the introduction of bus lanes. The analysis of accident type changes however suggested that bus lanes act as an additional clear zone, reducing vehicle collisions with roadside objects and reducing vehicle interactions with vehicles entering and emerging from side roads. Removing stopping buses from the traffic stream into bus lanes was also shown to reduce vehicle accidents, while bus lane treatments were also thought to increase sight distances at un-signalised intersections acting to reduce side vehicle accidents. Some treatments were also thought to increase traffic density acting to slow traffic creating safety benefits.

These findings are quite exciting, since not only are they statistically robust, but they also suggest an entirely new perspective on planning for bus priority measures is warranted. Road safety impacts of this scale are very important and suggest merits for priority schemes far beyond the conventional approaches adopted to justify them (based mainly on travel time savings). These findings suggest a new and important area for research for bus priority; road safety impacts and how to encourage positive outcomes. They also pave the way for further research to better understand the reasons for patterns of safety impact identified in this research. For example, it had been suggested that non-TSP measures produced a greater safety effect as it results in greater reduction in travelling speed compared to TSP measures. Accident analysis results also gave rise to a number of hypotheses on the safety effects of bus priority measures, which could be explored further as part of future research efforts.

Results from the analyses done also raised a number of questions concerning the validity of the findings. Firstly, the question on how Melbourne's experience of bus lanes compares with bus priority in other context contexts arises. Is the Melbourne experience of bus lanes different? Secondly, the safety effect estimate for bus priority was obtained using the Empirical Bayes safety evaluation, where the use of a large reference group was a key step taken to establish the safety performance of roads that are representative of the study sites in Melbourne. This then raises the question on whether choosing an alternative (and equally robust) before-after methodology would have affected the safety estimate result.

It is difficult to provide an answer for the first question because of the lack of equivalent studies of this type. The SmartBus context is also sub-urban, rather than inner city, hence the density of traffic interactions and pedestrian flows are likely to be lower compared to inner city settings. The unusual feature of the Melbourne experience where roads are typically widened to provide bus lanes also adds to the difficulty in answering this question. Finding the answer to the second question is comparatively easier, as this can be explored further with the use of an alternative approach (on the same dataset) to compute the safety estimate. It is with this in mind that the stage for the following chapter is set.

CHAPTER 5 IMPLICATIONS OF COMPARISON GROUP TYPE IN SAFETY EVALUATION

5.1 Introduction

Observational before-after studies are commonly employed in evaluating the safety effect of a specific road / traffic management measure (or treatment). Various study designs exist in mainstream research and practice. These include the Comparison-Group (CG), Empirical Bayes (EB) and Full Bayes (FB) methods (Gross et al., 2010, Highway Safety Manual, 2010). Amongst these, the EB and CG methods are likely to be common choices for practitioners given the complexity involved in the FB approach (Persaud and Lyon, 2007).

Both the EB and CG methods utilise crash records from reference (or comparison) sites to provide a safety effect estimate of a specific treatment that has been applied at a single or multiple treated sites. In theory, reference sites are assumed to be, apart from the treatment itself, similar to the treated sites. In reality, however, it is likely that a few of the treated sites possess unique geometrical / traffic features such as narrower lanes and bicycle lanes, which, if not properly accounted for, could affect the final safety effectiveness or crash modification factor estimate of the treatment. The EB methodology based on a large comparison group allows for such crash-related attributes to be controlled through the use of relevant crash modification factors[e] (CMFs). However, CMF values are often not readily obtainable in practice. For those available in the literature, it is likely that they would either not be applicable or have a different magnitude in the study context. This limitation can be overcome by using the CG method based on small match comparison group because reference sites could be selected such that they only differ by the treatment itself. However, the need for adequate matching of crash frequencies and comparability between treated and comparison sites are key issues that have to be addressed. Regression to the mean (RTM) effects are also typically not accounted for in the CG method.

Given the pros and cons associated with each approach, this chapter aims to explore the implications of adopting different study designs based on the EB and CG methods in road safety evaluation. It starts with a review of the EB and CG approach, in which key considerations in choosing between the two procedures are highlighted. Following this, an alternative approach that combines both the EB and CG methods is proposed. All

[e] *This is in line with section 10-7 of the Highway Safety Manual (2010), which states "CMFs are used to adjust the SPF estimate of predicted average crash frequency for the effect of individual geometric design and traffic control features".*

three approaches are then applied in a case study on bus priority. Finally, the chapter concludes with discussion of results in terms of implications in adopting different study designs and potential of adopting the combined EB-CG approach to compute safety effect estimates.

5.2 Research Context

The EB and CG methodologies have been applied in several observational before-after studies to identify the safety effects brought about by specific road / traffic management measures (or treatments) applied to roadway sites (Fayish and Gross, 2010, Garber et al., 2006, Griffith, 1999, Persaud et al., 2001). The theories behind the EB and CG methods are now well accepted in mainstream research and have also recently been incorporated in the Highway Safety Manual (2010). In recent years, there has been much development in the use of Full Bayes (FB) method, which can also account for spatial correlations between treated and comparison sites. Although findings from previous studies have shown that the FB method yields smaller standard errors, they have also indicated that its treatment effect estimates are largely comparable to those computed from the EB method (Lan et al., 2009, Miaou and Lord, 2003, Persaud et al., 2010). Given the high level of statistical training required in the application of the FB method (as its methodology is rather complex), it is likely that the EB and CG methods would continue to remain the mainstay for most practitioners (Persaud and Lyon, 2007).

The followings sections provide an elaboration on the features and pros / cons of the EB and CG methodologies.

5.2.1 Empirical Bayes Methodology

The EB methodology is well known for its robustness and ability to compute statistically-defensible crash reduction factors. Key amongst its strengths is the ability to account for regression to the mean (RTM) effects, which is a phenomenon that is likely to be present when sites are selected for treatments based on their accident records. The mechanism to address RTM effects comes in various forms, of which model-based predictions of the expected number of accidents through the use of Safety Performance Functions (SPF) appear to produce the best results (Elvik, 2008). SPFs are typically developed based a large sample of sites deemed to be comparable to the treated site, and are typically in the form of negative binomial models with an over-dispersion parameter used as a measure of how precise the model is in predicting the number of accidents that would have occurred on the treated sites had the treatment not been applied - its value is used as a weight to predict the expected number of accidents at each site given the observed occurrence of accidents in the before period. If present, RTM effects can distort the final results and lead one to conclude that the treatment yields greater safety benefits than it actually does

(Hauer, 1980). Persaud et al. (2001) has shown, by comparing results from a naïve before-after analysis, that RTM effects were significant in their safety evaluation of roundabout conversions in the United States.

Although one advantage of the EB method is that a pre-existing SPF can be used, caution has to be exercised when it is applied across a wide study area. This is because SPFs are likely to vary, especially from jurisdiction to jurisdiction, leading to erroneous outcomes if a single SPF is used. In recognising this, Garber et al. (2006) adopted a modified approach by adopting state-specific SPFs of non-treated sites to investigate the safety impacts of differential speed limits implemented on rural highways across different states in the U.S. The results showed statistically significant increases in the number of crashes at all sites, regardless of whether a state switched from or to differential speed limit or maintained its status quo on speed limits. From this, it led the authors to conclude that the speed limit policy had no safety impacts. Using a single SPF might have led to a totally different conclusion.

Another issue arises when separate CMF values have to be used to account for site-specific geometrical / traffic features such as narrower lanes or bicycle lanes that could potentially affect the safety effectiveness of the treatment in question. Unless all CMF values are available, free from reliability issues and applicable in the particular study context, the EB method will not properly account for confounding variables. A case in point is the work by Patel et al. (2007), in which the safety effectiveness of shoulder rumble strips on two-lane rural highways was investigated. Results suggested that the right shoulder width was a confounding variable at play, leading the authors to conclude that this could have affected rumble strip effectiveness. Although subsequent dis-aggregate analysis revealed that shoulder width effect was not statistically significant, the authors acknowledged that this could have been due to the small sample size. In the end, doubts remain on whether the final CMF value for the rumble strip had been free of confounding effects.

Another major limitation to using the EB method is that a sufficiently large sample of reference sites is required to develop the SPF. In the work by Fayish and Gross (2010) that examined the safety effectiveness of leading pedestrian intervals, the EB methodology could not be employed because there were insufficient numbers of signalized intersections that had similar geometric, traffic and operational characteristics but came without the treatment in question. As a result, the CG approach without the use of a SPF had to be adopted. This meant that RTM effects could not be addressed, but the authors argued that this would not be of concern as the treatment sites had not been selected on the basis of high crash counts. It was for the same reason that Griffith (1999) chose not to adopt the EB methodology, as it was deemed that sites had rolled-in continuous shoulder rumble strips on freeways installed based on a resurfacing schedule rather than poor accident records.

5.2.2 Comparison Group Methodology

The CG methodology is another well accepted approach adopted by researchers to evaluate safety effectiveness. Similar to the EB approach, accident records from reference sites are critical in the computation of safety effectiveness estimates. However, the CG method typically involves using a matched comparison group where reference sites are carefully chosen to match the characteristics of treated sites. Its theory was developed based on the concept of statistical experiments, in which a "comparable" site is introduced to account for all other factors (or confounding factors), other than the one under study, which could have had an impact on safety (Hauer, 1997). Seidowsky et al. (2011) has shown that accounting for confounding variables is important, as his study found they had a significant influence on the safety effects of dynamic hard shoulders.

Although the EB procedure also has the capability to account for confounding variables, the difficulty arises when multiple treatments had been applied (Richard and Srinivasan, 2011) or different crash-related characteristics exist on various treated sites. Herein lies the key appeal of the CG method, with sites able to be matched such that they only differ by the treatment itself. For instance, a treated site that comes with an extra wide shoulder could be matched with one that also has the same attribute (apart from the treatment). To this end, CG studies are similar to case-control designs in that it can account for multiple risk factors and confounding variables.

The major limitation in using the CG method is the need for matching of crash frequencies and comparability between the treated and comparison sites. For the former, Hauer (1997) has made the case that the requirement for matching crash frequencies is more important than one based on the sites' attributes (geometry, traffic characteristics, etc.). In terms of comparability, the rate of change in crashes in the comparison group has to be similar to the treated group in the before period, the idea being that identical crash-related variables would then be properly accounted for. The mathematical approach to address this is to compute the sequence of odds ratios from the historical crash counts. Sites in the comparison group are deemed to be comparable if there is statistical evidence to show that the sample means of the odds ratio is close to one (Hauer, 1997).

In theory, the CG method has the ability to account for RTM effects through the use of an SPF. However, if a SPF is needed, the EB methodology would have been the likely choice, as the user would not have to deal with matching and comparability issues in the CG method. Consequently, the CG method is generally only resorted to when RTM effects are considered to be minimal.

5.3 Key Considerations in Choice of Methodology

The preceding sections demonstrate that EB and CG methods have their strengths and weaknesses in the computation of CMFs. Between the two, it appears that that the EB method is better as it requires slightly lesser computational effort and can account for RTM effects. The EB procedure is also more likely to yield statistically significant results than the CG method, especially in situations where a few of the study sites have zero accident history.

The literature has shown that the choice between the EB and CG method is mostly dictated by the availability of accident data and judgement on whether RTM effects are likely to be present (Fayish and Gross, 2010, Griffith, 1999). Another key consideration, although not reported in the literature, is the need for researchers to account for site-specific attributes. For instance, it is possible that the installation of bicycle lanes on existing carriageways will result in narrower traffic lane widths, which means a CMF for narrower lane widths has to be applied when using the SPF in the EB method. Obtaining the relevant CMF value can be challenging in practice as a number have been found to be contradictory in the literature (Elvik et al., 2009). This is not surprising as previous studies were done across different states and countries. Disregarding the use of such CMFs might appear a convenient option but it would mean that all confounders could not be fully controlled for. Another option is to apply the EB procedure to compute each CMF value separately before a final run to determine the CMF for the treatment in question. However, this would be quite onerous and thus an unlikely avenue for practitioners. The CG method can overcome this limitation to a certain extent because reference sites can be chosen to match the treated sites' crash-related attributes. It is also possible to account for RTM effects when employing the CG approach. However, additional steps are required and its application is not ideal when study sites have zero accident records or when treatment and comparison sites are not well-matched in terms of crash frequency, traffic volume and operational characteristics, etc. What is left is for users to take into account limitations associated with either approach when making statistical inference from the final results (**Table 5.1**).

Table 5.1: Key Considerations when Using the EB and CG Methods

Methodology	Strength	Weakness
Empirical Bayes	- Regression to the mean effects could be addressed in a straightforward manner - Existing SPFs, if any had been developed earlier, could be used	- Confounding variables can be accounted for only if CMF values are known and with certainly that they are applicable in study context - Large numbers of reference sites are required for the development of a SPF - SPFs are likely to vary across different geographical areas
Comparison Group	- Sites can be matched such that confounding variables are accounted for	- Regression to the mean effects can be accounted for, but involves additional steps - Unable to evaluate sites with zero accident history - Need for matching and comparability when selecting reference sites

5.4 Research Aim

The aim of this phase of the research is to examine the implications of using different study designs where the comparison group types differ and to explore the use of a new combined approach to compute safety effect estimates. The study designs are based on the:

(a) Empirical Bayes (EB) approach based on a large reference group;
(b) Comparison-Group (CG) approach based on a smaller but matched reference group, with regression to the mean effects accounted for; and
(c) Combined EB-CG approach that incorporates (a) and (b) above

5.5 Methodology

The methodology used in this research entailed the use of both the EB and CG approaches as outlined in the Highway Safety Manual (2010). The steps involved in both procedures are presented in **Appendices A** and **C**, and briefly outlined below.

5.5.1 Empirical Bayes Approach (with large comparison group)

The EB approach, which had also been outlined in section 4.2, started with the development of SPFs that relates crash frequencies to traffic volume for road intersections (four-approaches and three approaches) and segments (four-lane undivided) based on data collected from a large pool of reference sites. Using these SPFs, the relevant crash modification factors were applied to account for the various crash-related attributes at treated sites when computing the predicted number of accidents at each treated location (assuming the treatment had not been implemented). Next, the expected crash frequencies for each study (or treated) site in the before period were determined by using the combined knowledge of crash frequencies from the reference sites and study sites:

$$T_{EB,i} = w_{B,i} \times T_{PB,i} + (1 - w_{B,i}) \times T_{OB,i} \tag{5.1}$$

where
$T_{EB,\,i}$ = Estimate of expected crash frequency at study site *i*
$T_{PB,\,i}$ = Predicted crash frequency based on the SPF model for study site *i*
$T_{OB,\,i}$ = Observed crash frequency at study site *i*
$w_{B,i}$ = Weightage based on the over-dispersion parameter from the SPF model and predicted crash count for study site *i*

With the expected crash frequency in the before period in hand, the corresponding figure in the after period was established based on the ratio of the predicted accident counts between the before and after periods. Following this, the odds ratio was computed by taking the division of the observed and expected crash frequencies in the after period. Finally, the safety effect was determined by using this odds ratio and having it corrected for the bias arising from using the estimated expected crash frequency in computing the odds ratio (refer to **Appendix A** for full details of the EB procedure).

5.5.2 Comparison Group Approach (with small matched comparison group)

The CG approach started with checks to ensure the comparison sites were well matched based on historical crash frequency and had crash trends similar to those in the treatment groups in the before period. This was done to account for unobserved factors such as trends, driving behaviour and advancement in vehicle technology, which could have an effect on changes in road safety levels. To do so, the sample odds ratio was computed for each sequential time series by using the crash counts of the treated and comparison sites in the before period (Hauer, 1997). The comparison sites were deemed to be "comparable" when there is no statistical evidence to show that the sample mean of the odds ratio is not equal to unity. Given that this approach might lead to negative lower confidence limit values for the odds ratio, the modified Allsop approach (Allsop et al., 2011) was also adopted as an additional check. Comparison sites with 95% confidence interval of the sample odds ratio mean excluding one (in the Hauer approach) or zero (in the modified Allsop approach) were replaced until a positive test outcome was obtained.

The rest of the steps were in accordance with the Highway Safety Manual (2010), in which the odds ratio for each treated site was computed as follows:

$$OR' = \frac{T_{OA}}{T_{EA}} \tag{5.2}$$

In this research, an additional step was taken is to address RTM effects through the use of the "method of sample moments" (Hauer, 1997). This involved the use of statistical properties from a separate group of reference sites to determine the expected accident count at the treated site in the before period. **Appendix C** provides details of odds ratio test and key steps involved in the CG procedure, including the "method of sample moments".

5.5.3 Combined EB-CG Safety Estimate

The completion of the EB and CG procedures set the stage for determining a combined $\theta_{EB\text{-}CG}$ estimate for the treatment in question. This estimate was computed by taking a weighted ratio of the results from both methods:

$$\theta_{EB-CG} = Weight \times \theta_{EB} + (1 - Weight) \times \theta_{CG} \tag{5.3}$$

where θ_{EB} = Safety estimate from the EB approach
θ_{CG} = Safety estimate from the CG approach

The weight was determined based on a subjective assessment of the nature of the dataset in relation to the limitations associated with the EB and CG method in determining the safety effect estimate. As a guide to deriving this weight, a 5-point Likert scoring system based on key considerations in the safety evaluation was proposed (**Table 5.2)**.

Table 5.2: Scoring Based Approach to Determine Weightage

Considerations	Score					
	1	2	3	4	5	NA
It is easy to set up safety performance functions for the reference sites						
Safety performance is unlikely to vary across sites						
Reliable CMFs are available to account for site-specific characteristics						
A number of study sites have zero accident history						
Study and reference sites vary significantly in terms of crash frequencies						
Score (Total)						

Note: 1 - Strongly disagree; 2 - Somewhat disagree; 3 - Neutral; 4 - Somewhat agree; 5 - Strongly agree

The scoring was designed to provide an indication of the method that would be more appropriate, in which lower scores point to the CG method and higher, EB method. The final weight was then determined using:

$$Weight = \frac{Score - n}{4n} \times 100\% \tag{5.4}$$

where n = total number of considerations that were given scores

For example, in situations where treated sites come with specific crash-related attributes, relevant CMF values from the literature or previous studies would be needed in the EB procedure. In the CG procedure, reference sites could be selected such that specific crash-related attributes are controlled for (**Table 5.3**). The amount of faith a user has in the EB estimate would depend largely on how reliable the CMF values are. Should there be doubts reliability of the CMF values, a score of 1 could be assigned, indicating the CG approach would be more appropriate.

Table 5.3: Procedural Differences in EB and CG Methodologies to Account for Crash-Related Attributes on Treated Sites

Methodology	Treated Sites	Reference / Comparison Sites	Remarks
Empirical Bayes	A = f(AADT,CMF_T,CMF_X)	A = f(AADT) x CMF_X	CMF_X values obtained from literature
Comparison Group	A = f(AADT,CMF_T,CMF_X)	A = f(AADT,CMF_X)	CMF_X controlled for in reference sites

Note: CMF_T and CMF_X represent the safety effects of the treatment in question and all other crash-related attributes at various treated sites

To obtain a sense of the precision of the $\theta_{EB\text{-}CG}$ value in equation (5.4), its variance was determined using:

$$Var(\theta_{EB-CG}) = Var(\theta_{EB}) + Var(\theta_{CG}) - 2Cov(\theta_{EB}, \theta_{CG}) \tag{5.5}$$

The EB and CG approaches were considered to be independent as different means in setting up the comparison group and correcting for the regression to the mean effects had been adopted. In light of this assumption, the covariance term in equation (5.5) was disregarded, yielding the final variance:

$$Var(\theta_{EB-CG}) = Var(\theta_{EB}) + Var(\theta_{CG}) \tag{5.6}$$

5.6 Application

In applying the above methodologies, the dataset that had been used in section 4.2 was similarly adopted here. This dataset comprised sufficient number of comparable sites that allowed for the development of safety performance functions for both road segments and intersections in the EB approach. An examination of the study sites, however, showed that some had certain unique features – two had new bicycle lanes implemented along with the new bus priority, while another had narrower traffic lanes after bus priority was implemented. As such, the safety performances for these sites are likely to be different to the rest of the sites. For this research, CMFs from previous studies in the U.S. and Europe (Gross and Jovanis, 2007, Elvik et al., 2009) were used to account for the narrower lane width and bicycle lane. Arguably, these factors might not be appropriate for use in Melbourne's context but were nonetheless used as they were the only reliable source available.

In the CG approach, a comparability check was first done on the dataset (results are captured in **Appendix D**). The results showed that the crash frequencies at the study and comparison sites did not vary significantly and would therefore not be an issue. However, an examination of the study sites' accident history revealed that some had recorded no accident history in the before period.

Given the nature of the dataset and key considerations in using both approaches, scoring was done using the previously-defined scoring system to determine the appropriate weighting for the EB-CG estimate (**Table 5.4**).

Table 5.4: Weightage based on SmartBus Program Dataset

Considerations	**Score**					
	1	**2**	**3**	**4**	**5**	**NA**
It is easy to set up the safety performance function for the reference sites					✓	
Safety performance is unlikely to vary across sites		✓				
Reliable CMFs are available to account for site-specific characteristics	✓					
A number of study sites have zero accident history					✓	
Study and reference sites vary significantly in terms of crash frequencies		✓				
Score (Total)	15					
Weighting (%)	50					

Note: 1 - Strongly disagree; 2 - Somewhat disagree; 3 - Neutral; 4 - Somewhat agree; 5 - Strongly agree

5.7 Results and Discussion

Results of the parameter estimates for the crash count models in the EB approach are presented in section 4.4.2, while that for the odds ratio test done prior to the safety effect estimation in the CG approach are summarized in **Appendix D**. **Table 5.5** captures the results based on the CG approach, while **Table 5.6** presents a summary of the final EB, CG and combined EB-CG safety effect estimates for bus priority at road corridors and intersections respectively.

On the whole, there was general agreement in the results obtained from both methods. Results from the CG approach provided confirmation that bus priority brought about overall positive safety effects, albeit at a lower significance level ($p<0.15$). At the corridor and intersection levels, the results showed that the EB procedure was able to generate a more precise safety estimate, i.e. one with lower variance (**Figure 5.1** and **Figure 5.2**). This can be attributed to the inability of the CG method to evaluate sites that had zero accident history, as apparent in **Table 5.6** where the lower observed crash counts in the CG methodology indicate that such sites had to be disregarded.

The CG estimates were also found to be higher than the EB estimates for both road corridors and intersections. Given that RTM effects had been accounted for in both approaches, this difference could be attributed mainly to the omission of sites with zero accident history as well as the effect of matching treatment sites with similar sites in the CG approach. The latter might have been significant in this study as a number of treated sites ended up with narrower traffic lane widths following the introduction of bus priority. In terms of road safety, the discrepancy of the final results from both methods on road corridors (9%) can be considered to be significant. Arguably, users would not be faced with the dilemma with regard to which result should be adopted as only one methodology would have been used in computing the safety effect in the first place. However, in the event that different users adopt either approach to compute safety effects, they would be left in doubt as to which result would be more applicable.

Table 5.5: Safety Evaluation based on CG Approach

Parameter	Types of Treatments		
	Non-TSP	TSP	Overall
Number of Locations	23	25	48
Total observed crash counts in the “after” period	65	91	157
Expected crash counts in the “after” period	84.3	94.8	179.1
OR’	0.771	0.960	0.877
OR	0.728	0.882	0.839
SE(OR)	0.13	0.18	0.11
Safety Effect, θ	27.2%	11.8%	16.1%*

Note: OR’ is the biased odds ratio (due to taking the ratio of random variables)
** denotes significance at 15% level*

Table 5.6: Safety Evaluation of Bus Priority at Road Corridors and Intersections

Parameter	Road Corridors (Non-TSP)		Road Intersections (TSP)	
	EB (large comparison group)	CG (small matched comparison group)	EB (large comparison group)	CG (small matched comparison group)
Number of study sites	25	23	31	25
Observed crash counts (after period)	66	65	94	91
Expected crash counts (after period)	80.3	84.3	105.4	94.8
OR’	0.822	0.771	0.892	0.960
OR	0.818	0.728	0.889	0.882
Safety effect, θ (%)	18.2	27.2	11.1	11.8
Standard error of θ (%)	11.7	13.1	10.6	17.8
*Combined safety effect, $\theta_{EB\text{-}CG}$ (%)	22.7		11.5	
Standard Error of $\theta_{EB\text{-}CG}$ (%)	8.8		10.3	

*Note: * Based on weightage of 50%*

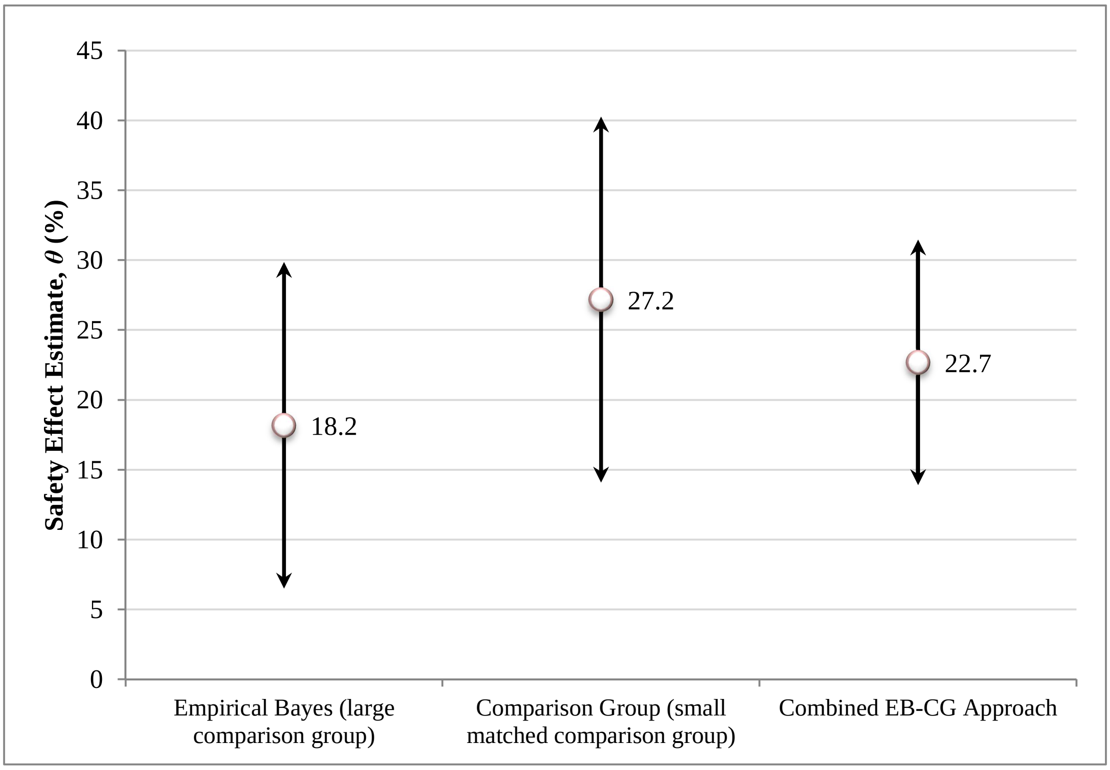


Figure 5.1: Safety Effect Estimates (with arrows representing range based on one standard deviation) for Bus Priority along Road Corridors

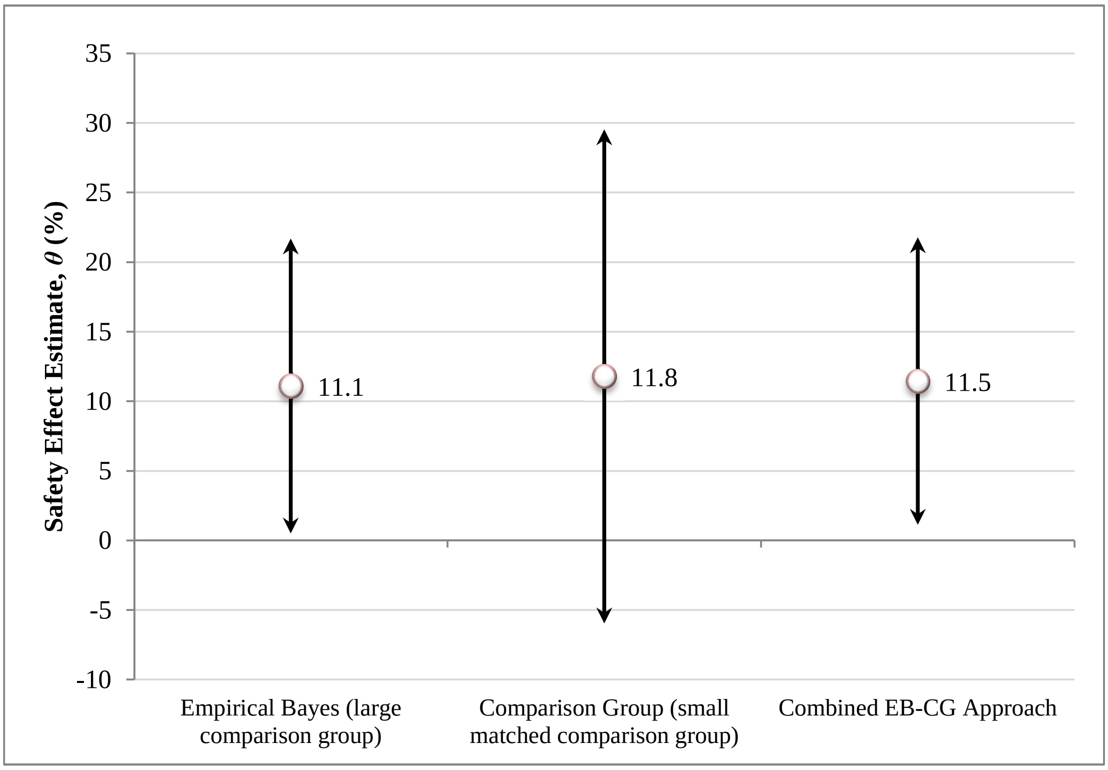


Figure 5.2: Safety Effect Estimates (with arrows representing range based on one standard deviation) for Bus Priority at Road Intersections

In such a situation, the advantage of using the combined EB-CG approach becomes apparent. First, this approach acts as a form of check-and-balance, as both results act to provide a better sense of the actual safety effect. Secondly, in the process of weighting results from both methods, users will be more aware of the limitations associated with each approach. Finally, as shown in the case study, there is a chance of obtaining a more precise safety effect estimate when the standard errors of the EB and CG estimates are comparable.

5.8 Conclusion

In conducting observational before-and-after studies, several study designs are available for researchers and the choice is often dictated by data availability and the nature of the site/s under study. A key consideration for the latter is whether a matched comparison group, where reference sites are chosen to closely match treated sites' characteristics, should be adopted. This study explores the implication of this choice through three study designs - (1) Empirical Bayes (EB) approach based on a large comparison group; (2) Comparison-Group (CG) approach based on a small matched comparison group with regression to the mean effects accounted for; and (3) a combined EB-CG approach.

Results showed that the safety effect estimate is greatly influenced by the choice of study design and comparison group type. The discrepancy between the EB and CG estimates could be attributed to the omission of sites with zero accident history as well as the effect of matching treatment sites with similar sites in the CG approach. How much of the discrepancy was contributed by the latter is not known but is certainly worthy of further investigation. Results further suggested benefits of adopting a combined EB-CG approach, as a more precise safety effect estimate can be obtained if standard errors of the EB and CG estimates are comparable. For the user, this approach could act as a form of check-and-balance and raise awareness of the limitations associated with using either approach on its own.

It is however acknowledged that the combined EB-CG approach comes with its own drawbacks. First, this approach does not fully overcome the limitations inherent in the EB and CG methodologies, as it still utilizes results from both approaches. Until a more robust methodology is developed in mainstream research, it is likely that users would continue to use either approach for their safety evaluations. This is because much effort is required in data collection and analysis in the EB-CG approach as compared to applying either methodology individually. As such, road agencies with budgetary constraints may find using such an approach impractical. In this regard, much work is required to further the development of the technique proposed in this research to a stage where practitioners find the advantages outweighing the extra effort required for data collection and analysis. Future research could therefore be targeted at formulating a unified approach in which limitations associated with using either methodology in practice could be addressed simultaneously. An afterthought that emerged from this study is that it could be potential advantageous to adopt an EB or EB based CG approach[f], depending on which approach is more suitable, for each site. For example, the EB approach could be employed for sites that have no accident history while the EB based CG approach could be used if the treated site had specific attributes that are better addressed using matched comparison sites. This methodology will reduce considerable amount of resources needed to collect data from reference sites for the combined EB-CG approach proposed in this research, and still be able to address RTM effects in the CG approach.

In summary, results presented in this chapter have demonstrated that findings (in terms of safety effect estimates) can differ depending on the choice of the methodological approach. It does suggest that multi-analyses have merits in that they provide one with a sense of where the actual estimate lies. In the same regard, there are also merits of using different datasets in search of an answer to the research question, "what is the safety effect of bus priority?" It is in this spirit that the next chapter is built on, as findings in the current and preceding chapters had been based on police records alone. To obtain a better sense of the safety effects of bus priority, a different (but still relevant) set of data - bus accident records - is used.

[f] *This involves the use of the safety performance function instead of "sample of moments" method to overcome the regression to the mean issue (Hauer, E., 1997).*

CHAPTER 6 ROUTE LEVEL SAFETY EFFECTS

6.1 Introduction

Findings from the before-after analyses of accidents in Chapter 4 revealed that bus priority had led to a reduction of 14% of all accidents involving injuries. This chapter sets out to further understand the safety effects of bus priority by examining its influence (in relation to other key risk factors) on bus-involved accidents. With much attention already to understanding crash characteristics and identifying accident causation factors at the incident-level (or micro-level) in the literature, this research centred on exploring bus priority effects on accidents at the route level (or macro-level).

Much of the work presented in this chapter originated in the published research paper Goh, K., Currie, G., Sarvi, M. & Logan, D (2014). Bus Accident Analysis of Routes With / Without Priority. *Accident Analysis & Prevention* 65, 18-27.

This chapter starts with a review of previous macro-level studies on bus safety. This is followed by a bus accident type analysis and accident frequency modelling which aims to identify the key factors and understand the influence of bus priority on bus accident occurrence. Following a presentation of results, the chapter concludes with a discussion on implications for bus priority research and planning.

6.2 Previous Macro-Level Bus Safety Studies

From the literature, only a handful of studies have explored bus safety at a macro-level: that is at route-section or zonal levels. Apart from Jovanis et al. (1991), only two other published studies were found. The first was by Cheung et al. (2008), who developed zonal-level and route-level models that related collision frequency to road geometry and transit related characteristics in Toronto, Canada. Model results indicated that higher traffic exposure (in terms of vehicle or bus kilometres travelled); lower posted speed and longer arterial road length were associated with increased risk of transit-involved collisions. More collisions were also recorded when bus frequency, bus stop density and percentage of near-side stops were greater. These results were expected given that conflicts between right-turning (or left-turning in Australia's context) vehicles and buses are likely to be higher when stops are located on the near side. More conflicts are also expected when more buses are on the road or when stops are located closer to one another. The second study by Quintero et al. (2013) centred on zonal-level collisions, in which prediction models were developed relating collisions to transit physical, operational elements and network indicators based on graph theory. The models showed that increased collisions were positively correlated with the number of stops, number of routes, bus stop density, overlapping degree and connectivity. It was interesting to note that high occupancy vehicle (HOV) lanes were also found to be positively correlated with collisions.

Although the above macro-level studies provide valuable insights into key risk factors in route and zonal-level collisions, they relate to both car and bus collisions and hence the risk factors for collisions involving only buses remain unclear. Both studies were also confined to applications in North America, and as such very little is known on the validity of such models in other countries, where the traffic and transit environments differ substantially.

6.3 Research Aim

This phase of the research aims to understand how bus accident types and frequency differs between routes with and without bus priority. It also aims to explore the development of a route-section level model for accidents involving buses in Melbourne, with the focus on understanding the safety effects of bus priority. For analytical rigour, two accident prediction models will be developed. With this approach, a secondary aim is to assess and compare the performance of the two models.

6.4 Research Data

Data used in this research was obtained from the Traffic Incident Management System (TIMS) and human resource database maintained by Ventura Bus and Grenda Transit (section 3.5.2 provides further details of the data). Due to a number of route changes that took place in 2008, only incidents which occurred between 2009 and 2011 were used for the analysis. During this time period, a total of 1,213 incidents occurred along 99 bus service routes that operate in eastern Melbourne. Of these, 114 records that involved intentional acts (e.g. objects thrown at bus), had unknown causes, missing information (e.g. missing location details) and were non-collision in nature were discarded. The remaining 1,099 accident records were used for the analyses in this study. Included in the dataset were details of the bus timetable, from which service frequencies and stop information were extracted.

The second set of data comprised Annual Average Daily Traffic (AADT) volume and information related to bus priority lanes along specific bus routes that were introduced as part of the SmartBus program in Melbourne. These were obtained from VicRoads' information system (VicRoads, 2012a) and the Victorian Department of Transport respectively. Further details of the data used for this research, including the SmartBus program, are provided in sections 3.4 and 3.5.

6.5 Methodology

Given the different bus priority strategies that were applied in Melbourne, where some stretches had a new kerbside lane added while others had the existing kerbside lane converted to a bus lane or clearway, the approach centred on gaining an understanding of bus safety at the aggregate route segment level. To do so, an empirical analysis of bus accident type and frequency analysis was first undertaken. Two accident prediction models were then developed to identify key traffic, transit and route factors associated with accident frequency as well as for model comparison purposes. The first model was developed using a mixed-effects negative binomial regression approach. A negative binomial distribution assumption was used for this model, which is a widely adopted approach in road safety research given its ability to handle accident count data that is non-negative and typically over-dispersed (Lord and Mannering, 2010). The second model was developed using neural network principles, as recent studies have pointed to excellent function approximation abilities of neural network models (Xie et al., 2007, Li et al., 2008, Vlahogianni et al., 2012) in predicting collisions or accidents. In this study, a neural network based on a commonly used back propagation algorithm was chosen and estimated.

6.5.1 Bus Accident Type and Frequency Analysis

Taxonomies of traffic accidents have been used widely by researchers, road management agencies, police and insurance companies to summarize and understand accident patterns and characteristics (Wåhlberg, 2002). In this study, a descriptive analysis was first carried out to identify bus accident characteristics before modelling was conducted to examine risk factors and the influence of bus priority on bus accident frequency.

6.5.2 Mixed-Effects Negative Binomial (MENB) Modelling of Bus Accidents

With the bus accident records in the form of a cross-sectional and time series (or panel) structure, heterogeneity and serial correlation issues may exist. The former is due to unobserved location-specific factors while the latter arises from the time series nature of the data. In road safety, the random effects negative binomial (RENB) modelling approach has been adopted in previous studies to address these spatial and temporal effects (Chin and Quddus, 2003, Kumara et al., 2003). In this research, a mixed effects negative binomial (MENB) regression approach, which came about from recent development in computational statistics, was adopted to model location and time-specific variables as crossed, independent effects. Compared to RENB, MENB regression modelling offers the following key advantages (Baayen et al., 2008):

- ✓ It allows for random effects to be crossed and not necessarily nested as assumed to be in traditional random effects modelling;

- ✓ It is more flexible in dealing with missing data issues; and
- ✓ It overcomes deficiencies in statistical power due to repeated observations;

With $E(A_{ij})$ representing the predicted number of accidents along bus route segment i at time j, the structure of the MENB model is given as:

$$E(A_{ij}) = \exp(X_{ij}\beta + L_i l_i + T_j t_j + \varepsilon_{ij}) \tag{6.1}$$

where

X_{ij}	=	Matrix representing factor contrasts and covariates
β	=	Vector of pooled coefficients (fixed effect)
L_i	=	Matrix to account for location-specific effect
l_i	=	Vector of coefficients representing location-specific
T_j	=	Matrix to account for time-specific effect
t_i	=	Vector of coefficients representing time-specific effects
ε_{ij}	=	Vector of residual errors

Following the combination of matrices L and T into to a single matrix Z, and random vector l and t into a single vector γ, the formulation can be re-written as:

$$E(A) = \exp(X\beta + Z\gamma + \varepsilon) \tag{6.2}$$

The residual error (ε) and random effects (γ) terms are assumed to take on the normal (Gaussian) distribution with means 0 and variances a and b respectively. **Table 6.1** provides a brief description and summary statistics of the covariates used in the MENB model. Similar to the aggregate analysis, the R^2_α as proposed Miaou (1996) was used to assess the model's goodness-of-fit:

$$R^2_\alpha = 1 - \frac{\alpha}{1 + \alpha_{\max}} \tag{6.3}$$

where α = Over-dispersion parameter for final MENB model; and
α_{max} = Over-dispersion parameter for base model with only a constant term

For the purpose of model comparison (MENB vs. neural network), the Root-Mean-Square Error (RMSE) was used:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m} Y_i - \hat{Y}_i} \tag{6.4}$$

Here, Y_i and $\hat{Y}_i$ are the observed and predicted accident frequency along route i, and m is the size of the dataset. The RMSE statistic provides a measure of the average mis-prediction of the model, with a value close to zero indicating that the model had predicted observed data well.

Table 6.1: Summary Statistics of Variables Used in MENB Model

Variable	Min	Max	Mean	S.D.
Accident Frequency (Collisions/year)	0	29	3.68	4.89
Year* (2009=1; 2010=2; 2011=3)	1	3	2	0.82
Location* (Route section 1 = 1 to Route section 99 = 99)	1	99	50	28.58
Length of bus route section** (km)	2.5	55.0	15.94	10.11
Annual Average Daily Traffic (AADT) of route section#	1,495	78,433	7,335	6,286
Number of bus services per week	6	314	111.43	87.63
Stop Density (Number of bus stops/km)	0.53	7.33	2.50	0.941
Presence of bus priority (With = 1; otherwise = 0)	0	1	0.15	0.36
Total Observations, n = 297				

Note: * *Coded as string variable as required in R software*
** *Defined based on bus service route and presence of bus priority*
# *The weighted average method is applied to compute the AADT value for segments that comprise more than one road section*

6.5.3 Neural Network Modelling

Neural networks are appealing in applications where there exist a non-linear and complex functional form of the relationship between inputs and outputs. This is because unlike statistical regression models, neural networks do not require a functional form to be established linking the dependent and independent variables. Another key advantage these networks offer is the general tolerance to data with arbitrary accuracy, i.e. good results can be generated when the model is presented with imperfect data inputs, provided sufficient hidden neurons are used (Hecht-Nielsen, 1990). These are likely to be the reasons for the increasing application of neural network modelling in the transit field (Bin et al., 2006, YuPin et al., 2010, Mazloumi et al., 2011).

The key disadvantages in using neural network approaches is model over-fitting, which results when the network is strong in fitting the random error (noise) in the data but not the underlying relationship. To address this issue and still ensure good generalization of the model, the "early stopping" technique was applied in this research during network training. This involved the monitoring of the validation set error such that network training was stopped when the validation error started to increase. The weights and biases when the minimum validation error was recorded were then used for the final neural network modelling. In this research, a three-layer feed-forward neural network based on the back-propagation approach that incorporates the Lavenberg-Marquardt (Hagan and Menhaj, 1994) algorithm (henceforth termed as BPNN) was adopted. The BPNN model structure is shown in **Figure 6.1**, where X_n are the input neurons that represent the accident related characteristics, Z_k the hidden neurons and Y, the output neuron in the model.

The underlying concept in this technique is based on the popular back-propagation algorithm, which works by updating the weights in the model such that the error between the actual and desired outputs (E) is minimized. This is essentially a four-step process that starts with a feed-forward computation where an input pattern x_t is presented to the network. The second step involves a back-propagation from the output layer, where the aim is to correct the weights $w_{k,1}$ to minimise the error E:

$$\Delta w_{k,1} = -\eta \frac{\partial E_k}{\partial w_{k,1}} \tag{6.5}$$

where η is the learning rate based on the gradient decent method (Hagan et al., 1996). In the Lavenberg-Marquardt algorithm, a parameter similar to η was adopted, which functions to regulate the training process. From Equation (6.5), it can be shown through the use of the chain rule of differentiation that:

$$\Delta w_{k,1} = -\frac{\eta}{2}(y-o) f^{'}(y_t^{inp}) z_k \tag{6.6}$$

Here, o represents the desired value for the output neuron based on the input pattern x_t, while y_t^{inp} is the summation of the weighted outputs from the hidden neurons z_k. In a similar fashion, the weights for the hidden layer can be computed in the third step:

$$\Delta w_{n,k} = -\eta . g^{'}(z_t^{inp}) x_k (y-o) f^{'}(y_t^{inp}) w_{k,1} \tag{6.7}$$

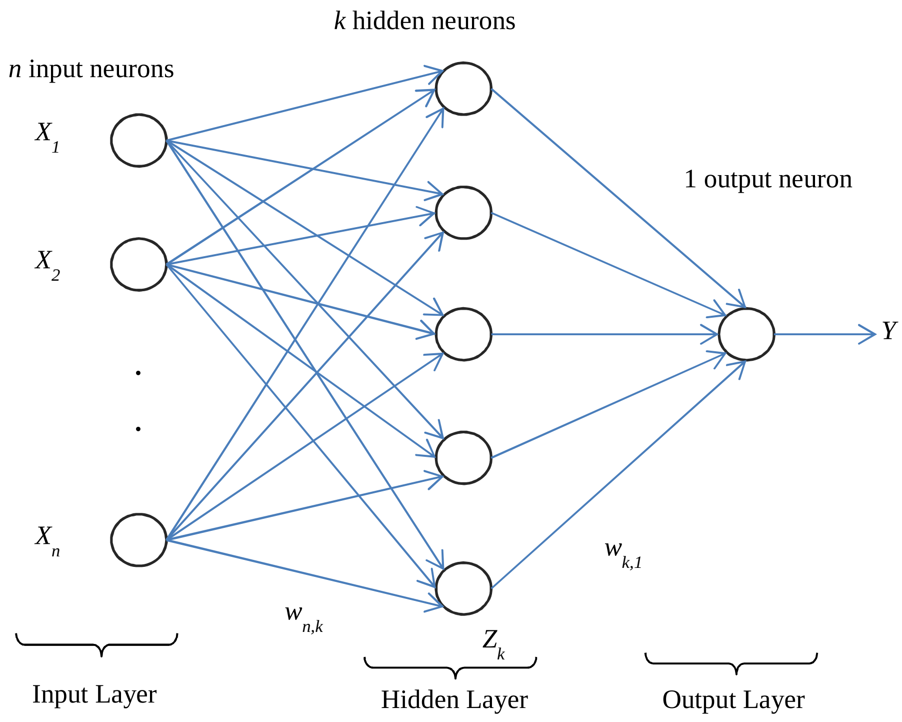


Figure 6.1: Topology of a Three-Layered Feed-Forward Neural Network

The final step of the back-propagation algorithm is the updating of the weights for each output and hidden neuron in the model:

$$w_{k,1}^{new} = w_{k,1}^{old} + \Delta w_{k,1} \tag{6.8}$$

$$w_{n,k}^{new} = w_{n,k}^{old} + \Delta w_{n,k} \tag{6.9}$$

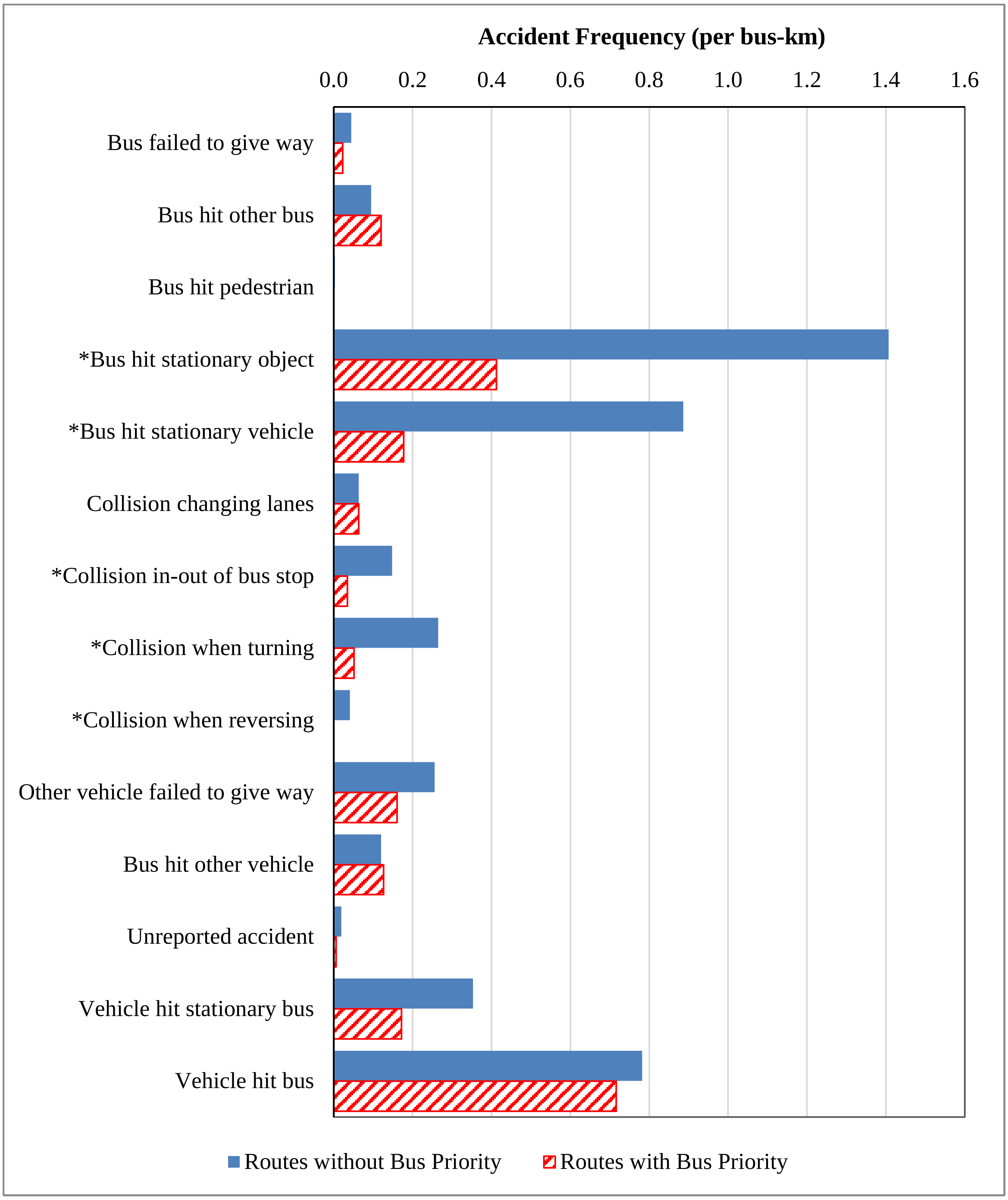
In this study, the BPNN model was developed using MATLAB (The MathWorks Inc., 2012). To facilitate comparison of model results, the same input variables that were found to be significant in the final MENB model were used in the development of the BPNN model. A single neuron was set in the output layer to represent the accident frequency. All transfer functions at the hidden and output layers were hyperbolic tangent sigmoid transfer functions. The dataset was also randomly separated into two parts (in a 3:1 proportion) for the purpose of training and testing the model. Another key step in developing the BPNN model was to determine the number of hidden neurons (k) (Kim, 1999). For this study, a range of values were utilised, i.e. k = 1, 2, 3,…, 9, 10, and the value that produces the smallest RMSE was chosen for the development of the BPNN model. Given that each run of a neural network model produced unique results, the BPNN model was ran 10 times to obtain the RMSE.

Finally, as a means of comparing model results and understanding the key underlying accident risk factors, sensitivity analyses were carried out to determine the relationship between accident frequency and each variable in the model. This was done by perturbing values of the variable of interest while keeping other variables unchanged. With the model generating a new network output for each simulated input, result variation could be recorded and the effect of the single variable of interest determined (Príncipe et al., 2000, Delen et al., 2006).

6.6 Results and Discussion

6.6.1 Bus Accident Type Analysis

Figure 6.2 presents the accident frequency (per bus-km) along routes with bus priority and those without. It is clear that the most common accidents involved collisions between buses and vehicles or stationary objects. These findings mirrored those in an earlier study which found buses hitting objects to be most common whilst those involving pedestrians to be rare occurrences (Wåhlberg, 2002).



*Note: *Indicates reduction which is statistically significant at the 5% level*

Figure 6.2: Accident Frequency (per bus-km) along Routes With / Without Bus Priority

When comparing between routes with and without bus priority, the most noticeable difference was in the proportion of accidents involving buses hitting stationary objects and vehicles. For the former, a significant ($p<0.05$) reduction of approximately 70% reduction was recorded. The latter registered a bigger drop (about 80%), which was also significant at the $p<0.05$ level. A similar reduction was recorded in the number of collisions in-out of bus stops and collisions when turning / reversing ($p<0.05$). These percentage changes are likely due to the effect of bus priority facilitating bus movements. Given that buses need not pull in and out of bus bays as frequently as before, manoeuvrability becomes less of an issue. Consequently, the risk of hitting roadside objects and colliding with stationary vehicles reduces. Although bus lanes provide exclusive right of way to buses, the downside is that buses have to contend with increased weaving movements due to other vehicles entering and exiting side streets. The relatively smaller reduction in proportion of accidents involving other vehicles hitting buses appeared to support this case (noting that such accidents were likely to be classified under the "vehicle hit bus" category with them taking place in bus lanes).

There were small percentage reductions in the number of accidents involving buses failing to give way along and lane-changing collisions, and slight increases in accidents involving buses hitting other buses or other vehicles. These differences, however, were not found to be statistically significant.

6.6.2 MENB Model

Table 6.2 presents the parameter estimates obtained from maximum likelihood algorithms in the glmmADMB package in the statistical software R, an open-source language and environment for statistical computing that is freely available at http://cran.r-project.org (R Development Core Team, 2012).

Table 6.2: MENB Model Results for Bus Accident Frequency

Variable	Estimate	P-value
Intercept	-6.640	0.000
Services per week	0.006	0.000
Ln(AADT)	0.431	0.001
Ln(Route Section Length)	0.773	0.000
Stop Density	0.389	0.000
Bus Priority = Yes	-0.766	0.002
Bus Priority = No	0 (Reference)	
Random Effect:	**Variance**	**Standard Deviation**
Year	0.357	0.598
Location	0.195	0.441
Dispersion parameter, α	0.242	
95% CI for α	[0.169,0.429]	
Log likelihood	-607.205	
AIC	1232.4	
R_α	0.807	

The dispersion parameter estimate was found to be significantly different from zero, which indicated that the negative binomial error structure was more suitable than the Poisson structure. The implications of the modelling results for each of the explanatory variables are discussed below. Apart from the area type variable, all other explanatory variables were found to be significant at the 5% level.

Model results showed that bus accident frequency at the route-section level increases with traffic volume (AADT), route length and service frequency. These results were as expected, given that these variables are exposure related, that is higher traffic volume, longer route length and higher service frequency would mean that buses are more exposed to interaction with other vehicles in the traffic stream. Route length in particular, has been shown to be a reliable predictor of crash frequencies (Vogt and Bared, 1998, Milton, 1998, Abdel-Aty and Radwan, 2000).

The model also indicated that having more bus stops per route km increases accident risks (p=0.000), while the presence of bus priority reduced accident risks (p=0.002). The former could be attributed to the fact that having more stops would mean buses having to brake and accelerate at bus stop locations more often. A similar finding was also recorded in other studies, where bus stop density was found to be positively correlated with accident occurrence (Chin and Quddus, 2003, Cheung et al., 2008). This made intuitive sense as higher stop density would mean increased rates of "stop-start" movements for buses at bus stop locations to pick up and drop off passengers.

Of interest in this study was the effect of bus priority given that current understanding of its safety effects remains unclear. Results suggested that the accident rate along routes with bus priority was approximately exp(-0.766) or 0.46 times the accident rate for routes without bus priority assuming all other variables are held constant. In other words, the presence of bus priority was associated with a 54% reduction in bus accident occurrence, of all severity levels. A similar albeit smaller positive effect was also found in another study (Booz Allen Hamilton, 2006), which revealed a 12% reduction in bus related accidents following the implementation of bus lanes in London. This finding is however opposite to those from previous studies in North America. For the case of Toronto, Canada, it was found that HOV lanes were not significant in explaining the variation in accidents (Cheung et al., 2008). Another study found that the 3+ HOV lanes were positively correlated with accidents in the Greater Vancouver Regional District, British Columbia (Quintero et al., 2013). The dissimilarity could be attributed to a different transit priority design adopted in Melbourne, which allow for a more straightforward way of separating buses from the mainstream traffic. Unlike the case in British Columbia, space based priority in the form of bus lanes in Melbourne are located on the slowest lane.

As such, buses do not have to manoeuvre across lanes to get in and out of the priority lanes.

The bus priority finding was also in agreement with results from Chapter 4 which found a 14% reduction in police-reported injury, serious injury and fatality accidents. The difference in the safety effects can be explained by the nature of the data analysed – accident data in Chapter 4 comprised only police reported accidents that involved fatalities and/or injuries, while that in the chapter included all accident types including property-only accidents that was captured by the bus company. What is therefore a noteworthy finding from the present study is that bus priority brings about significant benefits when bus-involved accident types are considered. This is an important finding given the time and financial impact accidents have on bus agencies and commuters.

6.6.3 BPNN Model

The best performing BPNN model was obtained with the use of 1 hidden layer with 4 neurons. **Figure 6.3** to **Figure 6.5** present the results of subsequent sensitivity analyses for a selected site, which depict the differing effects of AADT, stop density, route length and service frequency on accident frequency. Three-dimensional charts were generated as they provide a good sense of the relative sensitivity between accident frequency and two variables of interest.

From **Figure 6.3**, it is noticeable that AADT had a greater influence on accident frequency than stop density and there was a parabolic relationship between accident frequency and AADT. In general, accident risk increased linearly with AADT but at a lower rate when AADT was at the lower and higher end of the AADT range. The effect of stop density was also apparent, with accident frequency increasing with number of stops per kilometre.

The same observation can be made when examining the effect of route length (**Figure 6.4**). Similar to stop density, collision risk increases with longer routes but was less pronounced as compared to AADT. The BPNN model results also showed that accident risk increases at a higher rate with every unit increase in service frequency or stop density (**Figure 6.5**).

From these figures, it is apparent that the relationship between accident frequency and the variables under study is non-linear in nature. For instance, the rate of increase in accident frequency when AADT rises can be different, depending on the values that the other variables take on.

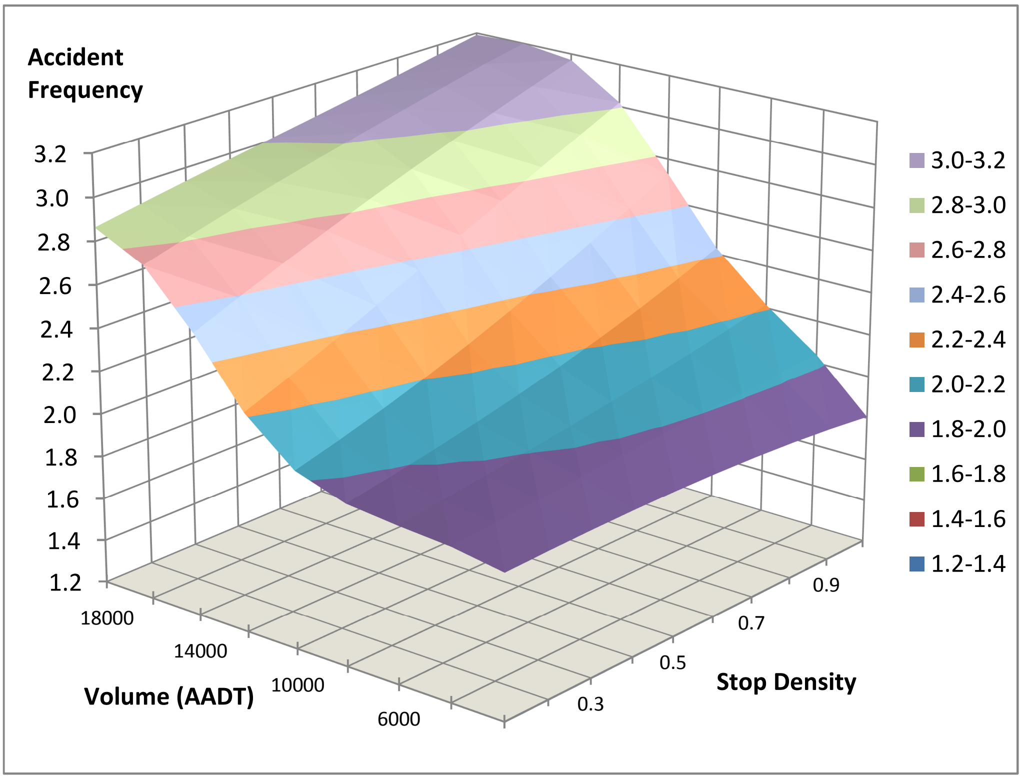


Figure 6.3: Effect of AADT and Stop Density on Accident Frequency (Route-section 25)

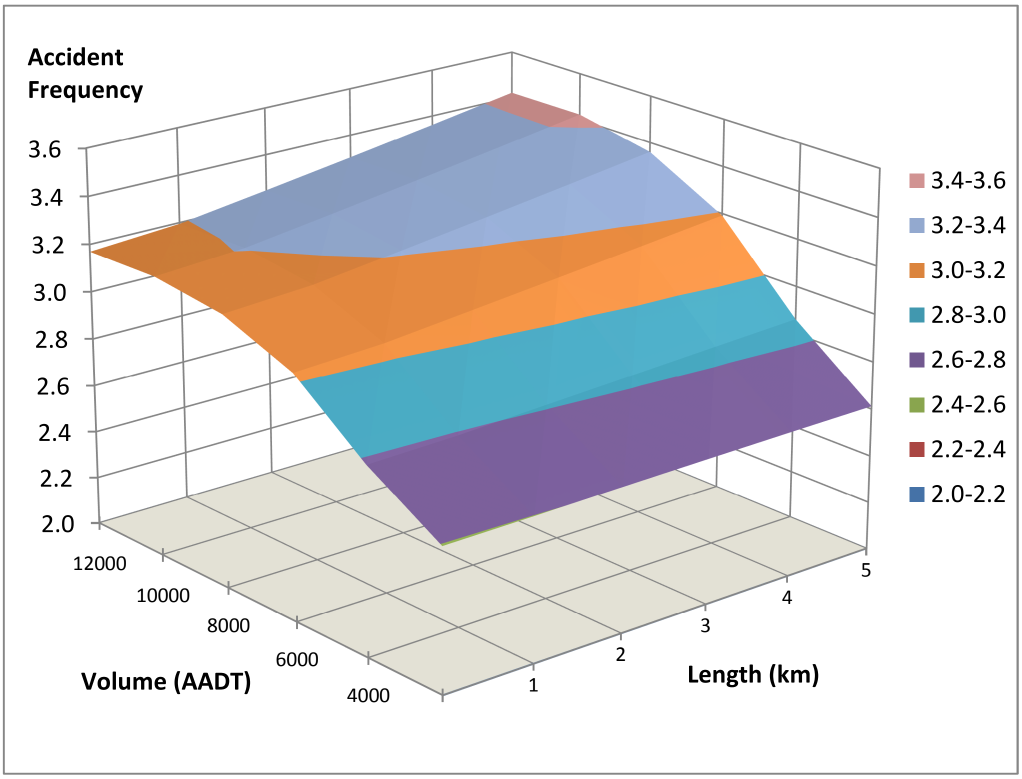


Figure 6.4: Effect of AADT and Route Length on Accident Frequency (Route-section 25)

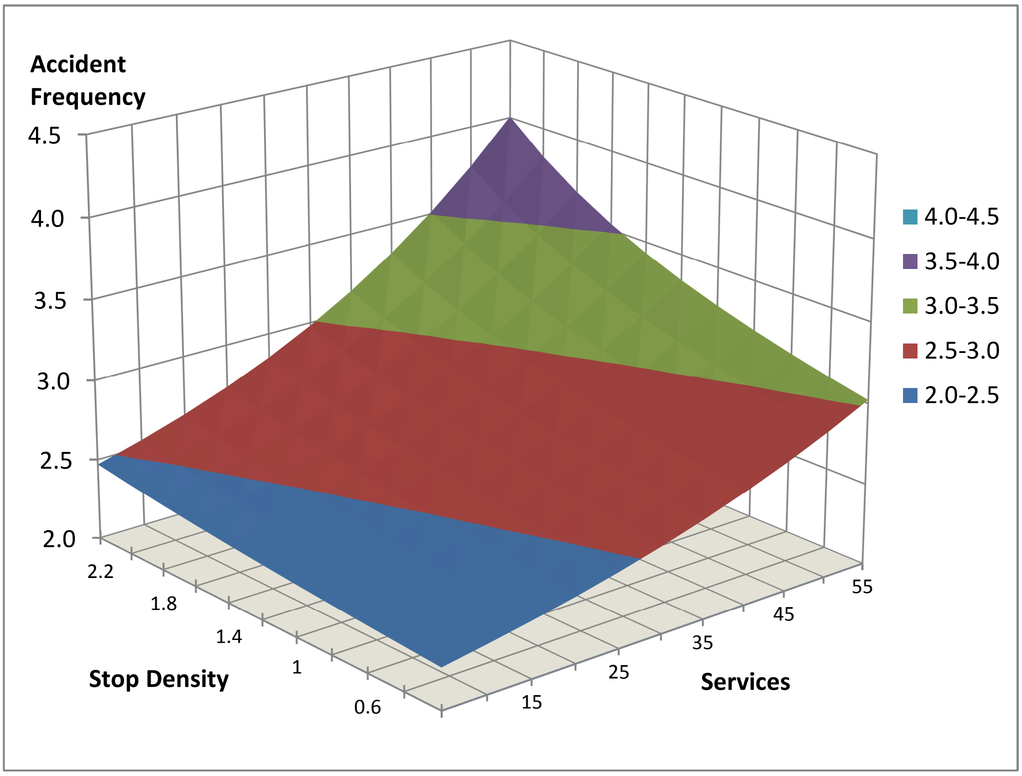


Figure 6.5: Effect of Stop Density and Service Frequency on Accident Frequency (Route-section 25)

6.6.4 MENB vs. BPNN Model

Results from the BPNN model were largely similar to the MENB model in terms of explaining how variables relate to bus-involved accident frequency. The RMSE results indicated that the performance of the MENB and BPNN model were comparable, with the former having a slightly better performance (RMSE = 2.59 vs. 2.75). This suggested that the MENB model had, as a result of accounting for unobserved location and time-specific effects, captured the complex functional form of relationship between the input and output variables well (something that BPNN models are renowned for).

The focus of the sensitivity analyses was on bus priority, as results would not only provide insights into the effects of bus priority but also a means to compare the models' performance due to the dichotomous state of the variable. To carry out this analysis, the original dataset was separated into 2 groups according to whether bus priority was present initially. The first comprised routes without bus priority (N=252) while the second consisted of routes with bus priority (N=45). Both sets of data were presented to the final MENB and BPNN model with the predicted accident frequency for buses from both models captured in **Table 6.3**.

Table 6.3: Sensitivity Analysis for Bus Priority

Model	Route-section Dataset	Predicted Accident Frequency (per km)	
		With Bus Priority	Without Bus Priority
MENB (RMSE=2.59)	Without bus priority (N=252)	0.093 (S.D.=0.090)	0.201 (S.D.=0.194)
	With bus priority (N=45)	0.499 (S.D.=0.293)	1.073 (S.D.=0.629)
	All route-sections (N=297)	0.167 (S.D.=0.226)	0.359 (S.D.=0.486)
BPNN (RMSE=2.75)	Without bus priority (N=252)	0.173 (S.D.=0.216)	0.234 (S.D.=0.259)
	With bus priority (N=45)	0.432 (S.D.=0.289)	1.682 (S.D.=1.421)
	All route-sections (N=297)	0.213 (S.D.=0.247)	0.457 (S.D.=0.800)

Based on results in **Table 6.3**, the following key observations were made:

- ✓ The safety effect of bus priority was apparent for all datasets. T-test results revealed that the safety effect of bus priority effect was statistically significant ($p<0.05$) in all datasets for both models.
- ✓ The BPNN model showed that bus priority had the effect of reducing route-section level accident frequency by 53.4%. Results from the MENB model showed that this effect was 53.5% (which is equivalent when using the parameter estimate obtained from the NB model in the previous section).

On the whole, the results showed that there is promise in adopting a mixed-effects negative binomial regression approach to account for time- and location-specific effects when modelling accident counts. In terms of RMSE, the performance of the MENB model was found to be better than the BPNN model in this study. With regard to the latter, it is noted that the application of neural networks for accident count prediction in practice had been limited due to the complexity in estimating these models and views that such models operate like black-boxes on the basis that individual relationships between the input and output variables are not developed by engineering judgment (Vogt and Bared, 1998). The above results however showed that a neural network can be a useful tool for accident count prediction as sensitivity analysis results were able to address the black-box issue and generate interpretable results when variables in particular take on a dichotomous state. To this end, it is perhaps useful for accident prediction modellers to consider developing equivalent parametric and non-parametric models (e.g. NB and BPNN) to assist with the development of neural network models, as sensitivity analyses can be done to provide useful insights into the inner workings of both models.

6.7 Discussion and Conclusion

Results from the accident analysis revealed a significant reduction ($p<0.05$) in the proportion of accidents involving buses hitting stationary objects and vehicles, as well as those involving collisions in-out of bus stops. These reductions are likely due to the effect of bus priority facilitating bus movements.

The MENB model results showed that bus accident frequency increases with traffic volume (AADT), route length, service frequency and stop density. They also point to the presence of bus priority reducing accident risks. Whilst the findings on effects of AADT, route length, service frequency and stop density were in agreement with previous studies, the bus priority effect (positive safety benefits) was found to be opposite to findings from previous studies in North America. This is likely to be attributed to the difference in transit priority design adopted in Melbourne, where bus priority lanes are located on the slowest lane and therefore allows for a more straightforward way of separating buses from the mainstream traffic.

Graphical plots from sensitivity analyses carried out on the BPNN model provided a visual sense of the relative influence of AADT, stop density, route length and service frequency on accident frequency. From the plots, it was noticeable that accident risk was more sensitive to AADT than other variables. Results also revealed that bus priority has the effect of reducing route-section level bus accident frequency by 53.4%, which is comparable to the effect estimated by the MENB model (53.5%). The better performance recorded by the MENB model (RMSE = 2.59) as compared to the BPNN model (RMSE = 2.75) suggest benefits in adopting a MENB regression approach to account for time- and location-specific effects when modelling accident counts.

Although findings from this study indicate that there is a positive road safety impact of bus priority at the macro-level, there could potentially be a mix of safety impacts (positive and negative) at the micro-level. The introduction of an exclusive bus lane for instance is likely to lead to reductions in on-path and off-path accidents, given that it can act as an additional clear zone and thus reduce car-car and car-roadside objects collisions. The likelihood of rear-end collisions involving buses will also decrease when bus priority schemes that entail segregating buses from main stream traffic are implemented. However, possible negative impacts may arise at side street locations, as buses may have to contend with cars filtering in and out of the bus lanes to enter or exit side streets. For bus lanes that result in the increase of carriageway width, pedestrian related accident risks may also increase due to longer crossing distance for pedestrians. In terms of accident severity, bus lanes are likely to reduce injury levels at bus stop and side street locations, as the speed differential between buses and other vehicles are lower. On the other hand, accident severity for pedestrians may rise as a result of greater exposure to traffic when crossing distances increase.

For policy makers, findings from this study could act to inform transit agencies in their policy and operational decisions. This is because the planning and design of transit routes by transit agencies have typically centred on planning related parameters such as patronage, operating cost, etc. Results from this study suggest that safety related considerations are just as important, and they could feature as part of overall cost-benefit analyses that are typically done for each new transit route.

In conclusion, whilst the study findings provide useful insights into bus accidents at the route-section level and could possibly act as useful planning tools for transit agencies, there remains much scope for future research in this area. In particular, further collection of bus accident data could be undertaken as a means to improve model validity and possibly identify other traffic, transit and route factors that are significant in explaining bus accident frequency. There is also the potential of further research focussed on exploring the disaggregate safety effects of different bus priority schemes as well as identifying key factors associated with different accident severity levels to further the understanding of bus safety at a route-section level.

The next chapter represents an attempt to examine the disaggregate safety effects of bus priority in terms of its influence on the bus drivers being deemed at fault when they are involved in accidents.

PART III:
DISAGGREGATE-LEVEL ANALYSIS

CHAPTER 7 ACCIDENT LEVEL SAFETY EFFECTS

7.1 Introduction

In this chapter, an analysis of the characteristics of bus accidents was undertaken and a mixed logit model developed to explore the probability of bus drivers being at-fault in bus-involved accidents in relation to the traditional safety determinants, i.e. driver, vehicle and environmental factors. Understanding the key characteristics in bus accidents and probability of bus drivers being at-fault will assist bus and road management agencies in making better informed safety-related decisions on bus travel. This is particularly important in Australia, as previous research has found bus occupant fatality rates to be higher in Australia (0.47 per 100 million bus-km) than the U.S. (0.28) and Canada (0.34) (Hildebrand and Rose, 2002). A key aim in this analysis is to determine whether bus priority plays a role (and if so, to what extent) in affecting the probability of bus drivers' being at-fault in bus-involved accidents in Melbourne.

The bulk of the work presented in this chapter originates in the published research paper Goh, K., Currie, G., Sarvi, M. & Logan, D (2014). Factors Affecting the Probability of Bus Drivers Being At-Fault in Bus-Involved Accidents. *Accident Analysis & Prevention*, 66, 20-26.

This chapter starts with an overview of previous studies on bus safety at the accident-level. This is followed by a description of the data and methodology adopted to investigate bus drivers' at-fault probability. Following a presentation of results, the chapter concludes with a discussion on the impact of bus priority and implications for bus companies.

7.2 Research Background

Research in bus safety has received relatively lesser attention and research interest, likely because public transport is known to be a very safe form of transportation as compared to other modes of transport (Chimba et al., 2010). The risk of being killed or seriously injured in a bus was found to be several times lower for bus occupants compared to car occupants (Albertsson and Falkmer, 2005, Yang et al., 2009). As highlighted in section 2.5, the majority of previous studies focused on occupant injuries and crash characteristics, with only a handful examining the role of driver, vehicle and environmental factors in bus crashes. Apart from the observation that these studies have generally fallen short of adequately representing all the traditional safety determinants, it was also clear that little attention had also been paid to the examination of accidents in terms of culpability (or crash responsibility). This is despite the recognition that addressing culpability when analysing accidents is important as earlier research has showed better correlation between driver characteristics and culpable accidents (Wåhlberg, 2008).

7.3 Traffic Incident Management System (TIMS) and Human Resource Data

The present study drew on accident and bus driver related data captured in the Traffic Incident Management System (TIMS) and human resource database maintained by the largest bus operator in Melbourne. This data is considered to be richer and of higher quality than police records or self-reported data as each accident is reviewed by officers from the bus company's incident management team and adjusters from the insurance company before an at-fault assessment is made for the purpose of insurance claims. While inherent bias may still exist, the data is considered to be robust given that different sources of evidence, e.g. CCTV and photographs, were used in the assessment.

As detailed in section 3.5.2, the data from TIMS contained all incidents which occurred between the year 2000 and 2011 that were captured for the purpose of settlement of insurance claims. In total, there were 7,059 accidents recorded along 99 different bus routes that operated in eastern Melbourne during the 2000 to 2011 time period. Herein, accidents are defined as any bus-involved collision involving other vehicle, stationary objects and people that results in property damage, injury or death.

The human resource database provided information relating to the bus driver that was involved in the accident. This includes age, gender, years of experience and previous accident records at the time of the accident.

7.4 Methodology

The methodology adopted for this research involved the exploration of bus accident characteristics followed by mixed logit modelling to identify key accident types and factors that influence the probability of bus drivers being deemed at-fault in bus accidents. For the latter, particular attention was paid to the role of bus priority.

7.4.1 Mixed Logit Modelling

While the dataset contain much vehicle, driver, roadway and environmental related information, certain driver-specific details such as educational level and risk perception which could influence the at-fault probability were not captured. Given that previous research has showed that these attributes could be influential in accidents and at-fault accidents (Iversen, 2004, Tseng, 2012), it was thus important to adopt a methodological approach that is able to account for the effects of unobserved factors. A preliminary analysis of the data also revealed that a number of drivers have multiple accident records (observations). Given the above, mixed logit modelling appears to be most suited for this study as it is able to handle panel data and account for influences of unobserved heterogeneity across observations. It is also most apt for accommodating the use of lagged variables (at-fault records) that is present in this study. In safety research, mixed logit modelling has been successfully applied to provide new important insights into the variations of the effects that variables have on seat-belt use and injury-severity distributions of accidents on highway segments (Gkritza and Mannering, 2008, Milton et al., 2008). For this study, mixed logit modelling on the probability of bus drivers being at-fault in bus-involved accidents was undertaken by defining the following function (Washington et al., 2011):

$$F_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{7.1}$$

where F_{in} is the at-fault function determining the at-fault category i (either deemed to be at-fault or not) for driver n; X_{in} is a vector of explanatory variables representing driver, vehicle, roadway, and environmental factors; βi is a vector of estimator parameters for the outcome category i and ε_{in} is the disturbance term. McFadden (1981) has shown that by assuming the disturbances to be generalised extreme value distributed, the model structure takes the form of:

$$P_n(i) = \frac{\exp(\beta_i X_{in})}{\sum_I \exp(\beta_i X_{In})} \tag{7.2}$$

where $P_n(i)$ is the probability of at-fault category i for driver n. In addition, a mixing distribution (Train, 2009) was introduced to allow for the parameter variations across drivers such that the at-fault probability takes on the following form:

$$P_{in} = \int \frac{\exp(\beta_i X_{in})}{\sum_I \exp(\beta_i X_{In})} f(\beta \mid \varphi) d\beta \tag{7.3}$$

where $f(\beta|\varphi)d\beta$ is the density function of β with φ referring to a vector of parameters of the density function (mean and variance), and all other terms as previously defined. Equation (7.3) represents the essence of the mixed logit model, as β is able to account for driver-specific variations of the effect of X on at-fault probability. Mixed logit probabilities are then a weighted average for different values of β across drivers where some elements of the vector of β may be fixed while others are randomly distributed. For the latter, the mixed logit weights are determined by the density function $f(\beta|\varphi)$, which can take on different forms, i.e. normal, log-normal, uniform, and triangular. In this research, various forms were tested and the form that provided the best statistical fit was chosen.

A simulation-based approach to estimating the maximum likelihood function in mixed logit modelling is typically employed as a key term in the conditional density for the random parameters is in a closed form and generally cannot be computed (Hensher et al., 2005). Simulation based on Monte Carlo integration with sequences constructed from number theory (Halton draws) is a popular choice as it has been shown to achieve convergence faster than the standard random draws (Train, 2009, Bhat, 2003). The number of draws is usually chosen such that a stable set of parameter estimates can be achieved without incurring too much computation time (Hensher et al., 2005). For this study, a simulation was done based on 200 draws, a quantity which has been shown to be sufficient to produce accurate parameter estimates (Gkritza and Mannering, 2008, Milton et al., 2008).

A key step taken in developing the model was the identification of suitable driver, vehicle and environmental factors that are envisaged to influence the responsibility of bus drivers in accidents. The selection of variables was done based on the literature and consideration of context-specific factors that are deemed to have some influence on bus drivers' at-fault probability. For instance, previous findings have suggested that there are safety implications in implementing transit priority (Cheung et al., 2008, Quintero et al., 2013, Goh et al., 2013). Although these effects relate to accident occurrence, there is a possibility that it could also have an impact on at-fault accidents. Bus priority was therefore included as a factor in the model.

The mixed logit model was estimated by using the NLOGIT software package (Econometric Software Inc., 2007). A total of 16 driver, vehicle, roadway and environment related variables were considered in this study (**Table 7.1**). All variables were tested in the initial model but through the model building process, variables found to be statistically insignificant at a 5% level were omitted from the final model. These included weather, pavement condition and land use. The model development also involved the selection of random parameters, for which the use of the Lagrange Multiplier test as a basis for accepting or rejecting fixed parameters (over random parameters) could be adopted (McFadden and Train, 2000). Given that this test does not identify which random parameters are to be included in the model, an alternative approach of using a forward and backward stepwise variable selection procedure was adopted in this study. The log likelihood value at convergence was used as a basis to identify the random parameters and optimal model (Hensher et al., 2005).

Table 7.1: Descriptive Statistics of Variables

Variables	Description	Mean	Std. Deviation
At-fault	Driver at-fault in accident = 1 Otherwise = 0	0.56	0.496
6-year trend	Accident occurred in 2006-11 period = 1 Accident occurred in 2000-05 period = 0	0.72	0.449
Season	Autumn and Winter = 1 Spring and Summer = 0	0.50	0.500
Weather	Rain / Ice / Fog = 1 Fine / Sunny = 0	0.04	0.198
Pavement condition	Wet / Slippery = 1 Dry = 0	0.05	0.210
Traffic condition	Moderate / Heavy = 1 Light = 0	0.56	0.497
Lighting condition	Daylight = 1 Otherwise = 0	0.85	0.354
Priority measures	Locations with bus priority = 1 Otherwise = 0	0.01	0.113
Age of bus	25 years or more = 1 Otherwise = 0	0.04	0.197
Length of bus	Less than 12m = 1 Otherwise = 0	0.29	0.454
Driver's age	60 years or more = 1 Otherwise = 0	0.34	0.472
Driver's gender	Male = 1 Female = 0	0.86	0.343
Driver's experience	Less than 2 years = 1 Otherwise = 0	0.42	0.494
Driver's accident record	Previous at-fault accident = 1 Otherwise = 0	0.66	0.472
Road Type	Divided = 1 Otherwise = 0	0.18	0.385
Speed Limit	50kph and below = 1 Otherwise = 0	0.36	0.479
Land Use	Residential = 1 Otherwise = 0	0.58	0.494

7.5 Results of Bus Accident Type Analysis

Table 7.2 presents a breakdown of the bus accidents that occurred from year 2000 to 2011. It is apparent that the most common accident type involved collisions between buses and other vehicles (63.0%). Over a third of such collisions were cases of buses hitting stationary vehicles and vice versa. Between the two, there were three cases of buses hitting stationary vehicles for every case of a vehicle hitting a stationary bus (ratio of 3:1). This finding suggests that bus drivers experience greater difficulty in braking and manoeuvring, given the size and weight of buses compared to private vehicles.

Table 7.2: Breakdown of Bus Accidents

Accident Type	Number	Percentage of Total (%)
(A) Hit Pedestrians	6	0.1
(B) Hit stationary objects	2,461	34.9
(C) Bus-to-bus collision	142	2.0
(D) Bus-vehicle collision	4,450	63.0
(i) Bus into stationary vehicle	1,244	17.6
(ii) Vehicle into stationary bus	429	6.1
(iii) During lane changing	127	1.8
(iv) When turning	511	7.2
(v) Others	2,139	30.3
TOTAL	7,059	100.0

The second most common accident type involved buses hitting stationary objects, which accounted for nearly 35% of all bus accidents. Similar to previous studies (Wåhlberg, 2002, Strathman et al., 2010), the least common accidents involved pedestrians (0.1% of all accidents).

7.6 Bus Drivers' At-Fault Probability – Results and Implications of Findings

The parameter estimates of the final mixed logit model of bus drivers' probability of being at-fault in bus-involved accidents are presented in **Table 7.3**. All estimated parameters apart from the constant term in the model are found to be statistically significant at the 5% level and have plausible signs. Parameters are considered random if their estimated standard errors were found to be statistically different from zero, while those that yielded statistically non-significant standard errors for their assumed distribution were set to be fixed (or non-random) across the population.

7.6.1 Temporal Effects

Model results showed that the 6-year trend and season variables were significant in influencing bus driver's probability of being at-fault. Both parameters were found to be non-random and positive, which pointed to a higher likelihood of being at-fault for bus drivers in the latter 6-year period (2006-2011) as well as in autumn and winter seasons. With regard to the latter, it is interesting to note that a similar finding was obtained (albeit for accident risk) in a previous study, where school bus crashes were found to be higher in the autumn and winter periods (Yang et al., 2009). In this study, it is likely that the resulting shorter daylight hours, coupled with challenges in operating a bus given its size and weight, contributed to a greater likelihood of being at-fault in accidents for bus drivers.

Table 7.3: Mixed Logit Model of Bus Drivers' Probability of Being At-Fault

Variable	**Parameter Type**	***β***	**S.E.**	***t*-Statistic**
Temporal				
6-year trend 2006-11 vs. 2000-05	Non-random	0.421	0.039	10.95
Indicator for autumn and winter	Non-random	0.091	0.037	2.47
Roadway and Environmental				
Indicator for divided road	Non-random	-0.430	0.050	-8.55
Indicator for speed limit of 50kph or below	Non-random	0.310	0.042	7.46
Indicator for traffic condition – moderate / heavy	Random	-0.210	0.038	-5.48
(standard deviation of parameter distribution)		(0.400)	(0.0363)	(11.01)
Indicator for daylight condition	Random	-0.135	0.052	-2.60
(standard deviation of parameter distribution)		(0.421)	(0.0297)	(14.16)
Indicator for bus priority	Random	-0.447	0.216	-2.07
(standard deviation of parameter distribution)		(2.280)	(0.450)	(5.06)
Vehicle				
Indicator for bus age - 25 years or more	Non-random	0.270	0.097	2.78
Indicator for bus length - 12m or less	Non-random	-0.243	0.042	-5.85
Driver				
Indicator for driver's age - 60 years or more	Random	0.197	0.042	4.67
(standard deviation of parameter distribution)		(0.578)	(0.0492)	(11.74)
Indicator for driver's experience - 2 years or less	Random	0.172	0.041	4.25
(standard deviation of parameter distribution)		(0.586)	(0.0432)	(13.59)
Indicator for male driver	Non-random	-0.191	0.058	-3.29
Indicator for previous at-fault record	Random	0.123	0.041	4.25
(standard deviation of parameter distribution)		(0.293)	(0.0331)	(8.86)
Constant		0.046	0.094	0.49
Observations		N = 7,059		
Log-likelihood at zero		- 4841.56		
Log-likelihood at convergence		- 4531.04		

Note: β and S.E. represent the parameter estimate and standard error respectively

7.6.2 Roadway and Environmental (Including Bus Priority) Effects

The next set of findings relates to roadway and environmental effects on the likelihood of being at-fault. Model estimates for the road type parameter, which was found to be non-random, showed that drivers on divided roads were less likely to be at-fault compared to other road types, e.g. undivided and one-way roads. Results for the speed limit indicator also pointed to road with lower speed limits (50kph or below) increasing the probability of drivers' being at-fault. These findings suggest drivers are possibly facing space constraints along one-way or undivided road types, where lane widths and speed limits are often lower than on divided roads (typically main arterial roads). In Melbourne, it is common to find vehicles parked along the kerbside of local streets and in shopping precincts. As such, bus drivers often have to manoeuvre around stationary vehicles frequently along its route. The chances of hitting stationary vehicles and hence being judged at-fault become higher for bus drivers in these contexts.

The parameter for traffic condition was found to be negative which suggests the probability of being at-fault reduces when traffic conditions are heavier. This result was surprising at first glance, but it does point to the possibility that drivers exercise greater caution when traffic conditions become heavier. This parameter was also found to be normally distributed with a mean of -0.210 and standard deviation 0.4. Based on these estimates, the parameter takes on a negative value for 69.8% of drivers and positive value for 30.2% of the drivers. It thus implies that the heavy traffic condition effect varies and heavier conditions increase the likelihood of being at-fault for a minority of drivers. The parameter estimate for daylight condition was also normally distributed with a mean and standard deviation of -0.135 and 0.421 respectively. This suggests the chances of drivers being at-fault in bus-involved accidents are higher during daylight conditions for 37.4% of drivers but lower for 62.6% of drivers. For the majority of drivers, this finding makes intuitive sense as daylight conditions (as compared to night time) provide better visibility for drivers. A less obvious possibility however is that drivers are generally more alert in the day as compared to night time, where growing driver fatigue may have set in (Strathman et al., 2010).

With regard to bus priority, the indicator variable was found to vary over the sample of drivers. The parameter estimated was found to be normally distributed with a mean and standard deviation of -0.447 and 2.28 respectively, which implies bus priority measures reduce the likelihood of being at-fault in an accident for the majority (57.8%) of drivers, but increases for some 42.2% of drivers. These findings are plausible as they are likely to be picking up the differences in driver behaviour, given that bus priority may have given some drivers a false sense of security leading them to let their guard down. For the majority of drivers, bus priority in the form of bus lanes may have acted to address the confined road-space issue mentioned earlier, as they typically provide buses with exclusive right of way. Consequently, the likelihood of a driver being at-fault is lower when an accident occurs.

7.6.3 Vehicle Related Effects

In terms of vehicle related factors, the age and length of bus were found to be significant. Both parameter estimates were fixed across the observed drivers, and pointed to lower probability of being at-fault for drivers when operating shorter buses (12m or less) but higher likelihood if the buses were 25 years or older. These results were not surprising given that longer and older buses are likely to be less responsive, e.g. when sudden hard braking is required, due to its size and possibility that components had suffered greater wear-and-tear (Zein and Navin, 2003). With all things being equal, it is expected that such buses provide drivers with lower margins of error and consequently higher likelihood of being at-fault in an accident. Arguably, the bus company could have adopted a maintenance regime where parts are replaced before they reach the end of their service lives. If so, the lower at-fault probability could be attributed to the better performance of modern buses rather than the state of the components.

7.6.4 Driver Related Effects

As for driver related factors, earlier studies have showed demographic variables such as age, gender and driving experience to be associated with accident risk (Evans and Courtney, 1985, Blom et al., 1987, Williams and Shabanova, 2003, Strathman et al., 2010, Di Milia et al., 2011). In this study, four driver-related factors were found to be significant in influencing the driver's probability of being at-fault. First, the indicator variable for drivers' age (60 years or above) was found to be normally distributed with a mean and standard deviation of 0.197 and 0.578. This meant the likelihood of being at-fault increases for 63.3% of drivers aged above 60. This does not come as a surprise as driving skills for drivers over 60 years of age may have declined. Secondly, the indicator variable for drivers with 2 or less years of experience turned out to be normally distributed with a mean of 0.172 and standard deviation of 0.586, which implies 61.6% and 38.4% of the distribution is greater and less than zero respectively. As such, the likelihood of being at-fault increases for less experienced drivers (2 years or less) in nearly 62% of the cases. A similar pattern was reported by Tseng (2012) who showed driving experience having a parabolic relationship with at-fault accidents of tour bus drivers. The random parameters in our study however indicate that there exist possible differences in driver behaviour across the age and experience categories.

Thirdly, the indicator variable for male drivers was found to be fixed with a parameter estimate of -0.191, which implies male drivers having a lower probability of being at-fault as compared to their female counterparts. Finally, the model results also showed that the chances of a driver being at-fault also appear to be related to whether he or she had been at-fault in a previous accident. This finding appears to lend support to earlier studies which point to the presence of accident prone personality in drivers (Di Milia et al., 2011) and increasing likelihood of a driver not being involved in a new accident the longer he/she goes without one (Hamed et al., 1998). With the parameter estimate estimated to be normally distributed with a mean of 0.123 and standard deviation of 0.293, it implies that having a previous at-fault record increases the likelihood of being at-fault in an accident for the majority (66.3%) of the drivers, but reduces for a minority (33.7%) of drivers. This finding is likely to be picking up the differences in risk-taking behaviour as a minority of drivers might have exercised greater caution while some remain relatively unaffected after a previous at-fault accident.

7.7 Conclusion

In this chapter, bus accident characteristics and the probability of bus drivers being at-fault in bus accidents in Melbourne were explored. Apart from the observation that previous research is limited in examining at-fault accidents, the key motivation behind this study was on gaining an understanding on how bus priority affects the probability of bus drivers' being at-fault in bus accidents.

An analysis of bus accidents revealed that similar to previous studies, the most common accident types were bus-vehicle and bus-objects collisions. For the former, there were more cases of buses hitting stationary vehicles than vehicles hitting stationary buses, which suggest that bus drivers experience greater difficulty in braking[g], given the size and weight of buses compared to private vehicles.

Results from the mixed logit model showed several driver, vehicle, roadway and environmental factors that influence the probability of bus drivers being at-fault. Parameter estimates indicated that drivers are less likely to be involved in an at-fault accident if they operate shorter (12m or less) and newer (25 years old or below) buses. The likelihood of being at-fault was also lower for drivers who are male and drive on routes that comprise mainly divided roads. Heavier traffic condition, daylight and the presence of bus priority were also found to reduce the likelihood of being at-fault.

[g] *Bus performance standards, as specified in Vehicle Standard (Australian Design Rule 35/05 – Commercial Vehicle Brake Systems) 2013, are also less stringent than for passenger cars, with maximum braking capacity lower than that of a car. The contrast is even more significant with the increasing application of ABS in cars allowing excellent braking in wet conditions when non-ABS heavy vehicles will experience significant degradation.*

However, these three parameters varied across drivers. Variables found to be associated with higher chances of being at-fault were the driver age (60 years and above), experience (2 years or less) and previous at-fault accident involvement. These patterns however varied across the drivers.

A key focus in the modelling was to understand the influence of bus priority on bus drivers' at-fault probability. Results showed that routes having bus priority were associated with a lower probability of being at-fault. It therefore suggested that bus drivers are currently facing manoeuvrability issues in tight confined road-spaces and along routes with much roadside friction. This alludes to the provision of exclusive right of way for buses or traffic management measures to reduce roadside friction as a possible way to address road-space and safety issues for buses. For bus and road management agencies, findings from this study point to bus priority bringing about considerable benefits for bus companies. Not only does bus priority provide for a better travel experience for bus drivers and commuter, it helps reduce financial cost for bus companies because bus drivers are less likely to be at-fault when they are involved in accidents.

There were other noteworthy findings that could help inform policy makers in their operational and safety-related decisions. First, overall results suggest drivers are less likely to be at-fault in accidents on divided roads. Secondly, results showed that bus age and size play a significant role in influencing the driver's probability of being at-fault. In this aspect, it revealed that the likelihood of being at-fault is higher for drivers with little experience (2 years or less) and those aged 60 years more. When taken together with the impact of bus priority, these suggest there could be benefits in assigning routes with bus priority and comprising mainly divided roads (as opposed to undivided collector / distributor roads) to less experienced drivers. It also points to the potential advantage of assigning new drivers to buses that are shorter and newer while allocating atypical buses, i.e. longer and those aged 25 years or more, to more experienced drivers. Although this study focussed on at-fault accidents, it is likely that many of the findings of this study apply to all bus-involved crashes as well, since in addition to driver behaviour, vehicle, road and environmental factors also play a significant role in the majority of crashes.

In practice the implementation of the suggested measures above can be challenging for some bus companies, e.g. those with route assignment based on drivers' seniority. Senior drivers may thus be displeased with having to operate older buses and along tougher routes. As a way ahead, it is likely that bus companies will have to arrive at a roster solution that also caters to individual preferences while rolling out the suggested measures. This may require a negotiation process and result in increased rostering complexity where individual-specific constraints are taken into account, but would ensure to some extent that job satisfaction for bus drivers would not be compromised.

In sum, findings from this study lent further support on further research in bus safety given the financial and social impact to bus companies, road users, commuters and the community whenever an accident occurs. Although findings have provided new insights into the risk factors and effect of having bus priority that influence the probability of being bus drivers being at-fault in bus-involved accidents, it is acknowledged that certain limitations exist. First, the database only provided accident characteristics but do not offer any explanation on why certain accident types are more prevalent. Second, while mixed logit modelling acts as a useful tool to account for behavioural variations in the dataset, it should be noted that the mixing distribution in the model was assumed to take on an arbitrary parametric form (normal distribution in this study). There is therefore scope to explore other forms of distributions that may yield better approximations to the real behavioural profile. Third, results from this study may only be unique to Melbourne because of certain distinctive features in its traffic and social environment, e.g. generally much lower pedestrian volume in Metropolitan Melbourne. At this stage, verifying the validity of the findings cannot be done until equivalent studies of this type are undertaken in other jurisdictions. Finally, certain driver behaviour attributes were also not captured and considered in this study. However, they are likely to be important, as model results have showed, in explaining the varying influence of variables affecting the probability of bus drivers being at-fault.

It is the latter point that provided the motivation for the next chapter, as it focuses on the use of micro-simulation modelling approach, which thus allows for an examination of the safety effects of bus priority in a controlled experiment setting.

CHAPTER 8 MICRO-SIMULATION MODELLING APPROACH

8.1 Introduction

This chapter centres on the use of microscopic simulation modelling to understand the road safety effects of implementing different “space based” bus priority schemes on a selected road corridor in Metropolitan Melbourne.

Results from the previous chapter revealed that the presence of bus priority had a positive influence on bus safety at the route-section level. The question on why this is so remains to be answered. This sets the thrust of this chapter, as it aims to explore bus priority effects in greater detail by examining how and why conflicts and crash risks change when bus priority is introduced.

This chapter originated in the paper Goh K., Currie, G., Sarvi, M. & Logan, D. (In Press) Investigating Road Safety Impacts of Bus Priority Using Experimental Micro-simulation Modelling. *Transportation Research Record - Journal of the Transportation Research Board*. (Accepted 9th February 2014). It starts with a review of previous research, with a focus on studies that had examined safety performance of roads with bus priority or had adopted surrogate safety measures in micro-simulation modelling for safety evaluation purpose. Details of the research context are presented, following which a description of the bus priority case study is provided. The data and methodology used are then described after which a detailing of the major study findings is done. Discussion of results and conclusions finalize the chapter.

8.2 Research Background

Various types of bus priority initiative exist internationally, each differing essentially by the amount of road space or time (or combination of both) that has been allocated for buses. Regardless of its form, there has been overwhelming evidence to show that bus priority measures bring about higher service levels and operational benefits (Sakamoto et al., 2007, Furth and Muller, 2000). Whilst this bodes well for commuters and bus agencies, its safety implications to other road users remain unclear as findings from previous research have been limited and more importantly, mixed (Goh et al., 2013). This is not surprising as the majority of previous studies have relied on historical crash records, which often come with data and methodological issues that could lead to erroneous results if not dealt with appropriately (Lord and Mannering, 2010). The recent emergence of surrogate safety measures in micro-simulation modelling has now presented an opportunity to examine the safety effects of bus priority in a controlled experiment setting thus overcoming the aforementioned issues.

8.2.1 Emergence of Surrogate Safety Measures

Much of previous work in micro-simulation based safety assessments were based on the pioneering work by Gettman and Head (2003), where five SSMs were eventually recommended for the purpose of safety evaluation in micro-simulation modelling - (1) Time to collision (TTC); (2) Post-encroachment time (PET); (3) Maximum speed (MaxS); (4) Maximum speed difference (DeltaS) and (5) Deceleration rate to avoid a collision (DRAC) between two conflicting vehicles. The usefulness of a sixth surrogate measure – headway (H) – for safety evaluation at junctions was investigated by Vogel (2003). Results showed that there was a greater variation in the TTC values as compared to H values, and was therefore a better indicator of actual danger. H values on the other hand would be useful for checking for tailgating behaviour.

Subsequent studies have also explored other SSMs. Ismail et al. (2009) for example assessed the adequacy of gap time (GT) and deceleration-to-safety time (DST) in addition to TTC and PET as safety indicators for pedestrian-vehicle conflicts. Results showed that conflicts were better identified when all four indicators were used together instead of any on their own. Of the four, the authors reported that PET was most reliable in detecting important incidents (defined as a conceivable chain of events that could lead to a collision between road users). In a separate study, Pirdavani et al. (2010) used PET as an indicator in their investigation on intersection safety. The results revealed PET to be a useful safety indicator as its values varied with different speed limits and volume. However, the authors argued that PET would only be useful for investigating transverse collisions and as such, other indicators such as TTC should be adopted if other types of collisions, e.g. rear-end and converging are of interest. Archer and Young (2009) used both PET and the number of red light violations as surrogate safety measures to evaluate the safety and traffic system efficiency of 5 alternative signal treatments at a metropolitan highway intersection. Using micro-simulation (VISSIM), the software was able to generate results to show that amber extension treatment yielded the greatest effect in terms of reducing red-light violations. Saccomanno et al. (2008) used TTC, DRAC and crash potential index (CPI) to compare traffic conflicts at roundabouts and signalized intersections. The latter, which is based on DRAC and maximum available deceleration rate, was used as the authors argued that DRAC alone would fail to consider vehicle-specific braking capability and varying traffic conditions. Results showed all three indicators were able to reflect the effect of geometry, weather and traffic volume. In a similar study, DRAC, TTC and proportion of stopping distance (PSD), which is the ratio between the remaining distance to the potential collision point and minimum acceptable stopping distance, were used as indicators to evaluate the safety effect of converting a stop sign controlled intersection to a roundabout (Astarita et al., 2012). The authors found that TTC and

DRAC, in particular, were better safety indicators in reflecting the reduction in number of vehicle interaction with the introduction of a roundabout.

From these studies, it is observed that the bulk had adopted TTC and DRAC as safety indicators, possibly because they are more intuitively appealing and reliable in detecting incidents. TTC, which can be easily understood as the expected time for two vehicles to reach a common point on the road assuming neither vehicle change their speed and trajectory, appears to be used commonly in both road corridor and intersection safety studies. DRAC on the other hand, is used more often when speed differentials and deceleration requirements of vehicles are considered to be important in the study context. Specifically, DRAC is defined as the deceleration needed by the following vehicle to come to a timely stop or attain the matching lead vehicle speed to avoid a rear-end crash, and is expressed as:

$$DRAC_{i,t} = \frac{(V_{i,t} - V_{i-1,t})^2}{2[(X_{i-1,t} - X_{i,t}) - L_{i-1,t}]} \qquad (8.1)$$

where
t = Time interval (s)
X = Position of vehicle (i = following vehicle, i - 1 = lead vehicle);
L = Vehicle length (m); and
V = Velocity (m/s^2)

Between the two, it appears DRAC is a better safety indicator as it overcomes a key limitation in TTC – not accounting for speed and spatial differences between vehicles. This is because TTC will consider two vehicles approaching each other at high speeds from a large distance to be no different in terms of safety to another pair of vehicles approaching each other at slower speeds but over shorter distances (Archer, 2005). This could be unrealistic as the former could potentially be risker given that much braking is needed.

The use of DRAC alone however raises concerns as researchers have recently argued that it does not account for vehicle-specific braking capabilities and prevailing road conditions (Cunto and Saccomanno, 2008, Saccomanno et al., 2008). To overcome this limitation, Cunto and Saccomanno (2007) proposed the use of a crash potential index (CPI) as provided in equation 8.2, in which values of the maximum available deceleration rates for different vehicle types are based on parameter values adopted by AASHTO (2004), as shown in **Table 8.1**.

$$CPI_i = \frac{\sum_{t=ti_i}^{t=tf_i} p(DRAC_{i,t} > MADR_{i,t})\Delta tb}{T_i} \qquad (8.2)$$

where t = Time interval (in which ti_i and tf_i are the initial and final time slice for a given time period for vehicle i)
T = Total simulated time interval;
b = Binary variable (=1 if $DRAC_{i,t}$>0 or 0 otherwise);
Δt = Observation time interval (s); and
$MADR$ = Maximum available deceleration rate (m/s^2)

Table 8.1: Truncated Normal Distribution Parameters for MADR (Source: AASHTO, 2004)

MADR distribution parameters	Vehicle Type	
	Car	Truck / Bus
Average (m/s^2)	8.45	6.82
Standard deviation (m/s^2)	1.40	1.40
Upper limit (m/s^2)	12.68	10.05
Lower limit (m/s^2)	1.23	0.60

8.2.2 Summary of Findings

In summary, previous research on the safety implications of bus priority have been few and far between. From the limited studies that had been done, results have generally been mixed. Readers have to also contend with potential data and methodological issues, which are inherent in historical crash data that had been used in these studies. As such, our understanding on why certain bus priority schemes had led to positive safety benefits while others have yielded opposite effects remain unclear. With the emergence of SSMs in micro-simulation modelling, there is now an opportunity to examine the safety effects of bus priority in a controlled experiment setting. The choice of the surrogate safety measure however has to be made with careful consideration of the study context.

8.3 Research Context

8.3.1 Hypotheses on Safety Benefits of Bus Priority

The safety review carried out in Chapter 4 gave rise to a number of hypotheses on the safety benefits of bus priority which are summarized in **Table 8.2**. It was clear that some of these could be tested in a micro-simulation environment, given that SSMs such as DRAC and TTC are particularly good at assessing risk associated with lane changing and breaking behaviours. DRAC in particular appears to be a useful indicator of rear-end and side swipe accident risks, and would be most suited for testing hypotheses associated with impacts at bus stop and intersection locations. On the other hand, corridor level safety issues associated with 'run-off' accidents (hypothesis 1) and issues associated with improved traffic visibility (hypotheses 2 and 6) could not be assessed using micro-simulation modelling alone. For this reason, the focus of this research was on intersection and bus stop locations.

Table 8.2: Hypotheses on Safety Benefits of Bus Priority

No.	Location	Hypothesis	Testable Using Micro-simulation / SSM?
1	Corridor	Reduced risk of run-off accidents with bus lane acting as roadside buffer	No
2	Corridor	Improved visibility for drivers with buses segregated from main traffic stream	Unclear
3	Uncontrolled Intersections	Reduced risk of rear-end accidents for vehicles entering side streets as bus lane allows vehicles (bus and turning traffic) to break away / separate from mainstream traffic and slow down before turning	Yes
4	Uncontrolled Intersections	Reduced risk of side-swipe accidents for vehicles entering main street as bus lane allows vehicle to pick up speed before joining mainstream traffic	Yes
5	Controlled Intersections	Reduced risk of rear-end accidents as vehicles move into bus lane before turning at intersection	Yes
6	Controlled Intersections	Improved intersection visibility for vehicles with buses segregated from main traffic stream	Unclear
7	Bus Stops	Reduced risk of vehicles hitting rear of slowing or stationary bus	Yes
8	Bus Stops	Reduced risk of side swipe accidents as a result of vehicle changing lane to overtake slowing or stationary bus	Yes
9	Bus Stops	Reduced side-swipe accident risk for buses moving off	Yes

8.3.2 Research Aim

This phase of the research aims to explore the road safety performance of a representative 3-lane road corridor in Melbourne across three road configurations - (1) mixed traffic; (2) kerbside lane relocated for bus use only; and (3) new kerbside lane created for bus use only (**Figure 8.1**).

As highlighted, given the limitations of SSMs in reflecting corridor level accident risks, the focus of this research will be on conflicts recorded at intersection and bus stop locations, where rear-end and side-swipe accidents are most prevalent and safety effects can be established in micro-simulation. Conflicts at the corridor level will still be recorded, but they are intended more for broad-based comparison of schemes rather than interpretation of safety effects.

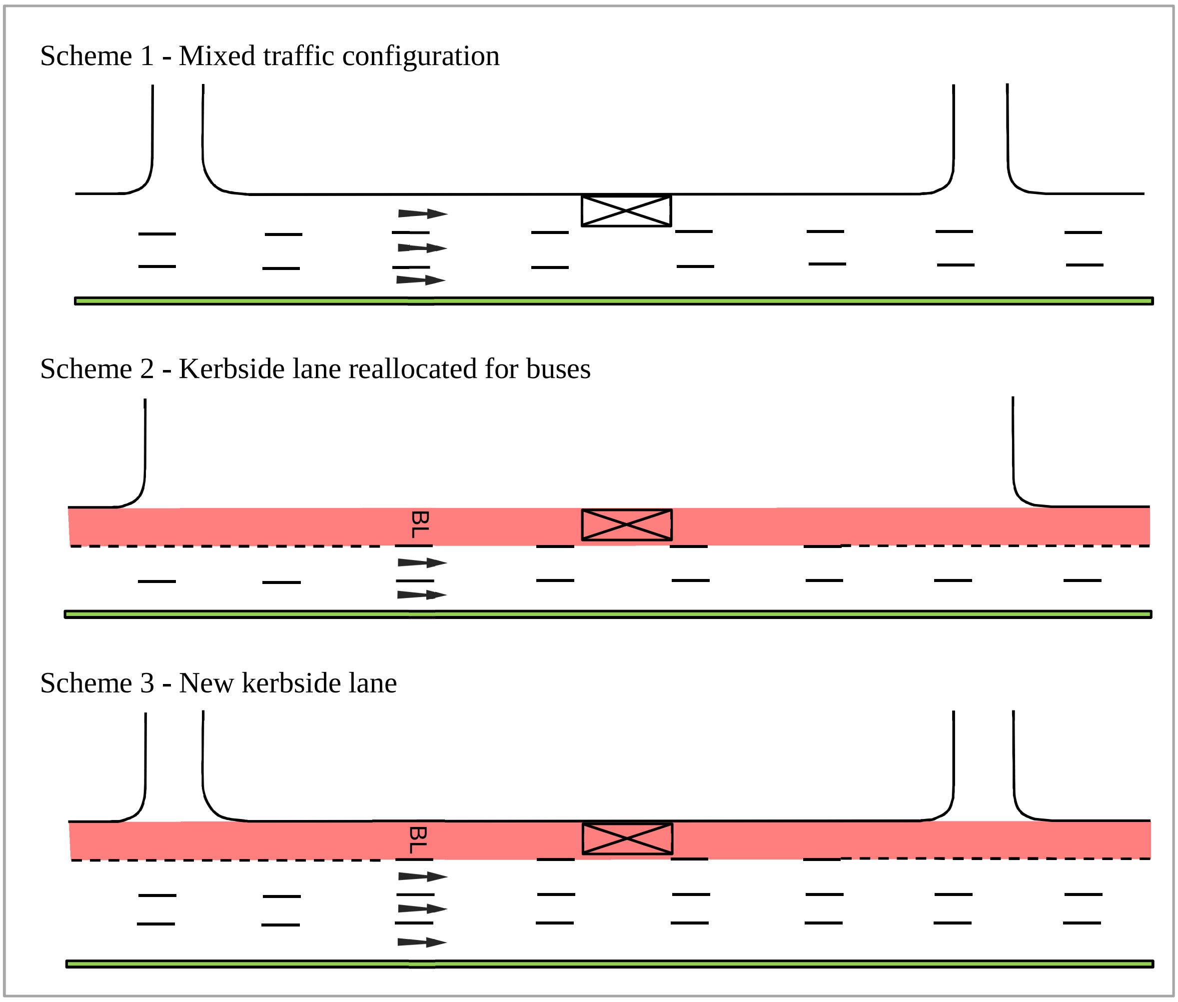


Figure 8.1: Exploring Safety Effects of Different Bus Priority Schemes

8.4 Case Study

To examine the effect of the bus priority measures in **Figure 8.1**, a case study approach was adopted in which a road corridor deemed to be representative in Metropolitan Melbourne was selected.

This corridor is a 1.6km stretch of three-lane divided arterial road in Metropolitan Melbourne - Blackburn Road from Wellington Road to Ferntree Gully Road (**Figure 8.2**). There are four intersections along this route, which has a speed limit of 70kph. Two bus services ply along this north-south route (with an additional from Normanby to Ferntree Gully Road), which currently operates as a mixed traffic configuration where no priority is provided for buses. There are five bus stops along each bound, and of these, only one is provided with a bus bay. With Blackburn Road operating in a mixed traffic condition with no bus priority (Scheme 1), it acts as a baseline for the collection of validation and calibration data for the model, following which it can then be used to determine the effects of the implementation of the two different space based bus priority schemes (Schemes 2 and 3).

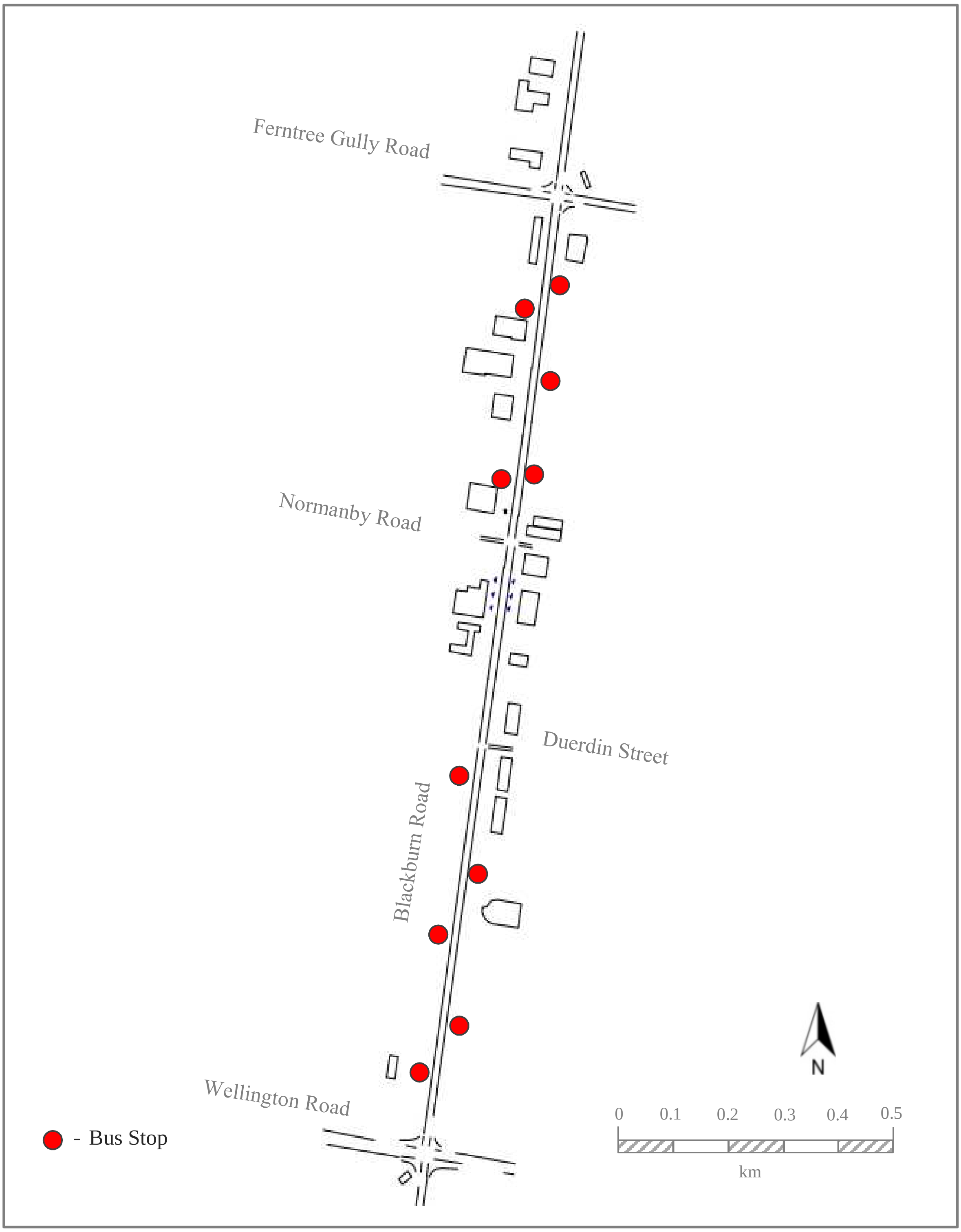


Figure 8.2: Road Corridor in Case Study

8.5 Modelling Approach

8.5.1 Data Collection

Traffic data collected for this study was obtained from the signal control (or SCATS) system maintained by the Traffic Operations Unit of VicRoads, Australia. This data included turning volume at the intersections, which act to inform the micro-simulation model on the turning percentages at each intersection. In addition, through the use of the video equipment detailed in section 3.5.2, traffic data on a representative section of the road corridor was recorded for two weeks (ten weekdays) in December 2012 (**Figure 8.3**). The afternoon peak period (17:00-19:00hrs) data was then extracted for the model development.

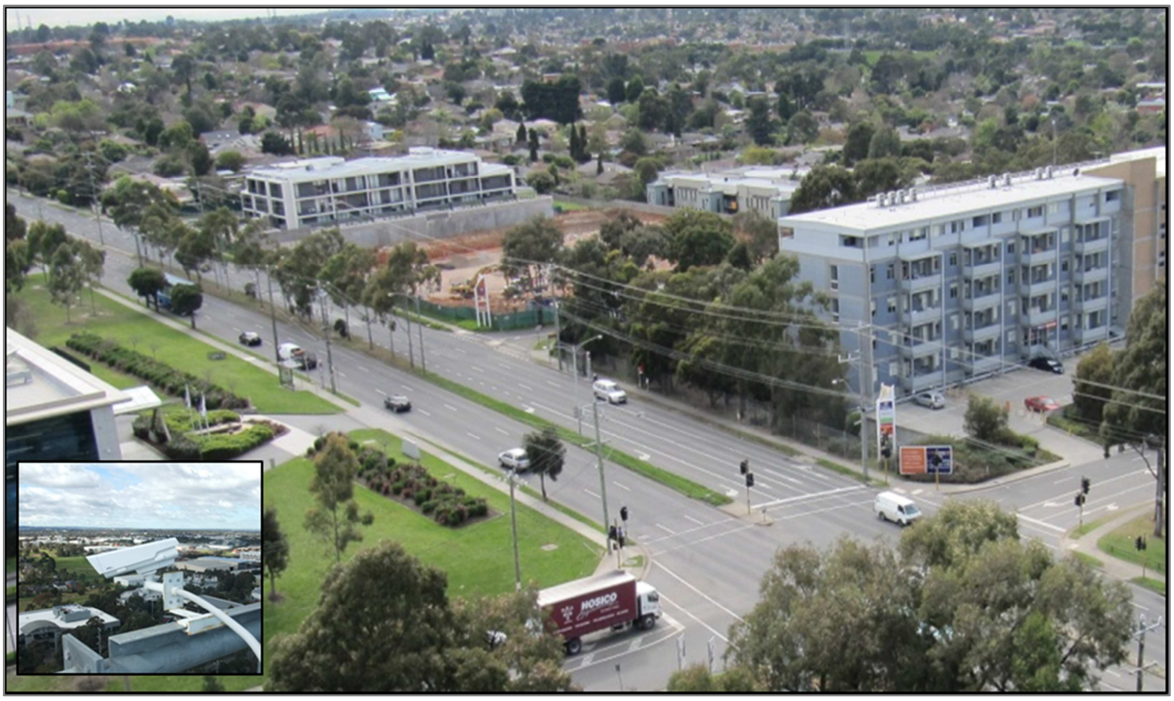


Figure 8.3: Video Equipment Used (Inset) and Coverage of Road Corridor

Empirical data were also collected through a northbound travel time survey on 3 weekdays during the afternoon peak period. From the video and travel time data, it was possible to check against the SCATS data to ensure traffic volume was comparable and help facilitate model calibration and validation - a crucial step in the micro-simulation modelling.

8.5.2 Micro-Simulation Modelling

AIMSUN (Advanced Interactive Microscopic Simulation for Urban and Non-urban Networks) micro-simulation tool (Version 7.0) was used to model the road corridor and explore the safety implication of implementing the different bus priority measures. AIMSUN allows for both microscopic and mesoscopic modelling of various networks including public transport operations (TSS-Transport Simulation Systems, 2012), and is a useful tool for the analysis and assessment of different transport planning schemes and traffic management measures. In this research, the AIMSUN base model was developed using an aerial photograph and map based GIS data of the site. Traffic data collected which included vehicle counts and traffic composition as described in the preceding section, were then used as inputs to the base model.

As highlighted earlier, a number of surrogate safety measures can be used for safety evaluation. From the literature, it is clear literature that TTC, PET and DRAC are most commonly used as they are likely to have stronger relevance to safety. Given that the case study is on a road corridor where rear-end and lane-change conflicts are of interest, DRAC was chosen as the surrogate safety measure. A second measure, CPI was also selected to account for vehicle-specific braking capabilities. For this research, a conflict was registered when DRAC exceeded the threshold value of $3.35 m/s^2$. This value was selected as previous studies have shown deceleration rates exceeding this level appear to reflect unsafe conditions (Archer, 2005, van der Horst, 1991). Video analysis was subsequently done using the motion analysis software MotionView - Advanced edition (AllSportSystems Inc., 2012), which allowed video data to be processed on frame-by-frame basis. Through this, DRAC conflicts over the two-week period were recorded for model calibration and validation purposes.

Given the danger that inappropriately calibrated models could lead to misleading findings (Park and Qi, 2005), much effort was focussed on model calibration and validation to ensure the base model (scheme 1) reflected actual driving safety-related behaviour well. Following the work by Huang et al. (2013), a two-stage approach was similarly adopted for model calibration and validation in this research. In stage 1, vehicle and behaviour parameters were fine-tuned so that the model accurately represented the observed traffic and driving behaviour (Fang, 2005, Cunto and Saccomanno, 2008). This step centred on ensuring that (1) travel time along the northbound carriageway of the road corridor and (2) queue discharge headway distribution of a selected intersection closely matched the observed data. The GEH-statistic was used to compare empirical and modelled travel time, while the Kolmogorov-Smirnov (K-S) and Mann Whitney U test statistic were used to compare observed and modelled headway distributions. Model parameters were adjusted until a GEH-value of less than 5 was achieved in more than 85% of the cases, and K-S and Mann Whitney U test results indicate that the observed and modelled headway are comparable. In stage 2, efforts were focussed on fine-tuning model parameters to replicate observed safety-related behaviour and conflicts. To obtain modelled conflicts, a separate software module titled "Surrogate Safety Assessment Model (SSAM)" (Gettman and Head, 2003) was used to extract conflict information from vehicle trajectory files generated by AIMSUN. Two commonly used error measures - mean absolute percentage error (MAPE) and mean absolute error (MAE) - were used to measure the differences between the observed and modelled conflicts for the purpose of finding the optimal set of model parameters:

$$\text{Observed Conflicts} = \overline{C}_O = \frac{1}{m}\sum_{i=1}^{m} C_O^i \tag{8.3}$$

$$\text{Modelled Conflicts} = \overline{C}_M = \frac{1}{n}\sum_{i=1}^{n} C_M^i \tag{8.4}$$

$$MAPE = \left|\frac{\overline{C}_M - \overline{C}_O}{\overline{C}_O}\right| \tag{8.5}$$

$$MAPE = \overline{C}_M - \overline{C}_O \tag{8.6}$$

where C_O and C_M represent the observed and modelled number of conflicts, respectively. The above represents a minor deviation to work by Huang et al. (2013), as it aims to find the optimal DRAC threshold value in the model that best replicate the number of pre-defined observed conflicts (DRACs < $3.35 m/s^2$).

Model validation was subsequently done by collecting an additional four hours of video data on two separate weekdays. Similar to the calibration process, the GEH, K-S and Mann Whitney U test were used to assess the model's ability to replicate observed travel time and queue discharge headway. Another criterion for successful model validation used was that the observed number of conflicts should be within the 90% confidence intervals obtained from 10 simulation runs. With the completion of model calibration and validation, simulation models were developed for each of the three scenarios. To ensure stable results (Young et al., 1989), each model was run 10 times with different random seed numbers. For each run, the number of modelled conflicts was then extracted at the following three locations:

- ✓ Intersection approaches (on two leftmost lanes);
- ✓ Bus stops (two leftmost lanes up to 50m upstream of all bus stops); and
- ✓ Entire corridor (all lanes of the carriageway)

Each model was also subjected to 5 levels of traffic demand to test the effect of volume on conflicts. The number of conflicts recorded over 10 runs was averaged and its value used as a basis for comparing the safety effects of different traffic and bus priority schemes. **Figure 8.4** summarizes the approach adopted in this study to obtain the conflicts from the micro-simulation models.

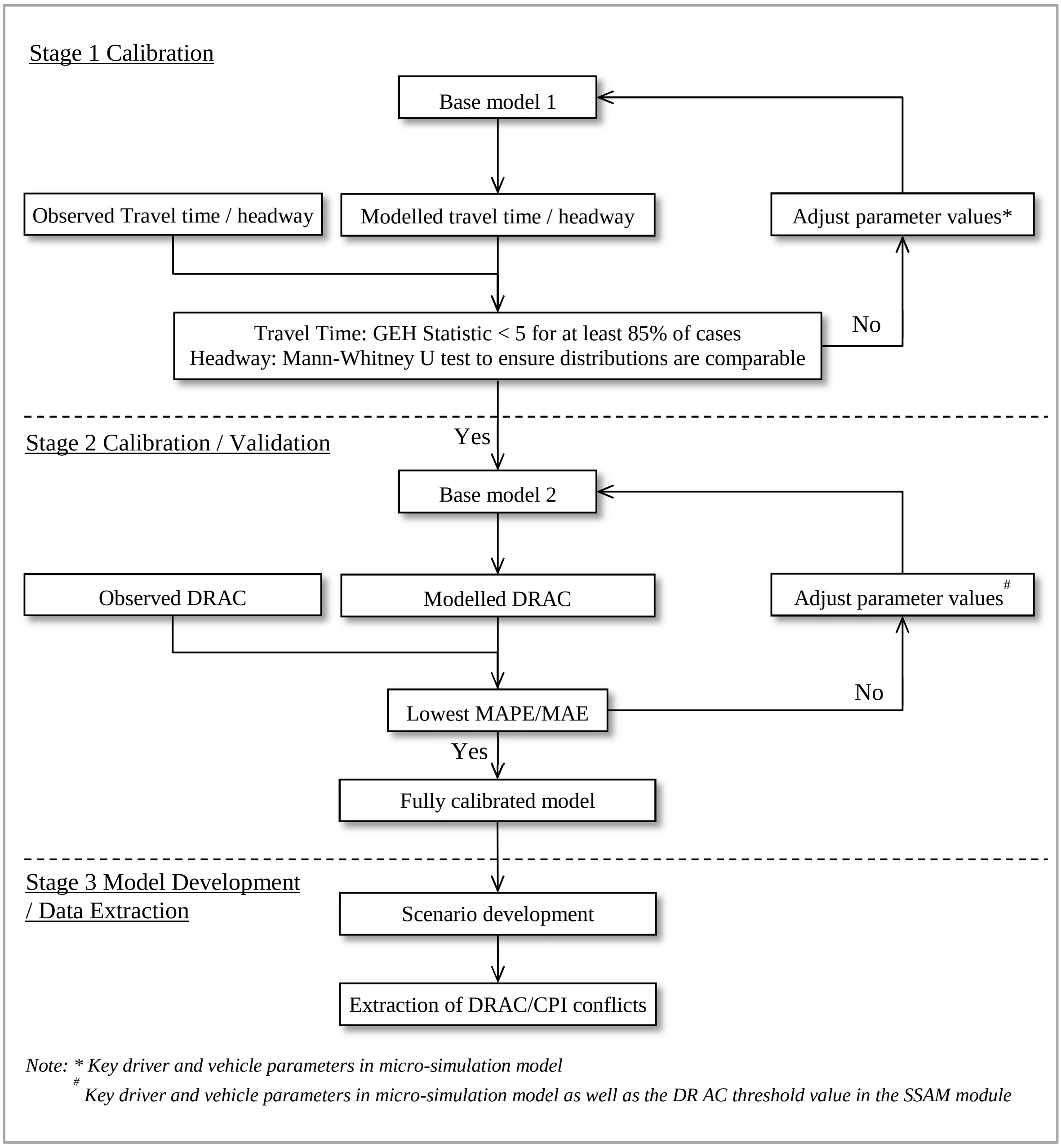


Figure 8.4: Staged Approach to Safety Evaluation in Micro-Simulation Modelling

8.6 Results

8.6.1 Model Development

Results from Stage 1 of the calibration process are presented in **Appendix E-1**. In stage 2, a sensitivity analysis revealed that the parameter that had the greatest impact on the number of modelled conflicts was the threshold value of DRAC in the SSAM. Based on the MAPE and MAE results, it was found that best goodness-of-fit was achieved when the DRAC threshold value was set at 3.30m/s^2 (**Figure 8.5**). This value was subsequently adopted for the conflict analysis in SSAM. The final calibrated model (with adopted parameter values provided in **Appendix E-2**) was validated using data extracted from the video recordings on 2 separate weekdays.

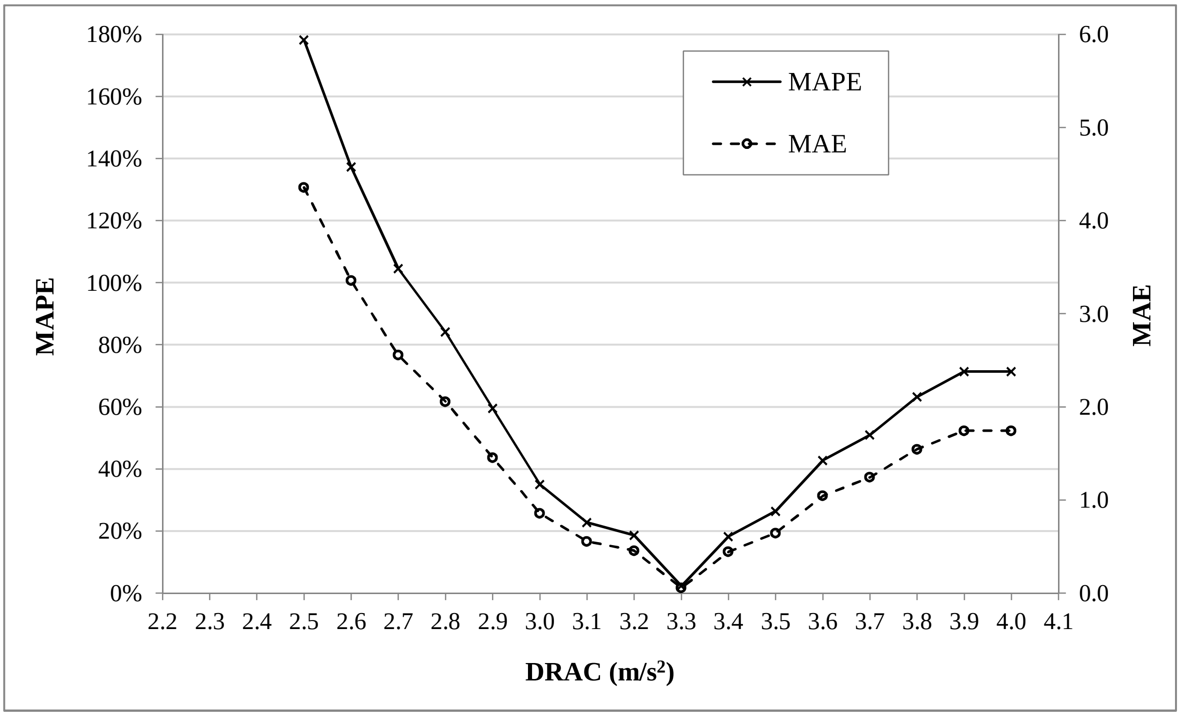


Figure 8.5: MAPE and MAE Values for Observed and Modelled Conflicts across Different TTC and DRAC Threshold Values

8.6.2 Conflict Analysis

Conflicts from the micro-simulation runs were recorded based on the traffic scheme, traffic volume and locations where conflicts took place. **Table 8.3** summarizes the number of conflicts (averaged over 10 simulation runs) from the micro-simulation model in terms of DRAC and CPI. Based on the model results, the following observations were made:

1. Traffic volume had a direct effect on number of conflicts in all three traffic schemes, as results of the Kruskal-Wallis H test showed that the number of conflicts were statistically significantly different across the five levels of traffic volume in each scheme tested in the micro-simulation model at the corridor-level. A plot of conflicts and traffic volume point to a curvilinear relationship between the two variables, i.e. the rate of increase in the number of conflicts increases with higher traffic volume.
2. Whilst traffic volume had an effect on conflicts in the mixed traffic configuration (scheme 1), its effect was less obvious at intersection and bus stop locations when space reallocation (scheme 2) or space creation for buses (schemes 3) were applied. Kruskal-Wallis H test results showed that the differences in the number

of conflicts at intersection locations in schemes 2 and 3 were not statistically significant when traffic volume varied from 600 to 1800 vehicles per hour. A similar finding was obtained at bus stops locations (**Table 8.4**). These findings appear to be reasonable because we would expect traffic in the leftmost lanes to be much lower in the schemes involving space reallocation and new lane creation for buses.

Table 8.3: Number of Conflicts (over 2-hour period) from Simulated Traffic Scenarios

Traffic Scheme	Location	Traffic Volume (Vehicle per hour)									
		600		900		1200		1500		1800	
		DRAC	CPI	DRAC	CPI	DRAC	CPI	DRAC	CPI	DRAC	CPI
1 - Mixed	Intersections	5.0	0.4	6.1	1.9	8.0	2.3	9.6	4.8	20.7	12.7
	Bus Stops	0.9	0.5	3.1	1.5	3.6	1.7	6.1	3.4	7.1	3.7
	Corridor	25.0	7.7	56.4	24.3	98.1	44.6	161.5	82.4	309.5	170.2
2 - Reallocation	Intersections	0.7	0.0	1.0	0.3	1.1	0.2	1.0	0.1	1.1	0.4
	Bus Stops	0.8	0.0	2.2	0.6	2.8	0.4	2.1	0.8	1.7	0.3
	Corridor	25.6	9.9	60.5	25.4	121.3	59.4	233.1	136.3	455.3	314.6
3 - New lane	Intersections	1.5	0.0	2.1	0.0	1.3	0.0	1.2	0.3	0.8	0.1
	Bus Stops	0.1	0.1	0.1	0.0	0.3	0.2	0.9	0.4	0.5	0.4
	Corridor	26.0	9.1	58.7	26.9	85.7	47.2	149.8	78.1	229.5	125

Table 8.4: Results of Kruskal-Wallis H Test for Volume Effect

Safety Measure	Location	Volume (Veh/hr)	Traffic Scheme		
			1	2	3
DRAC	Intersections	600 to 1800	0.00	0.92*	0.08*
	Bus Stops	600 to 1800	0.00	0.06*	0.10*
	Corridor-level	600 to 1800	0.00	0.00	0.00
CPI	Intersections	600 to 1800	0.00	0.33*	0.06*
	Bus Stops	600 to 1800	0.00	0.09*	0.19*
	Corridor-level	600 to 1800	0.00	0.00	0.00

*Note: *Indicates absence of statistical evidence to reject the hypothesis that the number of conflicts varies across different traffic volumes*

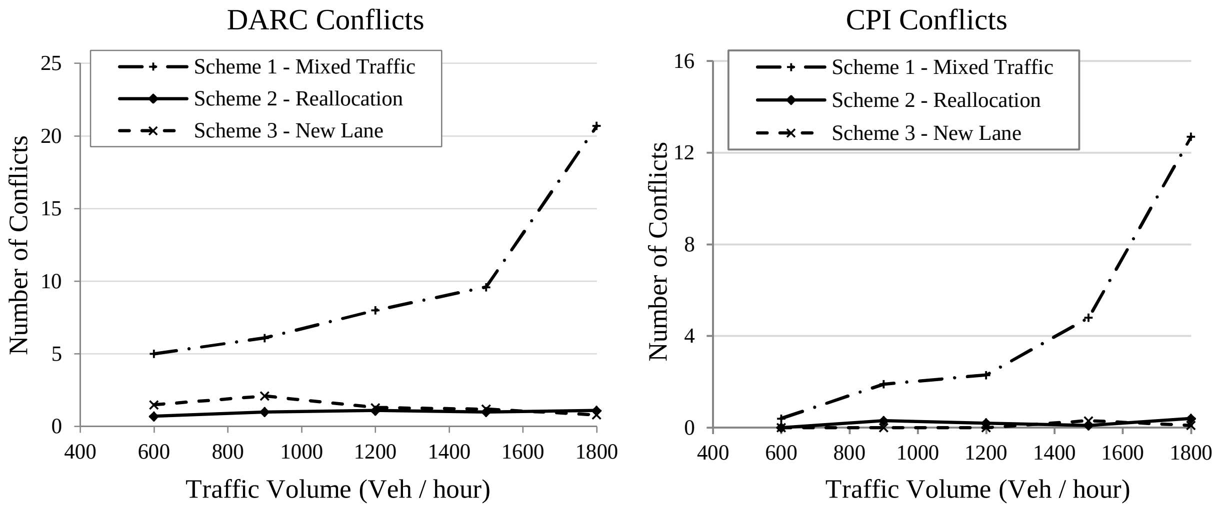
Table 8.5 captures the changes in the number of conflicts when schemes 2 and 3 were compared against scheme 1. The Mann-Whitney U test with statistical significance established at the 5% level was employed to detect statistical differences in the number of conflicts across traffic schemes. Results showed that:

1. At intersections, the number of conflicts was found to be consistently lower in schemes 2 or 3 than scheme 1, regardless of the type of safety performance measure adopted (DRAC or CPI). These differences were statistically significant ($p<0.05$) when the DRAC measure was used, or when the CPI measure was used and traffic volume exceeded 900 vehicles per hour (**Figure 8.6a**).
2. Similar observations were recorded at bus stop locations, in which the number of conflicts was found to be consistently lower in schemes 2 or 3 than in scheme 1. Differences in CPI or DRAC conflicts were however significant only when volume exceeded 900 vehicles per hour in scheme 2. For scheme 3, differences were significant when the DRAC measure was used but only above traffic volume of 1500 vehicles per hour when the CPI measure was used (**Figure 8.6b**).
3. At the corridor level, the number of conflicts was in general higher in scheme 2 and lower in scheme 3 as compared to scheme 1. However as noted earlier, corridor results were not a close focus of the analysis since SSM would only explore safety effects of bus priority at intersection and bus stop levels. What was interesting however is that some increases in conflicts were noted at the corridor level for scheme 2. Since actual evidence shows net reductions, the implications are that modelled increases in conflicts must be more than offset by safety effects not being modelled using micro-simulation. It implies a mix of safety impacts is occurring with scheme 2.

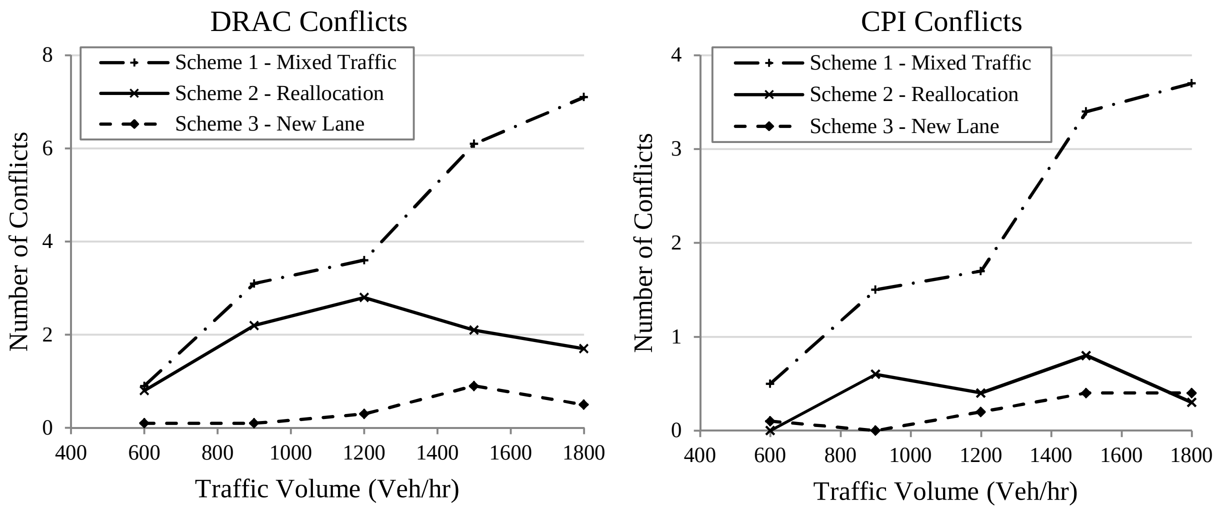
Table 8.5: Change in Number of Conflicts Compared to Scheme 1 (Mixed Traffic)

Safety Measure	Traffic Scheme	Location	Traffic Volume (vehicles / hour)				
			600	900	1200	1500	1800
DRAC	2	Intersections	-4.3*	-5.1*	-6.9*	-8.6*	-19.6*
	3		-3.5*	-4.0*	-6.7*	-8.4*	-19.9*
	2	Bus Stops	-0.1	-0.9	-0.8*	-4.0*	-5.4*
	3		-0.8*	-3.0*	-3.3*	-5.2*	-6.6*
	2	Corridor	0.6	4.1	23.2*	71.6*	145.8*
	3		1.0	2.3	-12.4	-11.7	-80.0*
CPI	2	Intersections	-0.4	-1.6	-2.1*	-4.7*	-12.3*
	3		-0.4	-1.9*	-2.3*	-4.5*	-12.6*
	2	Bus Stops	-0.5	-0.9	-1.3*	-2.6*	-3.4*
	3		-0.4	-1.5	-1.5	-3.0	-3.3*
	2	Corridor	2.2	1.1*	14.8*	53.9*	144.4*
	3		1.4	2.6*	2.6*	-4.3*	-45.2*

*Note: *Statistically different ($p<0.05$) as compared to number of conflicts in scheme 1 (mixed traffic)*



(a) Conflicts at Intersections



(b) Conflicts at Bus Stop Locations

Figure 8.6: Conflicts Recorded at Intersection and Bus Stop Locations

8.7 Implications of Findings

Firstly, overall results suggest that as compared to a mixed traffic configuration (scheme 1), the provision of bus lanes, regardless whether it was created though space reallocation (scheme 2) or space creation (scheme 3), act to lower the number of conflicts at intersection and bus stop locations. These results provide support for the hypotheses in **Table 8.2** associated with these locations:

At Intersections:

- ✓ Hypotheses 3 and 5 - Reduced risk of rear-end accidents for vehicles entering side streets as bus lanes allow vehicles (bus and turning traffic) to break away / separate from mainstream traffic and slow down before turning; and

- ✓ Hypothesis 4 - Reduced risk of side-swipe accidents for vehicles entering main street as bus lanes allow vehicle to pick up speed before joining mainstream traffic

At Bus Stop Locations:

- ✓ Hypothesis 7 - Reduced risk of vehicles hitting rear of slowing or stationary bus;
- ✓ Hypothesis 8 - Reduced risk of side swipe accidents as a result of vehicle changing lane to overtake slowing or stationary bus; and
- ✓ Hypothesis 9 - Reduced side-swipe accident risk for buses moving off

The results on bus priority bode well for bus and road management agencies as they suggest such schemes are likely to reduce risks of rear-end and lane-change (or side-swipe) conflicts significantly. This is an interesting finding because previous studies have shown that rear-end and side-swipe accidents rank amongst the top three most common accidents for buses (Zegeer et al., 1993, Yang et al., 2009).

Secondly, findings point to the importance of the additional capacity provided by scheme 3 in influencing road safety. The micro-simulation model suggests that scheme 3 has the best safety performance at the corridor level, followed by scheme 1 and then 2. Scheme 3's superior performance was likely to be due mainly to the additional capacity provided for private vehicles, which resulted in lower traffic density per lane and hence fewer conflicts amongst private vehicles. The difference between scheme 2 or 3 however became less obvious when traffic volume fell below 900 vehicles per hour, as both schemes brought about significant benefits at intersection and bus stop locations, without having any significant bearing on road safety at the corridor level.

Thirdly, modelled increases in traffic conflicts shown with scheme 2 (road space reallocation) at the corridor level are interesting because before-after empirical results in Chapter 4 showed that accidents had declined and not increased. The implication is that safety effects not being modelled in the micro-simulation must act to offset these effects. It also shows that there is a mix of safety impacts (positive and negative) but that the net impact is positive.

8.8 Conclusion

In this chapter, an exploration of the safety implications of implementing different "space based" bus priority schemes on a selected 3-lane road corridor in Metropolitan Melbourne was done. A microscopic simulation modelling approach was adopted, in which conflicts in terms of DRAC and CPI were analysed across three traffic configurations: Scheme 1 - vehicles in mixed traffic condition; Scheme 2 - kerbside lane relocated for bus use only; and Scheme 3 - new kerbside lane implemented for bus use only.

In terms of bus priority, findings from this study suggest that the provision of bus lanes, regardless whether it was created though space reallocation (scheme 2) or space creation (scheme 3), act to lower the number of conflicts at intersection and bus stop locations. A possible explanation for this finding is that bus lanes perform the role of acceleration or deceleration lanes at side street locations, as they allow vehicles to pull away or join the mainstream traffic when speed differential with the nearest vehicle is much lower.

The findings suggest an important area for further research in bus safety given the financial and social impact to bus companies, road users, commuters and the community whenever an accident occurs. Whilst this research has provided new insights into the varying safety effects of different bus priority traffic schemes, it is acknowledged that certain limitations exist. First, the focus of this study had been on a specific road corridor in Metropolitan Melbourne. Although the chosen site is considered to be representative of main arterial roads in the suburb areas (with major intersections typically spaced 1.6km apart), it is likely that results will differ for road corridors with different geometrical and operational characteristics. Further research is certainly needed to further investigate these effects. Second, this study had adopted two SSMs to capture traffic conflicts. Although both SSMs performed similarly with regard to their ability to differentiate between each of the priority schemes, results might have been different if other SSMs were used. Future research efforts could therefore centre on exploring other SSMs and identifying the best SSM for use in different contexts in safety studies. Third, the speed limit for the road corridor in the case study is 70km/h. With speed limits of 60km/h or 80km/h also common for arterial roads in Melbourne, it could be worthwhile to explore how conflicts patterns will differ for roads with different speed limits. Fourth, micro-simulation models are only able to reflect risks of accident types like rear-end or side-swipe accidents. The impact of bus priority on other accident types is thus worthy of further investigation. Finally and in relation to the previous limitation, this study has not assessed the ability of the safety performance measure to reflect actual crashes. As such, it could be worthwhile in future research to establish a statistical link between simulated conflicts and observed crashes.

The following chapter sets forth the attempt to address the latter limitation, as a conflict-crash relationship is established for the purpose of estimating the quantum of crash risk involved for vehicles behind buses. It dovetails with results from the micro-simulation modelling, which showed the number of conflicts at bus stop locations to be significantly higher in the mixed traffic configuration than when bus priority was provided for. A key question that arises from this, which will be attempted to be answered is "What is the level of crash risk involved for vehicles behind a bus that is slowing down or stationary at a bus stop in a mixed traffic configuration?"

CHAPTER 9 CRASH RISK FOR VEHICLES IN MIXED TRAFFIC

9.1 Introduction

The focus of this chapter is on an estimation of the rear-end crash risk of a vehicle behind a bus that is slowing down or stationary at a bus stop in a mixed traffic configuration.

The key motivation in establishing this risk quantum is the potential to understand and quantify the safety benefits of having bus priority that segregates buses from the mainstream traffic. This is because buses in a mixed traffic configuration face the risk of being involved in a rear-end accident when they decelerate or stop at bus stops for boarding and alighting passengers. Rear-end collision risks also exist for any of the following vehicles behind, as drivers may be caught unaware of the slowing or stationary vehicle ahead. Findings from this research may be useful for road management agencies and bus companies as evidence from the existing literature (section 2.5) have shown that rear-end collision ranks as one of the highest risks for buses and that bus stops is a common location where collisions occur (Wåhlberg, 2002, Wåhlberg, 2004a).

This chapter starts with a review of previous research on rear-end accident risks before presenting the research aim. Details of the methodology are then provided, where a description of the modelling approach to estimate crash risks for vehicles behind a bus is provided. This is followed by an application of the methodology on a selected site in Melbourne. Model results and implications of findings are presented before the chapter concludes with a discussion on the implications of the results.

9.2 Research Context

Previous studies on bus safety show that certain accident types are common for buses. Jovanis et al. (1991) found that the two most common collision types for buses are side-swipe and rear end (Jovanis et al., 1991). Findings from this study revealed that a high percentage of automobile occupant injuries resulted from rear-end accidents between private vehicles and buses, leading the author to suggest that stationary buses (either stopped for a queue of vehicles or to process passengers) pose the greatest risk to automobile occupants. In examining bus and coach occupant injuries, Björnstig et al. (2005) found that approximately half of the occupant injuries were due to buses or coaches being rear-ended by other vehicles. Zegeer et al. (1993) found likewise that rear-end accidents in which one vehicle stopped and sideswipe accidents to be the most common accident type in commercial bus crashes across five states in the U.S. A similar finding was obtained by Rey et al. (2002) when they investigated transit bus crashes in Florida, U.S. In analysing school bus crashes and injuries, Yang et al. (2009) also found cases of vehicles rear-ending buses as well as vehicles hitting buses when the latter were turning to be most common. With regard to accident location, published evidence suggests that bus stop locations and intersections are the most accident prone areas (Jovanis et al., 1991, Wåhlberg, 2002).

Numerous studies have been done to investigate rear-end crash risks. A number focused on applications in work zones. Meng et al. (2010) developed a probabilistic quantitative risk assessment model to estimate crash frequency based on the work zone characteristics. Similarly, Harb et al. (2008) developed conditional logistic regression and multiple logistic regression models to identify key work zone freeway crash characteristics. An analysis of rear-end accidents in work zones was also done by Qi et al. (2005), from which truncated count models based on historical crash data in New York were developed to identify work zone characteristics that are associated with crash frequency. Using crash data from work zones in California, U.S., Khattak et al. (2002) developed negative binomial models, which revealed that crash frequencies increase with increasing work zone duration, length and average daily traffic. Whilst the above studies relied on historical crash data, a recent study leveraged on video technology to analyse and evaluate rear-end crash risk at a work zone area in Singapore (Meng and Weng, 2011). Its approach is based on the traffic conflict technique, in which a surrogate safety measure (Deceleration Rate to Avoid a Crash) was used to measure rear-end crash risk, following which crash risk models were developed to examine the relationship between rear-end crash risk and its contributing factors.

There are other studies on rear-end crash risk that concentrated on freeway (or highway) and intersection locations. Wang and Abdel-Aty (2006) utilized generalized estimating equations with the negative binomial link function to model rear-end crash frequencies at signalized intersections. Results showed that heavier traffic, additional right and left-turn lanes, high speed limits on the major roadway, a large number of phases per cycle and high population areas are correlated with high rear-end crash frequencies. Hourdos et al. (2006) focussed on high-crash locations at a freeway by analysing video data collected by detection and surveillance equipment. Along with visual observations, an identification of the most relevant real-time traffic was done and subsequently incorporated into a model to estimate crash likelihood. Pande and Abdel-Aty (2008) developed probabilistic neural network models to identify traffic conditions that are associated with higher risks of rear-end crashes on a highway in the U.S. A similar approach of using data collected from inductive loop detectors was adopted by Oh et al. (2006a) to develop a methodology to identify rear-end collision potentials on freeways. Key in this methodology is the formulation of a rear-end collision risk index based on the safety distance in car-following situations to reflect freeway rear-end traffic collisions. Oh et al. (2009) followed up with a study that utilized sensor and communication technology to capture time-to-collision (TTC) and stopping distance for the purpose of developing a methodology to detect hazardous traffic events and evaluate the real-time safety performance of a freeway. In a subsequent study, Oh and Kim (2010) developed another approach to estimate rear-end crash probabilities on freeways based on real-time vehicle trajectory data. Through the development of a binary logistic regression model on lane-changing and derivation of crash probability based on TTC values, a crash risk index was developed in the analysis to establish rear-end crash potential for each subject vehicle along the freeway.

In summary, there have been numerous studies conducted to investigate rear-end crash risks. However, their focus had been on work zones, freeway and intersection locations. At present, our understanding on rear-end crash risks involving buses at bus stop locations remains unclear. This is surprising as the evidence from existing literature show that rear-end collision ranks as one of the highest risks for buses, and that collisions occurring at bus-stops are common.

9.3 Research Aim

Given the knowledge gap above, this phase of the research aims to estimate the crash risk potential for vehicles that are behind a bus which is slowing down or stationary at a bus stop in a mixed traffic configuration. Establishing the quantum of such risk involved will provide an appreciation of the safety benefit delivered by bus priority measures that segregate buses from mainstream traffic.

9.4 Methodology

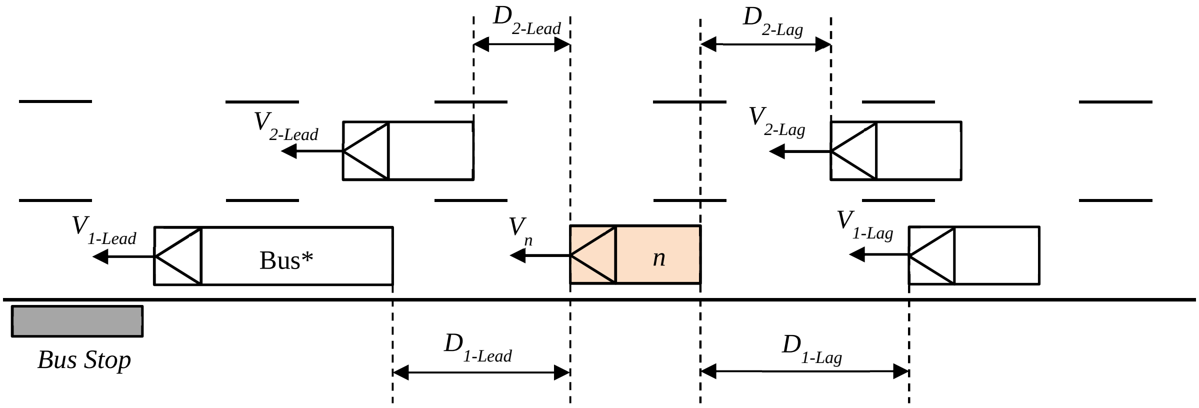
Drivers of vehicles travelling along a road with a mixed traffic configuration are faced with two options when they find themselves behind a bus that is slowing down to call or stationary at a bus stop ahead. To avoid a collision, they can choose to either: (1) slow down and wait for the bus to move off after processing passengers or (2) switch lanes to overtake the bus. **Figure 9.1** shows vehicle *n* in such a situation, in which collision risks exist if the driver of vehicle *n* fails to decelerate in time in the current lane. Should the driver decide to switch lanes to overtake the bus, there exists the risk of collision with the lead or lag vehicle in the adjacent lane. In both situations, a key factor in whether a crash would occur is the time-to-collision (TTC) between the subject and lead or lag vehicles, i.e. lower TTC values are associated with higher likelihood of collision.

Given the possibilities above, a three-stage approach was adopted to estimate the vehicle's crash risk potential:

(1) Calculation of lane change probability;

(2) Calculation of crash probability given a TTC value; and

(3) Estimation of crash risk potential based on values obtained in (1) and (2)



*Note: * Slowing down or stationary at bus stop*

Figure 9.1: Vehicle *n* Behind a Slowing or Stationary Bus

9.4.1 Lane Change Probability

With lane changing essentially involving decision-making between two choices, discrete choice modelling approach can be adopted to establish lane change probability. In this field, two widely adopted approaches are binary logit regression (BLR) and artificial neural network (ANN) modelling. For this research, both approaches as well as a third incorporating both BLR and ANN (hybrid approach) were used to model lane change probability. A key step in the methodology is the selection of the best performing lane-change model for the subsequent estimation of crash risk.

In the BLR approach, the lane change probability was formulated as:

$$p(LC_n \mid X_n) = \frac{\exp(X_n \beta)}{1 + \exp(X_n \beta)} \tag{9.1}$$

$$p(NLC_n \mid X_n) = 1 - p(LC_n \mid X_n) \tag{9.2}$$

where $p(LC_n|X_n)$ and $p(NLC_n|X_n)$ are the probabilities that the subject vehicle *n* will and will not switch lane respectively under traffic conditions X_n. In both equations, X_n represents a vector of explanatory variables affecting the decision of subject vehicle *n*. As part of the BLR model development, the "linktest" function in STATA (2005) was used and inspection of Variance Inflation Factors (VIF) values done to ensure the final model was free from specification errors and heteroscedasticity respectively.

In the ANN approach, a ANN model structure similar to that adopted in Chapter 6 was used for modelling for lane changing, i.e. a three-layer feed-forward neural network based on the back-propagation approach that incorporates the Lavenberg-Marquardt (Hagan and

Menhaj, 1994) algorithm. In this model (**Figure 9.2**), X_n are the input neurons[h] that represent the traffic conditions, Z_k the hidden neurons and Y, the output neuron in the model that represents the lane change probability. As highlighted in section 6.5.3, a key issue in neural network modelling is over-fitting, which results when the network is strong in fitting the random error (noise) in the data but not the underlying relationship. To address this issue and still ensure good generalization of the model, the "early stopping" technique was similarly applied when training the network. Likewise, the dataset was also randomly separated into two parts (in a 3:1 proportion) for the purpose of training and testing the model.

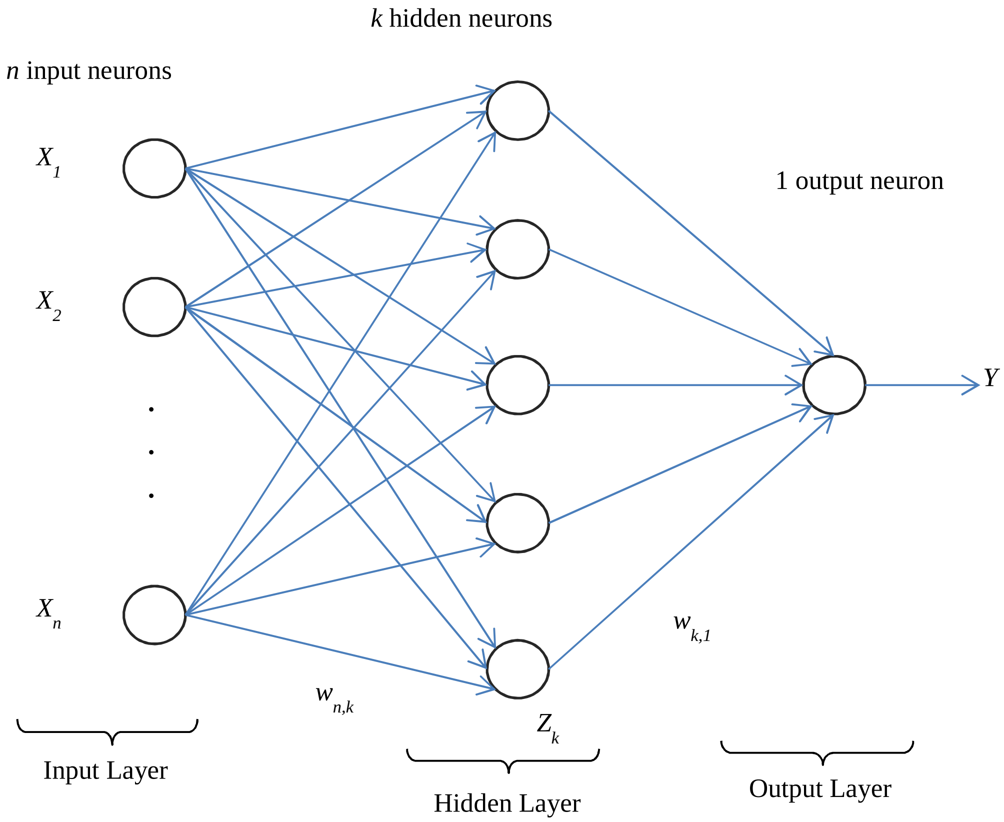


Figure 9.2: Three-Layer Feed-forward Artificial Neural Network for Modelling Lane Change Probability

A typical approach in ANN modelling is the application of an algorithm for selection of the input variable(s). In the hybrid BLR-ANN approach, a similar principle was used in which variables found to be significant as well as the predicted probability from the BLR model were used as inputs to the BLR-ANN model. **Figure 9.3** presents the key steps involved in the BLR-ANN approach.

[h] *X_n used in the ANN modelling are the variables that were found to be significant in the BLR approach*

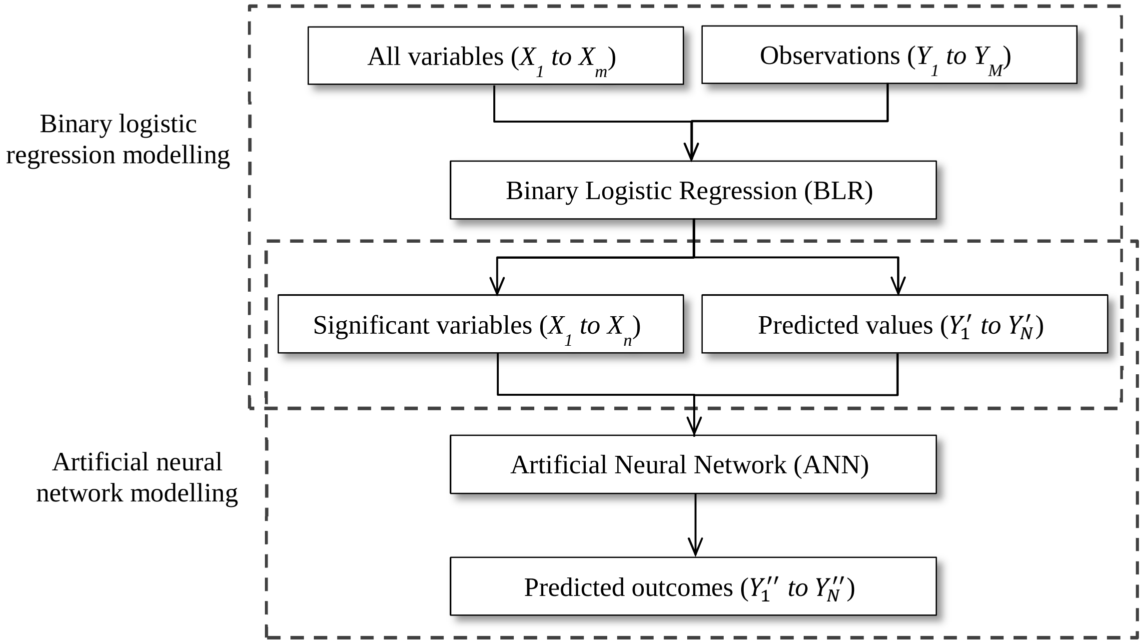


Figure 9.3: Key Steps in the Hybrid BLR-ANN Approach

9.4.2 Probability of a Crash and Crash Risk Estimation

The crash risk modelling was done using TTC values that were extracted from video data of the site under study. According to Amundsen and Hyden (1977), the TTC value is the time that remains from an instant *t* before a collision between two vehicles takes place (assuming both vehicles' direction and speed remain unchanged). If the subject vehicle *n* decides to remain in the lane in which the bus ahead has slowed down, then the TTC value can be derived as follows:

$$TTC_n^{1-Lead}(t) = \frac{D_{1-Lead}(t)}{V_n(t) - V_{1-Lead}(t)} \qquad \forall V_n(t) > V_{1-Lead}(t) \tag{9.3}$$

where $D_{1\text{-}Lead}$ is the gap between the subject and lead vehicle, while V_n and $V_{1\text{-}Lead}$ are the speeds of the subject and lead vehicle respectively at time *t*. If the driver of the subject vehicle decides to switch lane, then the corresponding TTC values between the subject and lead or lag vehicle in the adjacent lane can be determined as:

$$TTC_n^{2-Lead}(t) = \frac{D_{2-Lead}(t)}{V_n(t) - V_{2-Lead}(t)} \qquad \forall V_n(t) > V_{2-Lead}(t) \tag{9.4}$$

$$TTC_n^{2-Lag}(t) = \frac{D_{2-Lag}(t)}{V_{2-Lag}(t) - V_n(t)} \qquad V_{2-Lag}(t) > \forall V_n(t) \tag{9.5}$$

In the above equations, $D_{2\text{-}Lead}$ and $D_{2\text{-}Lag}$ are the gaps between the subject and lead, subject and lag vehicles respectively, while $V_{2\text{-}Lead}$ represents the speed of the lead vehicle and $V_{2\text{-}Lag}$, the speed of the lag vehicle in the adjacent lane.

It is generally accepted that TTC values are closely linked to crash potential. Following previous research (Oh and Kim, 2010, Weng and Meng, 2012), the probability of a crash based on a TTC value p can be assumed to take on the following exponential decay relationship in which:

$$p = e^{-TTC/\lambda} \tag{9.6}$$

where λ is a parameter that reflects crash propensity of a given road segment (its value differs across roads with different characteristics). λ can be computed based on the historical crash records of the study site and TTC profile obtained from the video data. The probability of a crash occurring in an hour can thus be computed as follows:

$$\text{Crash risk / hour} = \sum_{i=1}^{N} e^{-TTC/\lambda} \tag{9.7}$$

In this equation, TTC_i is the time-to-collision value recorded for vehicle i and N is the number of vehicles with TTC values recorded in an hour on a selected day. Following this, the probability of a crash between subject vehicle n and lead vehicle based on a given TTC can be estimated by the following:

$$p(Crash_n^{1-Lead})(t) = p(NLC_n \mid X_n)(t).p(Crash_n^{1-Lead} \mid TTC)(t) \tag{9.8}$$

Using the above approach, the probabilities of a crash between the subject vehicle n and the lead or lag vehicles in the adjacent lane can be similarly computed.

The establishment of probabilities of lane change and crash based on a given TTC sets the stage for the estimation of the rear-end crash risk based on a Monte Carlo simulation approach. **Figure 9.4** shows an overview of the variables involved in the simulation to estimate crash risk.

Given that the TTC information came from a sample of traffic data, it was important to account for uncertainty in the analysis. For this reason, the bootstrapping technique based a resampling size of 500 was employed to obtain the mean and variance of λ. The uncertainty in the final crash risk estimation was also accounted for through the use of a stochastic analysis software tool available in Crystal Ball (Decisioneering, 2013). This was used to analyse and generate the best-fit probability or frequency distribution for each variable with inherent uncertainty. The distribution information was then fed into a Monte Carlo simulation model to compute the mean and variance of the final crash risk estimate from 1,000 trials. Through this approach, a quantifiable degree of uncertainty was incorporated in the final crash risk estimate to reflect the likelihood that drivers at times in reality base their driving decisions on imprecise perceptions of the surrounding traffic (Ma, 2004).

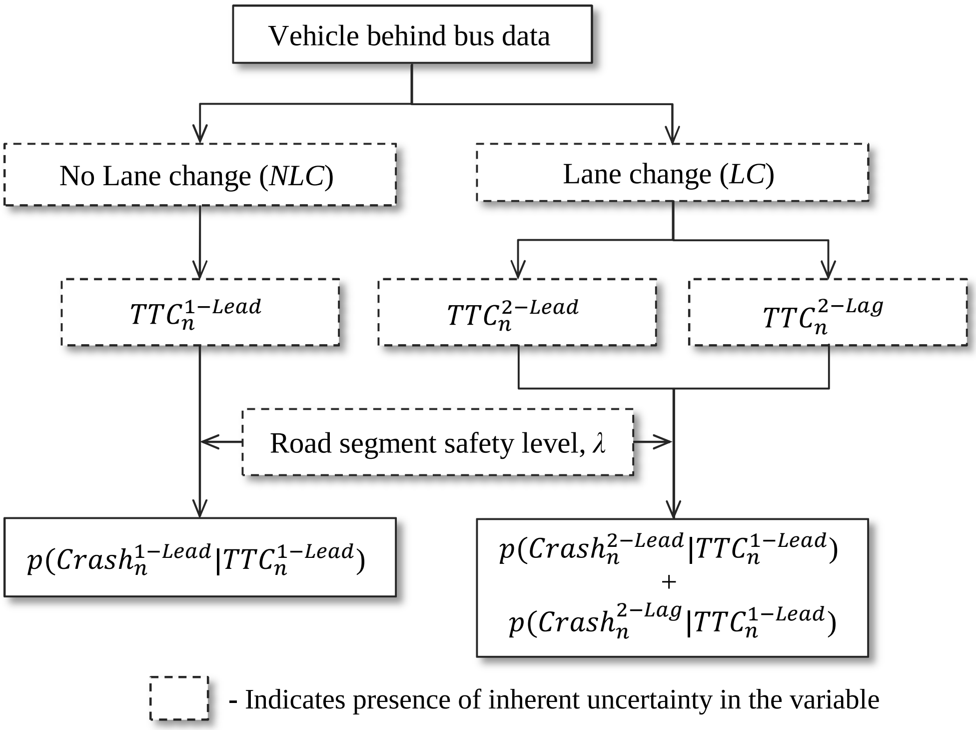


Figure 9.4 A Monte Carlo Simulation Approach to Estimate Crash Risk

9.5 Application and Data Collection

For this research, the three-lane divided arterial road with a speed limit of 70kph in Melbourne (Blackburn Road) used in Chapter 8 was selected for the rear-end crash risk estimation. The focus was on the area upstream of a bus stop located on the northbound carriageway of Blackburn Road (**Figure 8.3**), where movements of vehicles in relation to buses were tracked. The bus stop of interest serves three different bus services, with each operating at a service frequency that ranges between ten to sixty minutes.

As described in section 3.5.3, the video recording equipment mounted on top of a thirteen-story building was used to capture video recordings of the traffic in the vicinity of the bus stop over two weeks in December 2012. From the video recordings, vehicle trajectory information on weekdays were extracted at intervals of 0.2s using the Tracker software (Brown, 2013). This software facilitated axis definition in terms of orientation and origin setting for measurement purpose, thus allowing for calibration to be done prior to extraction of vehicle trajectory information. **Appendix F** captures details of the calibration done before the data extraction. The 3-year accident record of the site was also extracted from CrashStats (VicRoads, 2012b) for the purpose of computing the λ value and its statistical properties.

The final dataset consisted of a total of 338 sets of trajectory information, with each set comprising individual position (in x-y coordinates) for the subject as well as lead and lag vehicles in the current and adjacent lanes (**Figure 9.1**). From here, data on the following variables, which were chosen based on existing literature (Toledo et al., 2003, Moridpour et al., 2010, Moridpour et al., 2012), were extracted:

1) V_n - Speed of subject vehicle *n*;
2) $dV_{1\text{-}Lead}$ - Speed difference between subject and leading vehicle in the current lane;
3) $dV_{1\text{-}Lag}$ - Speed difference between subject and lagging vehicle in the current lane;
4) $dV_{2\text{-}Lead}$ - Speed difference between subject and leading vehicle in the adjacent lane;
5) $dV_{2\text{-}Lag}$ - Speed difference between subject and lagging vehicle in the adjacent lane;
6) $D_{1\text{-}Lead}$ - Distance between subject and leading vehicle in the current lane;
7) $D_{1\text{-}Lag}$ - Distance between subject and lagging vehicle in the current lane;
8) $D_{2\text{-}Lead}$ - Distance between subject and leading vehicle in the adjacent lane;
9) $D_{2\text{-}Lag}$ - Distance between subject and lagging vehicle in the adjacent lane; and
10) *BA* - Dummy variable to indicate whether bus is directly ahead in the current lane

9.6 Results and Discussion

9.6.1 Lane Change Probability

Table 9.1 presents results of the parameter estimates for the BLR model while **Table 9.2** captures the performance of the BLR, ANN and BLR-ANN models based on sensitivity, specificity, correct classification rate (CCR) and area under ROC curve (AUC). From **Table 9.1**, the BLR model indicated that speed differences between the subject and lead vehicles in the current ($dV_{1\text{-}lead}$) and adjacent lanes ($dV_{2\text{-}lead}$) are significant factors that influence lane change. Just as significant were the distances between the subject and lead vehicle ($D_{2\text{-}lead}$) as well as subject and lag vehicle ($D_{2\text{-}lag}$) in the adjacent lane. The coefficient signs for these variables were as expected and similar to previous findings (Moridpour et al., 2010), in that lane change was more likely when the speed of the lead vehicle in the current lane was smaller or lead vehicle in adjacent lane was greater. Results from a previous study also found that a larger gap between the subject and lead or lag vehicles in the adjacent lanes were associated with lane changing (Moridpour et al., 2012). An interesting result found in this research is that drivers were more likely to switch lanes if the bus was directly ahead (*BA*) as compared to being a few vehicles ahead. While such a finding was as expected, it suggests that drivers in Melbourne have good lane discipline as they are unlikely to switch lanes until the ones ahead of them (and behind a slowing or stationary bus) had done so. This mirrors what has been observed from the video recordings in that lane changing was done in an orderly and sequential manner on several occasions.

Table 9.1: Results of BLR Model on Lane Change Probability (based on training dataset)

Variable	β	S.E.	Wald Statistic	Odds Ratio	p-value
$dV_{1\text{-}lead}$	0.074	0.016	20.119	1.077	0.000
$dV_{2\text{-}lead}$	-0.059	0.027	4.861	0.943	0.027
$D_{2\text{-}lead}$	0.042	0.019	4.861	1.043	0.027
$D_{2\text{-}lag}$	0.044	0.009	21.331	1.045	0.000
BA	1.146	0.383	8.970	3.147	0.003
Intercept	-2.511	0.536	21.916	0.081	0.000
-2LL		187.87		387.78	(intercept only)
AIC		199.87		389.78	(intercept only)
BIC		221.89		393.45	(intercept only)
LR chi-square		<0.001			
Wald chi-square		<0.001			

Table 9.2: Performance of BLR, ANN and BLR-ANN Models

Measure	BLR	ANN	BLR-ANN	BLR	ANN	BLR-ANN
	Training Dataset (290)			Test Dataset (48)		
Sensitivity	0.8421	0.9204	0.9204	0.7143	0.8571	0.8571
Specificity	0.9034	0.8644	0.8588	0.8824	0.8529	0.8824
CCR	0.8790	0.8860	0.8830	0.8330	0.8540	0.8750
AUC	0.9290	0.9442	0.9458	0.9430	0.9097	0.0945
MSE	0.0989	0.0928	0.0851	0.0973	0.1153	0.0843

Note: Shaded figures indicate the best performing model for each measure and dataset

Results from **Table 9.2** show that the ANN and BLR-ANN approach resulted in better performing models, as they were able to correctly classify an additional 0.7% to 4.2% lane changing decisions as compared to the BLR model. Although this represents only a marginal improvement in model performance, the results point to the potential of adopting neural network approach as an alternative in modelling binary outcomes and usefulness when variables are nonlinear or have non-specific function form.

For this study, the BLR-ANN model was considered to have the best performance and its lane change probability prediction was thus selected as inputs for the subsequent computation of crash risk estimation.

9.6.2 Probability of a Crash and Crash Risk Estimation

Table 9.3**Table 9.3** captures results of the parameter estimates that was obtained when the Crystal Ball software was used to find the best-fitted distributions of the variables involved in the crash risk estimation, while **Figure 9.5** presents results of estimated crash risk (expected value and range based on one standard error) that emerged from the Monte Carlo simulation.

Table 9.3: Best-Fit Distributions for Variables (used as inputs in Monte Carlo simulation)

Variable	Best-Fit Distribution	Parameters			
λ	Beta	Min.= 0.10;	Max.= 0.44;	α = 41.48;	β = 53.44
NLC	Beta	Min.= 0.0;	Max.= 1.0;	α = 0.3;	β = 0.42
TTC_n^{1-Lead}	Log-normal	Location = 1.52	Mean = 11.33;	S.D. = 21.11	
TTC_n^{2-Lead}	Log-normal	Location = 0.51	Mean = 26.15;	S.D. = 46.44	
TTC_n^{2-Lag}	Gamma	Location = 1.74	Scale = 30.31;	Shape = 0.643	

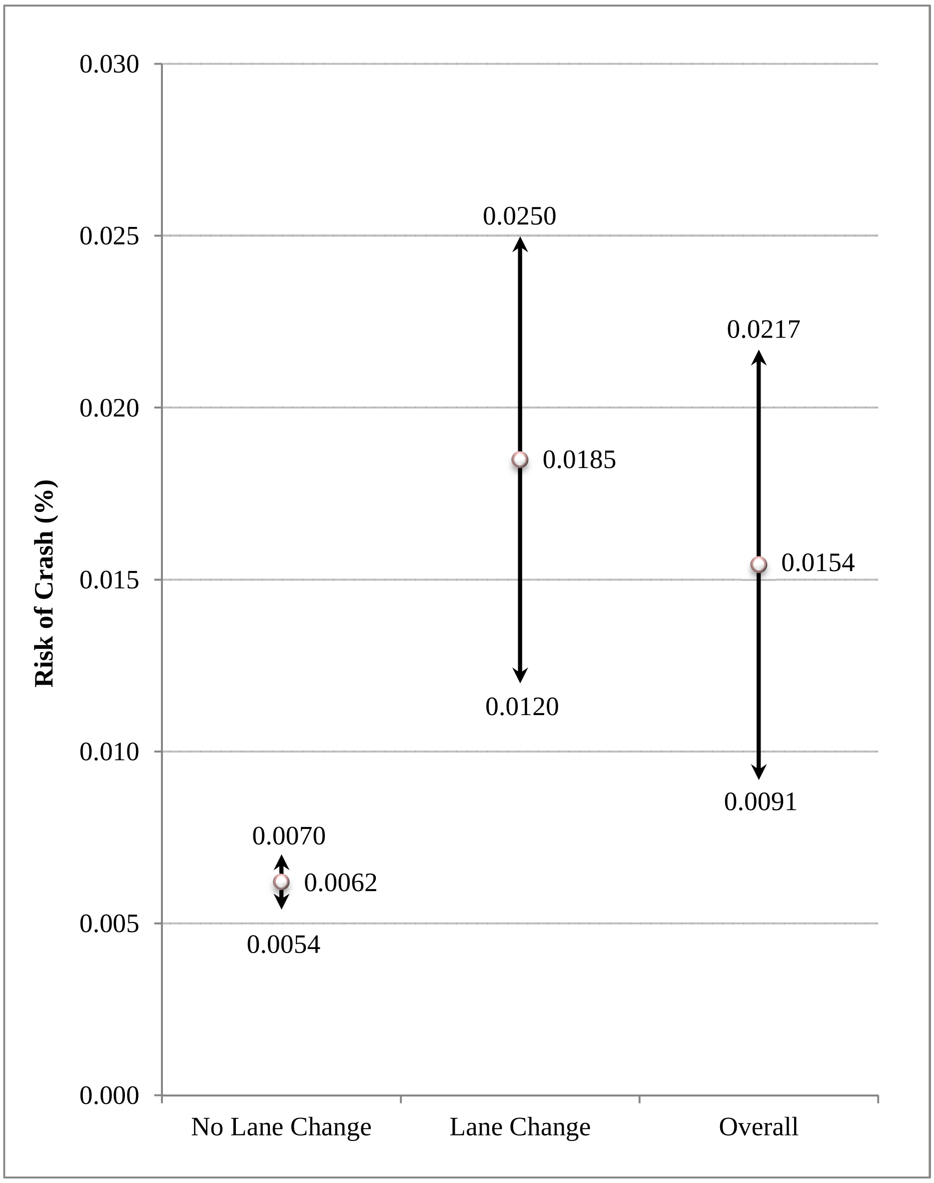


Figure 9.5: Monte Carlo Simulation Results (with dot and arrows representing the expected value and range based on 1 standard error) for Crash Risk

As reflected by statistics in **Table 9.3**, it was observed that the average TTC value for vehicles that do not change lanes (TTC_n^{1-Lead}) is generally lower than those that do

(TTC_n^{2-Lead} or TTC_n^{2-Lag}). However, TTC_n^{2-Lead} values in the lower range were found to be smaller in comparison to TTC_n^{1-Lead}, as reflected by the location (or shift) parameter values. This difference showed up in the final crash risk estimates, where the average crash risk for vehicles that changed lanes (LC) was found to be higher than those that do not (NLC).

Simulation results showed the average crash risk of vehicles in the NLC group and LC groups are 0.0062% (with a standard error of 0.0008%) and 0.0185% (with a standard error of 0.0065%) respectively. When both groups of vehicle were considered collectively, the crash risk was found to be 0.0154% (with a standard error of 0.0063%). Based on the latter crash risk value and assumption that an average of thirty (30) TTC conflicts occur a day, it worked out that there is an approximate 80% chance of one or more accidents taking place on an annual basis as a result of buses slowing down or being stationary at bus stops.

The risk estimates represent important findings for bus safety and in particular bus priority research, as the risk of rear-end crashes due to buses slowing down or being stationary at bus stops is generally eliminated when bus priority measures that segregate buses from mainstream traffic are implemented. This study represents the first attempt to quantify such risks and highlights the importance of considering safety implications in bus priority strategies. Results from Chapters 4 and 6 have shown that the implementation of bus priority in Metropolitan Melbourne led to an approximate 14% and 53.5% reduction in reported injury accidents and bus-involved accidents, respectively. Given that these reductions were recorded at the aggregate-level, it was not possible then to identify and quantify any specific safety effect at play. Findings from this research are therefore significant because the quantum of a component of the safety benefits delivered by bus priority is now known. In this regard, the results present an opportunity for policy-makers to account for safety benefits as part of the overall cost-benefit analyses typically done prior to bus priority implementation.

9.7 Conclusion

In this chapter, a three-stage modelling approach was adopted to estimate the crash risk for vehicles behind a slowing or stationary bus at a bus stop on a selected representative road in Metropolitan Melbourne. The main aim in establishing the quantum of risk involved was to gain an appreciation of the safety benefit that is delivered by bus priority schemes that segregate buses from the mainstream traffic.

The first stage involved the development of competing regression and neural network models to represent drivers' lane changing behaviour behind buses, while the second and third stages involved the establishment of crash risk probability followed by an estimation of crash risk. For the latter, a Monte Carlo simulation approach was adopted using time-to-collision and accident data collected from a selected road corridor. Results in the first stage revealed that speed differences between the subject and lead vehicles in the current ($dV_{1\text{-}lead}$) and adjacent lanes ($dV_{2\text{-}lead}$), distances between the subject and lead ($D_{2\text{-}lead}$) or lag vehicle ($D_{2\text{-}lag}$) in the adjacent lane as well as whether the bus is a lead vehicle (*BA*) are significant factors that influence lane change. The latter finding was interesting and likely to be reflective of driving behaviour in Melbourne, as it indicated that drivers are unlikely to switch lanes until the ones ahead that are behind the bus had done so. Results also showed that the hybrid regression-neural network approach yielded the best performing model. As such, predictions from this model were used as inputs in the second stage. Following a calculation of crash probability based on TTC values in stage 2, the Monte Carlo simulation results in stage 3 revealed that the average crash risk of vehicles that performed the lane change (LC) and those remaining in the current lane (NLC) are 0.0185% (with a standard error of 0.0065%) and 0.0062% (with a standard error of 0.0008%) respectively. The overall crash risk was found to be 0.0154% (with a standard error of 0.0063%).

The risk estimates serve as important findings for bus safety and bus priority research, as an estimate of the safety benefit delivered by bus priority that segregate buses from mainstream traffic is now available. In practice, this estimate could serve as an important consideration for policy-makers given this new knowledge of the quantum of risk involved in designing bus stops in a mixed traffic configuration as well as bus priority schemes where buses are segregated from mainstream traffic.

Whilst findings from this study can act as a useful planning tool for road agencies, there remain limitations that policy makers should be aware of. Firstly, the lane change modelling and fitting of TTC distributions were done based on a sample of (two weeks) data. As such, additional data can be collected to improve the model performance and reliability. Secondly, this research was based on a bus stop that is located along a three-lane divided road (with a speed limit of 70kph) in Metropolitan Melbourne. Although such roads are considered typical in Melbourne, results could differ when roads with different characteristics are considered. In this regard, further research could be done to establish a more precise value for the λ parameter and additional ones for different road types. Finally, a linear bus stop (mixed traffic configuration) was considered in this research. Hence, there exists much scope to investigate crash risks on roads with other bus stop configurations, e.g. indented bus bay.

PART IV:
SYNTHESIS AND CONCLUSIONS

CHAPTER 10 CONCLUSION AND RECOMMENDATIONS

10.1 Introduction

This thesis has been concerned with gaining in-depth understanding on the road safety implications of implementing bus priority (both space and time based) measures in Metropolitan Melbourne. The research work carried out to generate new knowledge in this area has been presented in the previous chapters. This chapter concludes this thesis through a summary and discussion of key findings that have emerged from the research, contributions to new knowledge, implications for bus priority research and practice as well as areas where future research could be undertaken in this field.

10.2 Summary of Key Findings

10.2.1 Aggregate-Level Safety Analysis

Research at the aggregate level was done to first assess the overall road safety impact of bus priority measures that had been implemented in Melbourne through a before-after safety evaluation. Given the availability of different study designs in before-after studies, subsequent efforts were made to explore the implications of using different comparison group types when employing the Empirical Bayes and Comparison Group approaches in safety evaluation. Finally, the safety effects of bus priority were further evaluated through an analysis of bus-involved accidents and safety performance of bus routes with / without bus priority. The major findings from this research at the aggregate level are summarized as follows:

- ✓ Results of before-after safety evaluation based on the Empirical Bayes approach showed that the implementation of bus priority treatments led to a 14% reduction in accidents (after accounting for regression to the mean effects). Non-Traffic Signal Priority treatments (mainly bus lanes) yielded a stronger positive safety effect (18.2%) compared to TSP treatments (11.1%).
- ✓ The number of Fatal and Serious Incidents dropped considerably from 42 to 29 per annum. This was found to be significant at the 80% using the rigorous WSRT test.
- ✓ Safety review findings revealed a reduction in intolerable accidents risks and some concerns in the 'after' situation that relate to interaction of buses and traffic at bus lane setbacks and increasing pedestrian road crossing distances due to the introduction of bus lanes. The analysis of accident type changes suggested that bus lanes are acting as an additional "clear zone" reducing vehicle collisions with roadside objects and improving vehicle interactions with vehicles entering and

emerging from side roads. Bus lane treatments are also thought to increase sight distances at un-signalised intersections acting to reduce side vehicle accidents. Some treatments are also thought to increase traffic density acting to slow traffic creating safety benefits.

- ✓ When different comparison group types were employed in the Empirical Bayes (EB) and Comparison Group (CG) approaches, discrepancies were obtained in the final estimates for bus priority on road corridors (18.2% vs. 27.2%) and road intersections (11.1% vs. 11.8%). These differences can be attributed to the omission of sites with zero accident history and the effect of matching treatment sites with similar sites in the CG approach.
- ✓ A new approach that combines both EB and CG results yielded final safety estimates of 22.7% (road corridors) and 11.5% (road intersections). Although this approach requires additional effort in data collection and analysis, it could potentially provide a more precise safety estimate.
- ✓ For routes with bus priority, there were fewer accidents (significant at $p<0.05$) involving buses hitting stationary objects (70% lesser) or vehicles (80%), and those occurring at bus stop locations (80%).
- ✓ Results from the MENB and BPNN models showed that bus priority had the effect of reducing route-section level accident frequency by about 53.5%. The MENB model recorded better performance which suggests benefits in adopting the MENB approach to account for time- and location-specific effects in accident count modelling.

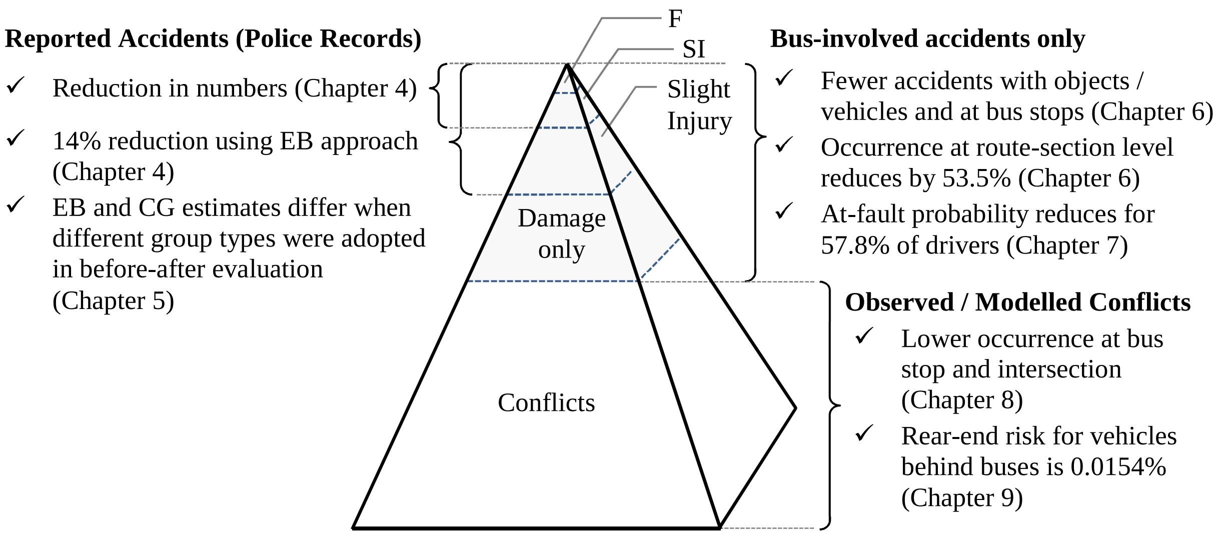
10.2.2 Disaggregate-Level Safety Analysis

Research at the disaggregate level focussed on exploring bus accident characteristics and the impact of bus priority in relation to the key risk factors that influence the probability of bus drivers being at-fault in bus-involved accidents. Through a micro-simulation modelling approach, the safety implications of implementing different “space based” bus priority measures were also investigated. Finally, research was done to estimate the rear-end crash risk quantum for vehicles that are behind a slowing or stationary bus at a bus stop in a mixed traffic configuration. This was done to further an understanding of the safety benefits delivered by bus priority measures that segregate buses from mainstream traffic. The key findings from this disaggregate-level research are as follows:

- ✓ Accidents involving bus-vehicle and bus-objects are the two most common accident types for buses in Melbourne.

- ✓ Results from mixed logit modelling showed that bus length / age, driver's gender / age / experience / accident record, road type, speed limit, traffic / daylight conditions, and the presence of bus priority affect the likelihood of bus drivers being at-fault in bus-involved accidents. The parameter for bus priority was found to be random and indicated that bus priority does not reduce this likelihood for some drivers (42.2%).
- ✓ Micro-simulation results showed that the provision of bus lanes, whether they are created through space reallocation or creation leads to a reduction in the number of conflicts (which suggest lower rear-end and lane-change accident risks) at intersections and bus stop locations.
- ✓ The average crash risk of vehicles that are in a TTC conflict with a decelerating or stationary bus at a bus stop was found to be 0.0154% (with a standard error of 0.0063%). Based on the assumption that an average of thirty (30) TTC conflicts occur a day, it works out that there is an approximate 80% chance of one or more accidents taking place annually as a result of buses slowing down or being stationary at bus stops.

As a summary, the key findings from this research on the safety impacts of bus priority can be presented in relation to the safety pyramid adapted from Hydén (1987), as shown in **Figure 10.1**.



Note: Shaded area indicates crashes while F and SI refer to fatal and serious injury accidents, respectively

Figure 10.1: Key findings in terms of safety pyramid adapted from Hydén (1987)

10.3 Contributions to New Knowledge

This research has made contributions in six major areas relevant to the safety effects of bus priority and bus safety. These are itemized and elaborated below:

- ✓ Establishing the safety effects of bus priority in Melbourne (Chapter 4) – Although bus priority safety effects have been investigated in previous studies, they have focused on applications in the U.S. and Europe. Results from these studies have yielded mixed results and as such our understanding on its safety effects remains unclear. This research represented an attempt to investigate in-depth the safety effects of bus priority in Melbourne. Results show that positive safety benefits are delivered, which is contrary to those found in the U.S. A possible hypothesis that arose from this research is that buses in Melbourne are able to move into bus priority lanes with greater ease as compared to those in the U.S. Bus lanes could also act as an additional "clear zone" and improve sight distances at un-signalised intersections, thus acting to reduce off-path and side vehicle accidents.

- ✓ Presenting an alternative way to establish safety estimates (Chapter 5) – Various study designs are available in before-after safety evaluation. Whilst the choice is often dictated by availability and nature of the data, little attention has been paid to understanding how the choice of study designs affects the final safety estimate. This research explored the implications of using different comparison group types (large, unmatched vs. small but matched) in the Empirical Bayes and Comparison Group approaches and proposed an alternative of using both the EB and CG methodologies in computing the safety estimate. Although additional efforts (mainly in data collection and analysis) are required, case study results showed the potential of the alternative EB-CG approach in yielding a more precise safety estimate (i.e. one with lower standard error).

- ✓ Understanding the effect of bus priority and other risk factors that influence accident occurrence at the bus route-section level (Chapter 6) – Only a handful of studies had explored transit or bus safety at the route-section or zonal level. These were also mainly confined to applications in North America and relate to both auto and transit collisions. As such, risk factors for collisions involving only transit vehicles remain unclear. In this research, two accident prediction models, i.e. MENB and BPNN, were developed to understand how bus priority (in relation to other key factors) influence bus accident frequency at the route-section level. Model results showed that the implementation of bus priority had led to a 53.5% reduction in bus-involved accidents in Melbourne. Through a comparison of model performance, the results also showed the potential in using MENB modelling to account for unobserved location and time-specific effects in the data.

- ✓ Understanding the effect of bus priority and other risk factors that influence bus drivers' at-fault probability in bus-involved accidents (Chapter 7) – Previous research on bus accidents has generally fallen short of accounting for all the traditional safety determinants, i.e. driver, vehicle and environmental factors at the same time. More importantly, none had examined factors that influence at-fault probability of bus drivers in bus-involved accidents. This research employed a mixed logit modelling approach to identify fixed and random parameters for some thirteen driver, vehicle and environmental factors that influence bus drivers' at-fault probability. Through this process, the presence of bus priority was found to lower at-fault risk. However, its parameter was found to be random which implies that this effect does not apply to some 42.2% of bus drivers.

- ✓ Differentiating the safety effects of different "space based" bus priority measures (Chapter 8) – There had been no previous studies done to compare the safety effects of different bus priority measures. This research made a contribution in this area by exploring the road safety performance of a selected 3-lane road corridor across three road configurations (1) no bus priority; (2) kerbside lane reallocated for bus use; and (3) new kerbside lane added for bus use. Results from this research showed that the introduction of kerbside bus lanes leads to fewer conflicts (and hence lower rear-end and side-swipe accident risks) at intersection and bus stop locations.

- ✓ Establishing the safety benefit of bus priority measures that segregate buses from mainstream traffic (Chapter 9) - There have been numerous studies conducted to investigate rear-end crash risks. However, their focus had been on work zones, freeway and intersection locations. An understanding on rear-end crash risks involving buses at bus stop locations is still unclear. This research employed a three-stage modelling approach to represent drivers' lane changing behaviour and establish crash risk probability for estimating the crash risk of vehicles behind a slowing or stationary bus. Results from the Monte Carlo simulation revealed that the quantum of the average crash risk is 0.0154% (with a standard error of 0.0063%).

10.4 Implications for Bus Priority Research and Planning

Given the results that have been obtained in this research, it would be apt to attempt a synthesis and discuss the implications of findings on bus priority research and planning.

Firstly, the aggregate-level findings that bus priority brings about positive safety effects are exciting as they suggest an entirely new perspective in planning for bus priority measures. The quantum of safety benefit found in this research suggest it is significant enough for road management agencies to consider merits for priority schemes that are beyond bus travel time savings and operational benefits. From a planning perspective, results from this research suggest bus priority could feature as part of the overall cost-benefit analyses that are typically done for each new bus route. The establishment of the average crash risk for vehicles behind a slowing or stationary bus (0.0154%) provide a possible way of quantifying the benefit of bus priority schemes where buses are segregated from mainstream traffic.

On this issue, it is worth noting that there could be a mix of safety impacts at the micro-level. Results from the safety review suggest that the introduction of an exclusive bus lane for instance is likely to lead to reductions in on-path and off-path accidents, given that it can act as an additional "clear zone" and thus reduce car-car and car-roadside object collisions. The likelihood of rear-end collisions involving buses will also decrease when bus priority schemes that entail segregating buses from main stream traffic are implemented. On the other hand, possible negative impacts may arise at side street locations, as buses may have to contend with cars filtering in and out of the bus lane to enter or exit side streets. For bus lanes that result in the increase of carriageway width, pedestrian related accident risks may also increase due to longer crossing distance for pedestrians.

Secondly, findings from this research on route-level bus accidents could go a long way in providing additional justifications for the provision of bus priority measures, especially in North American and Australian contexts where the majority of road travel is by private vehicles.

Thirdly, the research findings suggest that bus companies and drivers in particular stand to benefit considerably in terms of safety, as results showed that bus priority had a greater influence in reducing bus-involved accidents (53.5%) as compared to all accidents (14%). This is a noteworthy finding as the social and financial cost involved in bus accidents are likely to be greater than private vehicle accidents. This is because the number of occupants in buses is likely to be greater as compared to private vehicles. The severity of accidents is also expected to be greater when buses are involved (given the weight and size of buses).

Fourth, findings on drivers' at-fault probability could act to further inform policy makers in bus and road management agencies in their operational and safety related decisions. Results suggest bus priority is able to address manoeuvrability issues faced by bus drivers in areas where road space is confined and along routes with much roadside friction. With the finding that at-fault probability is higher for less experienced drivers, they suggest there could be benefits in assigning routes with bus priority to this group of drivers.

Finally, while results from this research provide much insight into the safety effects of bus priority, they are likely to only represent the "tip of the iceberg" in terms of what is known. This is because findings in other bus priority contexts are likely to be different to what was found for Melbourne's case. Pedestrian volumes, for instance, are particularly low in Melbourne. Bus priority schemes are also implemented in sub-urban areas of Melbourne, with a number done by introducing a new lane instead of reallocating an existing lane for buses. As such, there is certainly much scope for further research in this area to explore the influence of these features (which may not be typical in other countries) on the safety impact of bus priority. It is in with these considerations that the next section is presented.

10.5 Areas for Future Research

The areas where future research can be undertaken to advance existing knowledge on bus priority safety effects and bus safety are identified below:

- ✓ Before-after analysis results showed that "space based" bus priority measures produced a greater safety effect compared to "time based" ones, while the accident analysis results revealed that certain accident types are more prevalent for buses. Further research could therefore be done to better understand the reasons for the patterns observed. The results also gave rise to a number of hypotheses on the safety effects of bus priority measures, which could be explored further as part of future research efforts.
- ✓ Results from the before-after analyses also begged questions on how Melbourne's experience of bus lanes (applied in suburban contexts) compares with bus priority in other areas and whether Melbourne's experience is unique. As such, further research efforts could focus on carrying out equivalent studies on bus priority overseas.
- ✓ In terms of before-after study designs, this research had focused on the use of two common approaches in EB and CG. Hence, there remains scope for exploring the implications of using other study design, e.g. full-Bayes, cross-section methods, to gain an appreciation on how such a choice affects the final safety estimate and its precision.
- ✓ To further our understanding of bus accidents at a route-section level, additional data could be collected to identify the disaggregate safety effects of different bus

priority measures and key factors associated with different accident severity levels. The latter could prove to be especially useful in helping quantify the safety benefits of bus priority schemes.

- ✓ It is acknowledged that certain driver behaviour attributes (such as education level), which were not available in this research, could have had an influence on bus drivers' at-fault probability. As such, it might be worthwhile to collect such data in future to examine whether they improve the explanation power of the mixed logit model developed in this research. In this model, attempts could also be made to explore other forms of distribution to see if they yield better approximations to the real behavioural profile of bus drivers.
- ✓ The estimation of crash risk in Chapter 9 was done based on the assumption that the probability of crash based on a given TTC value takes on an exponential decay relationship. In the real world, the link between such surrogate safety measures / conflicts and crashes could be more complex. It would certainly be worthwhile to devote part of future research efforts to establishing an improved statistical relationship between conflicts and crashes.
- ✓ Results of the crash risk estimation were also based on drivers' behaviour near a far-sided bus stop in a mixed traffic configuration. Hence, there is much scope to examine the safety impacts of bus priority operating in different traffic schemes and other bus stop configurations such as part-time bus lanes or indented bus bays.

10.6 Final Discussion and Conclusions

The safety implications of providing bus priority have been examined through an analytical, statistical and micro-simulation modelling approach in this research. Results from the analyses suggest that the safety benefits of bus priority not only include a decline in injury accidents but also reductions in property-only damage and conflicts for buses. The quantum of safety benefit was found to be significant, which suggests that there could be merits to consider priority schemes beyond bus travel time savings and operational benefits alone. For road management agencies, it could therefore be worthwhile to account for the positive safety impacts of bus priority in cost-benefit analyses that are typically carried out in transit planning.

From a methodological perspective, this research showed that it could be advantageous in accident count modelling to adopt approaches that account for location- and time-specific effects as well as unobserved factors that are likely to be present in the accident dataset. It also highlighted the usefulness of addressing individual effects when modelling drivers' behaviour.

In concluding, it is worth highlighting two points that have a bearing on an understanding of the safety implications of bus priority. Firstly, the research done was based purely on the Melbourne's context. Whether similar safety effects can be achieved when applying Melbourne's experience in other jurisdictions remain unknown. Secondly, whilst the methodologies adopted in this research are considered robust, it is acknowledged that they each come with their own limitations. Given this, the work presented in this thesis provides much impetus for future research in this field. In particular, future efforts could aim to build on the knowledge gained from this research by exploring and uncovering specific disaggregate safety effects brought about by bus priority.

APPENDIX A – KEY STEPS IN EMPIRICAL BAYES (EB) PROCEDURE

This appendix presents the key steps in the EB before-after procedure that were taken to compute the safety effect of bus priority that had been implemented on roads in Melbourne (treated sites). The steps below apply to road segments, but the same principle can be used to compute the safety effect estimate for road intersections:

(1) Accident data from the group of sites with characteristics similar to the treated sites (apart from the treatment itself) to represent a reference population are collected.

(2) Based on data collected in step (1), a model in which the expected annual number of accidents *E(A)* along an arterial road is taken to be a function of its traffic flow, Q_0 (in terms of AADT) and length, *L* was developed:

$$E(A) = \alpha_0 \times Q_0^{\beta_1} \times L^{\beta_2} \tag{A-1}$$

(3) In line with section 10-7 of Highway Safety Manual (2010), the predicted number of accidents for each treated site in the before and after period (T_{PB} and T_{PA}) is adjusted through the use of a relevant modification factor (CMF_x) to account for any site-specific attribute, such as narrower lane widths as a result adding a new bus lane:

$$T_{PB} = [E(A)]_{before} \times CMF_x \tag{A-2}$$

$$T_{PA} = [E(A)]_{after} \times CMF_x \tag{A-3}$$

(4) The expected number of accidents in the before period (T_{EB}) for each treated site was then determined using the observed (T_{OB}) and predicted crash counts (T_{PB}) in the before period:

$$T_{EB} = w_B \times T_{PB} + (1 - w_B) \times T_{OB} \tag{A-4}$$

where w_B is the weight assigned to account for the predictive strength of the model established in equation (A-1):

$$w_B = \frac{1}{1 + \kappa \sum_{before\ years} T_{PB}} \tag{A-5}$$

where κ is the over-dispersion parameter value obtained from the model in (A-1).

(5) The expected number of accidents in the after period, T_{EA} was determined as:

$$T_{EA} = \frac{T_{PA}}{T_{PB}} \times T_{EB} \tag{A-6}$$

For sites where more than two or more years' worth of accident data is available, the ratio T_{PA} / T_{PB} represents the total number of accidents predicted in the entire before and after periods.

(6) The odds ratio for each treated site, which can be seen as the value of doing something over nothing, was then derived by computing the ratio between the number of observed accidents (T_{OA}) over the number of expected accident (T_{EA}) in the after period:

$$OR' = \frac{T_{OA}}{T_{EA}} \tag{A-7}$$

(7) Given that the odds ratio *OR'* is potentially biased (Hauer, 1997), an adjustment was made to obtain the unbiased odds ratio (*OR''*) estimate:

$$OR'' = OR' \Big/ \left(1 + \frac{Var(T_{EA})}{T_{EA}^2}\right) \tag{A-8}$$

where $Var(T_{EA}) = \left(\frac{T_{PA}}{T_{PB}}\right)^2 \times T_{EB} \times (1 - w_B)$ (A-9)

(8) The pooled (average) effect *OR*, or safety effect θ_{EB}, and corresponding variance were then determined by summing the quantities from the individual sites:

$$OR = \frac{\sum T_{OA}}{\sum T_{EA}} \left(1 + \frac{\sum Var(T_{EA})}{\left(\sum T_{EA}\right)^2}\right)^{-1} \tag{A-10}$$

$$\theta_{EB} = 1 - OR \tag{A-11}$$

$$Var(OR) = (OR)^2 \left(\frac{1}{T_{OA}} + \frac{\sum Var(T_{EA})}{\left(\sum T_{EA}\right)^2}\right) \left(1 + \frac{\sum Var(T_{EA})}{\left(\sum T_{EA}\right)^2}\right)^{-2} \tag{A-12}$$

APPENDIX B – RISK ANALYSIS DEFINITION, LEVEL RATINGS AND CATEGORY ASSIGNMENT

Definition of Risk Analysis Rating

Category	Definition	Guide
Frequency of Occurrence		
Frequent	Likely to occur often	10 times per year or more
Occasional	Likely to occur several times	less than 10 times per year but more than once per year
Remote	Likely to occur during the system's operational life	less than 1 per year but more than once every 10 years
Improbable	Unlikely to occur but possible	less than 1 in 10 years but more than 1 in 100 years
Incredible	Unlikely to occur	Once every 100 years or less
Accident Severity		
High	Multiple fatalities and/or severe injuries	Head-on collision; Right-angle collision; High speed collision
Medium	Single fatality or severe injury, with possible other minor injuries	Pedestrian or cyclist struck by car; Side-swipe collision; Medium speed collision
Low	Minor injuries or property damage only	Low speed collision; Pedestrian or cyclist fall
Negligible	Property damage only	Car reverses into post

Risk Level Rating

Risk Category		Accident Severity Category			
		Negligible	**Low**	**Medium**	**High**
Accident Frequency Category	**Frequent**	Undesirable	Intolerable	Intolerable	Intolerable
	Occasional	Tolerable	Undesirable	Intolerable	Intolerable
	Remote	Acceptable	Tolerable	Undesirable	Intolerable
	Improbable	Acceptable	Acceptable	Tolerable	Undesirable
	Incredible	Acceptable	Acceptable	Acceptable	Tolerable

Risk Category Assignment

No.	Safety Hazard	Frequency	Severity	Category
Pre-Implementation				
1	At locations without bus bays, the risk of rear end collision increases when buses slows down or make sudden stops for commuters at bus stops	Occasional	Medium	Intolerable
2	Inadequate intersection sight distance raises the risk of side collisions as motorists from a side street would not have a good field of vision to check for traffic	Occasional	Medium	Intolerable
3	At locations where bus bays are provided, buses run the risk of side-swipe collisions when attempting to merge with the main traffic	Occasional	Low	Undesirable
4	Any inadequate clear zones on the side-table raise the risk of motorists colliding into roadside objects if they veer off-path	Remote	High	Intolerable
Post-Implementation				
5	The introduction of an additional lane for buses would mean pedestrians need extra time to cross the road	Occasional	High	Intolerable
6	Motorists may resort to illegal use of bus lanes to beat the heavy traffic during peak hours	Remote	Medium	Undesirable
7	The operational hours and use of red pavements for bus lanes are not consistent across sites, which could lead to confusion for motorists	Improbable	Medium	Tolerable
8	At locations where bus lanes end, buses run the risk of side-swipe collision if there is insufficient length for merging	Remote	Medium	Undesirable
9	The introduction of bus lanes raises the risk of side-impact collisions involving buses at locations where vehicles enter or exit side streets	Occasional	Medium	Intolerable
10	At large intersections, buses may not be able to clear the intersection in time if the length of the “B” phase duration is insufficient	Remote	Medium	Undesirable

APPENDIX C – KEY STEPS IN COMPARISON GROUP (CG) PROCEDURE

This appendix presents the key steps in the CG before-after procedure that were taken to compute the safety effect of bus priority that had been implemented on roads in Melbourne (treated sites):

(1) A group of sites with characteristics similar to the treated sites (apart from the treatment itself) were collected and matched to treated sites on a 2:1 or 1:1 basis.

Comparability Check based on Odds Ratio Test

(2) The odds ratio test based on the Hauer approach (Hauer, 1997) was applied to determine whether the comparison sites were suitable for estimating the accident count in the treated sites assuming the treatment had not been applied in the after period. Using the following notations,

Before Period	Treated Site	Comparison Site
t-1	$T_{O,t-1}$, $T_{E,t-1}$	$C_{O,t-1}$, $C_{E,t-1}$
t	$T_{O,t}$, $T_{E,t}$	$C_{O,t}$, $C_{E,t}$

where T_E and O_E are the expected values in the treated and comparison sites that correspond to the observed counts, T_O and C_O, in the before time period concerned, the odds ratio ω_t for each pair of counts in successive years (t-1,t) in the before period was computed as:

$$\omega_t = \frac{T_{E,t-1}C_{E,t}}{T_{E,t}C_{E,t-1}} \tag{C-1}$$

Using of the observed counts as approximation for the odds ratio sample would result in a biased estimate. As such, the following equations were used to obtain the unbiased odds ratio estimate and variance:

$$\hat{\omega}_t = \frac{T_{O,t-1}C_{O,t}}{T_{O,t}C_{O,t-1}}\left[1+\frac{1}{T_{O,t}}+\frac{1}{C_{O,t-1}}\right]^{-1} \tag{C-2}$$

$$\hat{s}^2_{\omega t} = \hat{\omega}^2_t\left(\frac{1}{C_{O,t}}+\frac{1}{T_{O,t-1}}+\frac{1}{T_{O,t}}+\frac{1}{C_{O,t-1}}\right) \tag{C-3}$$

A problem with the above approach is that it might lead to negative lower confidence limit values for the odds ratio. Given that this outcome is not possible in reality, the modified Allsop approach (Allsop et al., 2011) in which a logarithm transformation of the odds ratio was adopted by defining $y = \ln\omega$. Following the work by Allsop et al. (2011), the unbiased estimator for the variable y for each pair of counts in successive years (t-1,t) in the before period was determined by:

$$\hat{y}_t = \ln C_{O,t}\left(1-\frac{1}{2C_{O,t}(\ln C_{O,t})}\right)^{-1} + \ln T_{O,t-1}\left(1-\frac{1}{2T_{O,t-1}(\ln T_{O,t-1})}\right)^{-1}$$

$$-\ln T_{O,t}\left(1-\frac{1}{2T_{O,t}(\ln T_{O,t})}\right)^{-1} - \ln C_{O,t-1}\left(1-\frac{1}{2C_{O,t-1}(\ln C_{O,t-1})}\right)^{-1} \quad \text{(C-4)}$$

(3) With crash counts obtained from a total of m time points in the before period, the expected value and variance of the sample mean the modified Allsop (and similarly Hauer) approach were determined by:

$$\bar{y} = \frac{1}{m-1}\sum_{t=1}^{m-1}\hat{y}_t \quad \text{(C-5)}$$

$$s_{\bar{y}}^2 = Max\left\{\frac{1}{(m-1)(m-2)}\left[\sum_{t=1}^{m-1}\hat{y}_t^2-(m-1)\bar{y}^2\right], \frac{1}{(m-1)^2}\sum_{t=1}^{m-1}\left(\frac{1}{C_{O,t}}+\frac{1}{T_{O,t-1}}+\frac{1}{T_{O,t}}+\frac{1}{C_{O,t-1}}\right)\right\}$$

$$+\frac{2}{(m-1)^2}\sum_{t=2}^{m-1}\text{cov}(\hat{y}_{t-1},\hat{y}_t) \quad \text{(C-6)}$$

In this research, comparison sites were not considered if the 95% confidence interval of the sample mean does not include one (in the Hauer approach) or zero (in the modified Allsop approach). In such a case, another comparison site was selected until a positive test outcome was obtained.

<u>Estimation of expected accident count in treated sites</u>

(4) Following the odds ratio test, the expected accident count in the treated site assuming the treatment had not been applied was then estimated. Using the following notations,

Period	Treated Site	Comparison Site
Before	T_{OB}, T_{EB}	C_{OB}, C_{EB}
After	T_{OA}, T_{EA}	C_{OA}, C_{EA}

the comparison ratio (r_c) that represents the percentage change in the comparison sites' accident counts between the before and after period was computed:

$$r_c = \frac{C_{OA}}{C_{OB}}\times(1+\frac{1}{C_{OB}}+s_w^2)\times CMF_x \quad \text{(C-7)}$$

where CMF_x is the relevant crash modification factor to account for any site-specific attribute, if any (in this research, comparison sites were chosen to match any site-specific attribute in the treated sites, obliterating the need for the application of CMF_x) and s_w^2 is the estimated variance of the odds ratio for the pair of treated and comparison site as defined earlier.

(5) The expected number of accidents in the before period (T_{EB}) for each for each treated site was then determined based on knowledge of the mean and variance of counts from sites from a reference group[i]:

$$T_{EB} = \alpha \times E(\kappa) + (1-\alpha) \times T_{OB} \quad \text{(C-8)}$$

where $E(\kappa)$ represents the average crash counts of the reference group and α represents the "weight" which can be computed as follows:

$$\alpha = 1 \Big/ 1 + \frac{Var(\kappa)}{E(\kappa)} \quad \text{(C-9)}$$

(6) The expected number of accidents in the after period, T_{EA} was then determined as:

$$T_{EA} = r_c \times T_{EB} \quad \text{(C-10)}$$

(7) The odds ratio for each treated site, which can be seen as the value of doing something over nothing, was then derived by computing the ratio between the number of observed accidents (T_{OA}) over the number of expected accident (T_{EA}) in the after period:

$$OR' = \frac{T_{OA}}{T_{EA}} \quad \text{(C-11)}$$

(8) Given that the odds ratio OR' is potentially biased (Hauer, 1997), an adjustment is made to obtain the unbiased odds ratio (OR''):

$$OR'' = OR' \Big/ 1 + \frac{Var(T_{EA})}{T_{EA}^2} \quad \text{(C-12)}$$

where $Var(T_{EA}) = (T_{EA})^2 \times \left(\frac{1}{T_{OB}} + \frac{1}{C_{OB}} + \frac{1}{C_{OA}} + Var(\omega) \right)$ (C-13)

and ω represents the unbiased ratio between the treated and comparison sites' percentage change in the accidents counts as obtained in equation (C-2).

(9) The pooled (average) effect OR, or safety effect θ_{CG}, and corresponding variance were then determined by summing the quantities from the individual sites:

$$OR = \frac{\sum T_{OA}}{\sum T_{EA}} \left(1 + \frac{\sum Var(T_{EA})}{\left(\sum T_{EA}\right)^2} \right)^{-1} \quad \text{(C-14)}$$

[i] *Based on "Sample of Moments" method by HAUER, E. 1997. Observational Before-and-After Studies in Road Safety: Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety, Oxford, Elsevier Science Ltd., this involves using crash data from the reference groups (with characteristics similar to the treated sites) to address regression to the mean effects.*

$$\theta_{CG} = 1 - OR \tag{C-15}$$

$$Var(OR) = (OR)^2 \left(\frac{1}{T_{OA}} + \frac{\sum Var(T_{EA})}{\left(\sum T_{EA}\right)^2} \right) \left(1 + \frac{\sum Var(T_{EA})}{\left(\sum T_{EA}\right)^2} \right)^{-2} \tag{C-16}$$

APPENDIX D – COMPARABILITY CHECKS FOR COMPARISON GROUP METHOD

Odds Ratio Test – Approach and Results

No.	Location / Site	From	To	Comparison Site/s	Hauer Approach: Odds ratio, ω Period 1-2	Hauer: Odds ratio, ω Period 2-3	Hauer: Odds ratio, ω Mean	Hauer: Confidence limit Lower	Hauer: Confidence limit Upper	Hauer: *Test result	Modified Allsop Approach: Odds ratio, ω Period 1-2	Modified Allsop: Odds ratio, ω Period 2-3	Modified Allsop: Odds ratio, ω Mean	Modified Allsop: Confidence limit Lower	Modified Allsop: Confidence limit Upper	Modified Allsop: *Test result
1	Banksia St	Dora St	Rosanna Rd	D11	NA	0.00	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
2	Banksia Rd / Lwr Heidelberg Rd	-	-	A12	1.20	0.70	0.95	0.26	1.64	✓	0.44	0.14	0.29	-1.01	1.01	✓
3	Stud Rd	George St	High St	D3	0.00	0.57	0.29	-0.51	1.08	✓	NA	0.00	0.00	NA	NA	NA
4	Stud Rd	High St	George St	D5	NA	0.00	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
5	Stud Rd / High St	-	-	A14	0.20	1.14	0.67	-0.64	1.98	✓	NA	NA	NA	NA	NA	NA
6	Stud Rd	George St	Glenifer Rd	D4	1.00	0.26	0.63	-0.40	1.66	✓	0.36	-0.98	-0.31	-0.92	0.92	✓
7	Stud Rd / George St	-	-	B10	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
8	Stud Rd	Kellets Rd	Fulham Rd	D7	1.02	0.57	0.80	0.18	1.42	✓	0.32	-0.19	0.06	-0.87	0.87	✓
9	Stud Rd	Fulham Rd	Wellington Rd	D8	0.38	0.84	0.61	-0.04	1.26	✓	-0.46	0.23	-0.11	-1.02	1.02	✓
10	Stud Rd	Sunshine St	Bergins Rd	D5	0.12	1.11	0.61	-0.77	1.99	✓	NA	NA	NA	NA	NA	NA
11	Stud Rd	Timbertop Dr	Sunshine St	D1	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
12	Stud Rd	Brady Rd	McFees Rd	D10	0.60	0.07	0.33	-0.41	1.07	✓	NA	NA	NA	NA	NA	NA
13	Stud Rd / Monash Fwy	-	-	C4	1.79	0.44	1.12	-0.75	2.99	✓	0.82	-0.44	0.19	-0.78	0.78	✓
14	Stud Rd	Monash Fwy	Heatherton Rd	D11	2.21	0.25	1.23	-1.48	3.94	✓	1.08	-0.99	0.04	-0.93	0.93	✓
15	Dandenong-Frankston Rd / Kirkham Rd	-	-	B11	1.00	0.40	0.70	-0.13	1.53	✓	NA	NA	NA	NA	NA	NA
16	Dandenong-Frankston Rd	Jayco Dr	Willow Rd	D12	0.29	1.00	0.64	-0.35	1.63	✓	NA	NA	NA	NA	NA	NA
17	Dandenong-Frankston Rd / Jayko Dr	-	-	B13	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
18	Dandenong-Frankston Rd	Seaford Rd	Excelsior Dr	D2	NA	0.50	0.50	NA	NA	NA	NA	NA	NA	NA	NA	NA
19	Dandenong-Frankston Rd / Seaford Rd	-	-	A13	NA	0.44	0.44	NA	NA	NA	NA	-0.36	-0.36	NA	NA	NA
20	Dandenong-Frankston Rd / Klauer St	-	-	B12	NA	0.00	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
21	Mickleham Rd	Tullamarine Fwy	Broadmeadows Rd	D14	0.70	0.35	0.52	0.05	1.00	✓	0.04	-0.58	-0.27	-0.91	0.91	✓
22	Johnstone St / Pearcedale Pde	-	-	B1	NA	0.22	0.22	NA	NA	NA	NA	NA	NA	NA	NA	NA
23	Dalton Rd	Keon Pde	Wood St	E1	0.05	2.40	1.23	-2.03	4.48	✓	NA	NA	NA	NA	NA	NA
24	Springvale Rd / Wellington Rd	-	-	A1	0.15	1.29	0.72	-0.86	2.30	✓	-1.29	0.57	-0.36	-1.19	1.19	✓
25	Millers Rd/ McArthurs Rd	-	-	B2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
26	Millers Rd/ Blackshaws Rd	-	-	A2	0.00	NA	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
27	Geelong Rd / McDonald Rd	-	-	B3	NA	0.00	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA

No.	Location / Site	From	To	Comparison Site/s	Hauer Approach: Odds ratio, ω Period 1-2	Period 2-3	Mean	Confidence limit Lower	Upper	*Test result	Modified Allsop Approach: Odds ratio, ω Period 1-2	Period 2-3	Mean	Confidence limit Lower	Upper	*Test result
28	Market Rd / Sunshine Rd	-	-	B4	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
29	Wright St / Hampshire Rd	-	-	B5	0.00	0.67	0.33	-0.59	1.26	✓	NA	NA	NA	NA	NA	NA
30	Anderson Rd / Ballarat Rd	-	-	A3	0.00	NA	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
31	McIntyre Rd	Suffolk Rd	Bershire Rd	E2	0.00	NA	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
32	McIntyre Rd / WRR southern signal	-	-	C1	0.15	0.91	0.53	-0.52	1.58	✓	-1.06	0.42	-0.32	-1.05	1.05	✓
33	McIntyre Rd / WRR northern signal	-	-	C2	0.00	NA	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
34	WRR exit ramp / Keilor Park Dr	-	-	C3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
35	Keilor Park Dr	Western Ring Rd	Milleara Rd	D15	0.38	NA	0.38	NA	NA	NA	NA	NA	NA	NA	NA	NA
36	Milleara Rd	McPherson St	Buckley St	E3	1.60	NA	1.60	NA	NA	NA	NA	NA	NA	NA	NA	NA
37	Buckley St	Milleara Rd	Dickson St	E4	0.94	0.15	0.55	-0.54	1.64	✓	0.43	-1.06	-0.32	-1.28	1.28	✓
38	Buckley St / Russell St	-	-	B6	NA	0.00	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
39	Bell St	Tullamarine Fwy	Sydney Rd	E5	0.75	2.18	1.46	-0.51	3.44	✓	-0.13	0.91	0.39	-0.79	0.79	✓
40	Bell St	Gilbert Rd	St Georges Rd	D16	0.77	0.46	0.61	0.18	1.05	✓	0.05	-0.38	-0.17	-0.85	0.85	✓
41	Burgundy St / Mount St	-	-	B7	0.00	NA	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
42	Manningham Rd	High St	Williamsons Rd	D13	0.27	0.86	0.56	-0.25	1.37	✓	NA	NA	NA	NA	NA	NA
43	Williamsons Rd	King St	George St	D13	NA	0.00	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
44	Williamsons Rd / Doncaster Rd / Tram Rd	-	-	A4	0.42	1.85	1.14	-0.84	3.12	✓	-0.57	0.90	0.17	-0.83	0.83	✓
45	Wellington Rd	Monash Fwy	Brandon Park Dr	D17	0.00	NA	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
46	Monash University / Wellington Rd	-	-	B8	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
47	Wellington Rd	Nantilla Rd	Springvale Rd	D18	NA	0.00	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
48	Sir John Monash Drive / Dandenong Rd	-	-	A5	0.86	NA	0.86	NA	NA	NA	0.21	NA	0.21	NA	NA	NA
49	Dandenong Rd / Koornang Rd	-	-	A6	2.18	0.51	1.35	-0.96	3.66	✓	1.06	-0.26	0.40	-1.13	1.13	✓
50	Dandenong Rd / Murrumbeena Rd	-	-	A7	0.32	NA	0.32	NA	NA	NA	-0.44	NA	-0.44	NA	NA	NA
51	North Rd	Dandenong Rd	Huntingdale Rd	D19	1.01	1.08	1.05	0.94	1.15	✓	0.20	0.32	0.26	-0.70	0.70	✓
52	Warrigal Rd / Dandenong Rd	-	-	A8	0.73	0.40	0.56	0.11	1.02	✓	0.23	NA	0.23	NA	NA	NA
53	Wellington Rd / Jells Rd	-	-	A9	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
54	Wellington Rd / Jacksons Rd	-	-	B9	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
55	Wellington Rd / Springvale Rd	-	-	A10	0.00	NA	0.00	NA	NA	NA	NA	NA	NA	NA	NA	NA
56	Wellington Rd / Blackburn Rd	-	-	A11	1.32	1.09	1.20	0.89	1.52	✓	0.61	NA	0.61	NA	NA	NA

Note: "NA" arises because one or more terms in the denominator of the equation is zero, thus the odds ratio cannot be computed
** "✓" or "✘" indicate comparison sites that passed or failed the odds ratio test respectively*

(1) List of Control Sites (Road Corridors and Intersections)

No	Location / Site	From	To	Control Site/s (CS)	Key Characteristics
1	Springvale Rd / Lower Dendenong Rd	-	-	A1	Type A - Signalised Intersections
2	Ferntree Gully Rd / Clayton Rd	-	-	A1	
3	Paramount Rd / Sunshine Rd	-	-	A2	
4	Millers Rd / Kororoit Creek Rd	-	-	A2	
5	Barallat Rd / Gordon St	-	-	A3	
6	Barallat Rd / Duke St	-	-	A3	
7	Doncaster Rd / Wetherby Rd	-	-	A4	
8	Mitcham Rd / Springvale Rd	-	-	A4	
9	Waverley Rd / Darling Rd	-	-	A5	
10	Grange Rd / Neerim Rd	-	-	A5	
11	Dandenong Rd / Chadstone Rd	-	-	A6	
12	Dandenong Rd / Kooyong Rd	-	-	A6	
13	Clayton Rd / Bayview Avenue	-	-	A7	
14	Ferntree Gully Rd / Huntingdale Rd	-	-	A7	
15	Dandenong Rd / Clayton Rd	-	-	A8	
16	Clayton Rd / North Rd	-	-	A8	
17	Stud Rd / Avalon Rd	-	-	A9	
18	Westhall Rd / Spring Rd	-	-	A9	
19	Ferntree Gully Rd / Blackburn Rd	-	-	A10	
20	Springvale Rd / Ferntree Gully Rd	-	-	A10	
21	Westhall Rd / Centre Rd	-	-	A11	
22	Westhall Rd / Heatherton Rd	-	-	A11	
23	Springvale Rd / High St	-	-	A12	
24	Warrigal Rd / North Rd	-	-	A12	
25	Warrigal Rd / High St	-	-	A13	
26	Springvale Rd / Waverley Rd	-	-	A13	
27	Warrigal Rd / Centre Rd	-	-	A14	
28	Dimboola Rd / Pascoe Vale Rd	-	-	B1	Type B - Signalised T-Junctions
29	Airport Drive / Sharps Rd	-	-	B1	
30	Blackshaws Rd / Hansen St	-	-	B2	
31	Melton Highway / Pamelia Drive	-	-	B2	
32	McDonald Rd / Somerville Rd	-	-	B3	
33	Sommerville Rd / Paramount Rd	-	-	B3	
34	Sommerville Rd / Market Rd	-	-	B4	
35	Geelong Rd / Grieve Parade	-	-	B4	
36	Ballarat Rd / Hampshire Rd	-	-	B5	
37	Ballarat Rd / Northumberland Rd	-	-	B5	
38	Buckley St / Flower St	-	-	B6	
39	Buckley St / Roberts St	-	-	B6	
40	Lower Plenty Rd / Bellevue Avenue	-	-	B7	
41	Upper Heidelburg Rd / Montgomery St	-	-	B7	
42	Wellington Rd / Westminster Drive	-	-	B8	
43	Wellington Rd / Nantilla Rd	-	-	B8	
44	Wellington Rd / Tirhatuan Drive	-	-	B9	
45	Wellington Rd / Taylors Lane	-	-	B9	
46	Springvale Rd / Dunlop Rd	-	-	B10	
47	Springvale Rd / Kingsway	-	-	B11	
48	Springvale Rd / Railway Parade North	-	-	B12	
49	Springvale Rd / Mackay St	-	-	B13	

No	Location / Site	From	To	Control Site/s (CS)	Key Characteristics
50	Northern Ring Rd / Edgars Rd	-	-	C1	Type C - Interchange (Intersection of freeway with arterial road
51	Northern Ring Rd / Dalton Rd	-	-	C2	
52	Northern Ring Rd / Plenty Rd	-	-	C3	
53	Warrigal Rd / Monash Fwy	-	-	C4	
54	Blackburn Rd / Monash Fwy	-	-	C4	
55	Springvale Rd	High St	Railway Pde	D1	Type D - Divided Arterial Road
56	Springvale Rd	Railway Pde	Waverley Rd	D2	
57	Springvale Rd	Waverley Rd	FT Gully Rd	D3	
58	Springvale Rd	Police Rd	Mary St	D4	
59	Springvale Rd	Mary St	Heatherton Rd	D5	
60	Springvale Rd	Heatherton Rd	Athol Rd	D6	
61	Springvale Rd	Athol Rd	Cheltenham Rd	D7	
62	Springvale Rd	Cheltenham Rd	Hutton Rd	D8	
63	Greenwood Highway	Somer Rd	Banksia Rd	D9	
64	Warrigal Rd	Cantebury Rd	Burwood Hwy	D10	
65	Warrigal Rd	Centre Rd	S. Dandenong	D11	
66	Warrigal Rd	C. Dandenong	L. Dandenong	D12	
67	Manningham Rd	Bulleen Rd	Thompsons Rd	D13	
68	Williamsons Rd	Foote St	King St	D13	
69	Mickleham Rd	Somerton Rd	Johnstone St	D14	
70	Melrose Drive	Mickleham Rd	Western Ring Rd	D14	
71	Dinah Parade	Rachelle Rd	Milleara Rd	D15	
72	Airport Drive	Western Ring Rd	Sharps Rd	D15	
73	St Georges Rd	Miller St	Bell St	D16	
76	Ferntree Gully Rd	Monash Fwy	Springvale Rd	D17	
77	Blackburn Rd	Monash Fwy	Ferntree Gully Rd	D17	
78	Dandenong Rd	Blackburn Rd	Springvale Rd	D18	
79	Ferntree Gully Rd	Clayton Rd	Huntingdale Rd	D18	
80	Dandenong Rd	Browns Rd	Eastlink	D19	
81	Childs Rd	Betula Avenue	Plenty Rd	E1	Type E - Undivided Arterial Road
82	McIntyre Rd	Furlong Rd	Western Ring Rd	E2	
83	St Albans Rd	Furlong Rd	Ballarat Rd	E3	
84	Milleara Rd	Holden Avenue	Buckley St	E3	
85	Buckley St	Hoffmans Rd	Cooper St	E4	
86	Waverley St	Buckley St	Holmes Rd	E4	
87	Brunswick Rd	Citylink	Sydney Rd	E5	
88	Heidelberg Rd	Chandler Highway	The Boulevard	E5	

Note: Treated sites are matched with control sites based on similarity in key characteristics

APPENDIX E-1 – RESULTS OF MICRO-SIMULATION MODEL CALIBRATION

Tables E1 and E2 capture the observed and modelled travel times along Blackburn Road from Wellington Road to Ferntree Gully Road in each sub-stage of the calibration process. Travel time calibration is considered completed when the GEH-statistic is less than 5 for more than 85% of the cases.

Table E1: Observed Travel Time

Observed Travel Time (Afternoon Peak Period)			
Date	**Trip 1**	**Trip 2**	**Trip 3**
11th Dec 2012	185.5	122.0	96.0
12th Dec 2012	215.5	158.0	103.5
13th Dec 2012	201.0	135.0	123.0

Table E2: Modelled Travel Time in Stage 1 Calibration

Travel Time from Micro-Simulation Model			
Run	**Default**	**1st Calibration**	**2nd Calibration**
1	156.36	136.80	143.08
2	260.98	141.01	143.55
3	161.97	138.88	147.60
4	153.88	145.12	147.36
5	169.03	139.51	149.44
6	155.00	144.33	141.60
7	161.06	141.40	148.96
8	173.23	136.99	146.42
9	154.17	140.19	145.80
10	153.83	143.33	145.81
Average	**169.95**	**140.76**	**145.96**
Proportion of cases where GEH-Statistic < 5	0.778	0.889 (OK)	0.911 (OK)

Further calibration is done to ensure there is reasonable goodness-of-fit between observed and modelled queue discharge headway distribution for a 30-minute period (17:30-18:00hrs). To do so, non-parametric tests - Kolmogorov-Smirnov and Mann Whitney U tests - were employed to compare the observed and modelled distributions. These tests were chosen as they are suitable alternatives to the more restrictive t-test, in which the data is assumed to follow the normal distribution. Visual inspection of the headway distribution showed that this assumption cannot be fulfilled, hence the use of K-S and

Mann Whitney U tests. **Table E3** presents results of these tests through the model calibration process.

Table E3: Non-Parametric Tests (at $p<0.05$) for Comparing Headway Distribution

Model	Mann Whitney U Test		Kolmogorov-Smirnov Test	
	Statistic	Retain null hypothesis*?	Statistic	Retain null hypothesis*?
Default	0.007	×	0.024	×
Stage 1 – 1st Calibration	0.032	×	0.190	✓
Stage 1 – 2nd Calibration	0.098	✓	0.140	✓

*Note: * The null hypothesis is that the observed and modelled headway distributions are the same*

APPENDIX E-2 – PARAMETER VALUES ADOPTED IN VARIOUS STAGES OF MODEL CALIBRATION

Parameters		**Micro-simulation Model**			
		Default	**Stage 1A**	**Stage 1B**	**Stage 2**
Global					
Look-Ahead Model	Zone 1 Distance D_{Z1} (m)	15	**200**	200	200
	Zone 2 Distance D_{Z2} (m)	5	**150**	150	150
Reaction Time (s)		0.75	0.75	**1.0**	1.0
Reaction Time at Stop (s)		1.0	1.0	**1.35**	1.35
Simulation Time Step		0.75	0.75	**0.5**	0.5
Vehicle					
Car – length / width (m)		4 / 2	4 / 2	**4.6 / 2**	4.6 / 2
Bus – length / width (m)		12 / 2.4	12 / 2.4	**12 / 2.4**	12 / 2.4
Rigid – length / width (m)		8 / 2.25	8 / 2.25	**7.5 / 2.3**	7.5 / 2.3
Semi-trailer – length / width (m)		-	-	**19 / 2.4**	19 / 2.4
Car - maximum acceleration (m/s^2)		3	3	**2.4**	2.4
Bus - maximum acceleration (m/s^2)		1	1	**1.18**	1.18
Rigid - maximum acceleration (m/s^2)		1	1	**1.18**	1.18
Semi-trailer - maximum acceleration (m/s^2)		-	-	**0.86**	0.86
Car – normal / max. deceleration (m/s^2)		4 / 6	4 / 6	**4 / 6**	4 / 6
Bus - normal / max. deceleration (m/s^2)		2 / 5	2 / 5	**2.5 / 5**	2.5 / 5
Rigid - normal / max. deceleration (m/s^2)		3.5 / 5	3.5 / 5	**2.5 / 5**	2.5 / 5
Semi-trailer - normal / max. deceleration (m/s^2)		-	-	**2.2 / 4.5**	2.2 / 4.5
Traffic					
Minimum headway (s)		0	0	**0.4**	0.4
Behaviour					
Car – Speed limit factor		1.0	1.0	**1.04**	1.04
Bus – Speed limit factor		1.0	1.0	**1.00**	1.00
Rigid – Speed limit factor		1.0	1.0	**1.04**	1.04
Semi-trailer – Speed limit factor		1.0	1.0	**1.04**	1.04
Surrogate Safety Measure					
TTC threshold value (s)		1.5	1.5	1.5	**1.7**
DRAC threshold value (m/s^2)		3.35	3.35	3.35	**3.30**

Note: Figures in bold represents changes in each subsequent calibration, while those underlined are values adopted from AustRoads Project NS1229 – Micro-simulation Standards (ARRB Group, 2007)

APPENDIX F – AXIS CALIBRATION FOR EXTRACTION OF VEHICLE TRAJECTORY DATA

Using the Tracker (Brown, 2013) software, the axis was set up as shown in **Figure F-1** to extract trajectories of vehicles along Blackburn Road. The actual X and Y coordinates of ten points between these two lanes were then obtained via site measurements for the purpose of calibrating this axis. Following this, the corresponding image coordinates were extracted using the Tracker software and following function employed to calibrate the axis and achieve minimal error in the measurements:

$$\partial^* = Arg\ Min_Y P(\partial, Y_i') \ where\ P(\partial) = \sum_{i=1}^{10} \partial^{Y_i'} Y_i' \quad \text{(F-1)}$$

Y_i' is the image Y-coordinate of the point and ∂, the modification factor to be applied to minimize the measurement error. **Table F-1** captures the actual and image coordinates of the ten points. Through the optimization process, it was found that a ∂ value of 1.00777 yielded the smallest measurement error (1.12%). This value was subsequently applied after extracting vehicle trajectories information in Tracker.

Figure F-1: Axis Setup for Blackburn Road in Tracker

Table F-1: Axis Calibration for Distance Measurement in Tracker

Point i	Actual		Video		Factor = $\partial^{Y_i'}$	Y_i''	$\delta Y = Y_i - Y_i''$	Error
	X_i	Y_i	X_i'	Y_i'				
1	3.7	0	-2.82	0.08	1.00	-0.35	0.35	-
2	3.7	3	-2.86	2.70	1.02	2.71	0.29	9.58%
3	3.7	12	-2.67	10.9	1.09	11.84	0.16	1.32%
4	3.7	15	-2.75	13.2	1.11	14.58	0.42	2.82%
5	3.7	36	-2.48	29.4	1.26	36.89	-0.89	-2.48%
6	3.7	39	-2.43	30.9	1.27	39.33	-0.33	-0.84%
7	3.7	48	-2.37	36.6	1.33	48.63	-0.63	-1.30%
8	3.7	51	-2.50	38.0	1.34	50.97	0.03	0.05%
9	3.7	60	-2.30	42.9	1.39	59.88	0.12	0.21%
10	3.7	63	-2.32	44.3	1.41	62.52	0.48	0.77%
							AVERAGE	**1.12%**

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