Traffic Modelling and Safety

Analysis on Motorway Ramps

Xu Wang

BEng, MEng

Griffith School of Engineering

GRIFFITH UNIVERSITY

Submitted in fulfilment of the requirements of the degree of

Doctor of Philosophy

May 2018
STATEMENT OF ORIGINALITY

This work has not previously been submitted for a degree or diploma in any university.

To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

(Signed)___  ______
ACKNOWLEDGEMENT

To begin with, I would like to express my deepest gratitude to my supervisors Dr. Xiaobo Qu, Prof. Dong-Sheng Jeng, and Dr. Lei Hou who provided invaluable assistance with my studies during the period of candidature at Griffith University. Without their continuous support, constructive advice, patient guidance and exceptional encouragement, this thesis would not have been possible. During the past three and half years, I have been encouraged to overcome difficulties and doubts as a result of their motivation and professional knowledge. Furthermore, their passionate and rigorous attitude to research has had a profound effect on me. I will treasure those skills and attitudes throughout my life and they will encourage me to keep pursuing my research goals in the future.

I owe my thanks to Griffith University for giving me this significant study opportunity and research scholarship. My appreciation is extended to all academic, administrative, and technical staff at the Griffith School of Engineering for their generous help and professional support during my PhD studies.

Finally, thanks to my family, for always encouraging me to continue my education. Special thanks are due to my wife Mingfei Qiu, and to my parents Min Xu and Youde Wang, for their boundless love, support and belief in me. Thank you for assisting me in becoming the person I am today.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>STATEMENT OF ORIGINALITY</td>
<td>2</td>
</tr>
<tr>
<td>ACKNOWLEDGEMENT</td>
<td>I</td>
</tr>
<tr>
<td>TABLE OF CONTENTS</td>
<td>II</td>
</tr>
<tr>
<td>SUMMARY</td>
<td>VII</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>XII</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>XVI</td>
</tr>
<tr>
<td>GLOSSARY</td>
<td>XVIII</td>
</tr>
<tr>
<td>NOTATION</td>
<td>XXI</td>
</tr>
</tbody>
</table>

1 INTRODUCTION ................................................................. 1

1.1 Background ............................................................ 1

1.2 Objectives ............................................................. 4

1.3 Contributions ......................................................... 6

1.4 Thesis Outline .......................................................... 7

2 LITERATURE REVIEW .......................................................... 10

2.1 Review of Australia Road Standard ......................... 10
Table of Contents

2.2 Queensland Based Ramp Categorization .................................................. 12

2.3 Vehicle Emission Models............................................................................. 16
  2.3.1 Instantaneous fuel consumption model ............................................. 17
  2.3.2 Four-mode elemental fuel consumption model ............................... 18
  2.3.3 Running speed fuel consumption model ......................................... 22
  2.3.4 Average travel speed fuel consumption model ............................... 22
  2.3.5 Comprehensive modal emission model ......................................... 23

2.4 Crash Surrogate Measures ....................................................................... 26
  2.4.1 Time to collision ............................................................................... 27
  2.4.2 Time integrated time to collision ..................................................... 29
  2.4.3 Deceleration rate to avoid crash ....................................................... 30
  2.4.4 Crash potential index ....................................................................... 30
  2.4.5 Aggregated crash index .................................................................... 31

2.5 Monte Carlo Method .................................................................................. 32

2.6 Hotspot Identification Methods Based on Different Indicators .............. 33
  2.6.1 Crash frequency method ................................................................. 33
  2.6.2 Societal risk-based crash method .................................................... 34
  2.6.3 Empirical Bayesian method ............................................................ 34

2.7 Test Criteria for HISD Methods ............................................................... 36
  2.7.1 Method consistency test ................................................................. 36
  2.7.2 Total rank differences test .............................................................. 36

3  FREEWAY RAMP CONFIGURATION PART I – TRAVEL TIME ANALYSIS ................................................................................................................. 38
# Table of Contents

3.1 Background ........................................................................................................ 38

3.2 Site Description and Data Collection .................................................................... 40

3.3 Calibration and Validation of VISSIM Simulation Model .................................... 43

3.4 Impact of HGVs .................................................................................................. 47

3.5 Impact of Traffic Volume ...................................................................................... 52

3.6 Summary .............................................................................................................. 57

4 FREEWAY RAMP CONFIGURATION PART II – EMISSION ANALYSIS .......................... 59

4.1 Background ........................................................................................................ 59

4.2 Site Description and Development of Simulation Model ...................................... 60

4.3 Impact of HGVs .................................................................................................. 61

4.4 Impact of Traffic Volume ...................................................................................... 66

4.5 CO$_2$ Emissions Contour Chart .......................................................................... 69

4.6 Summary .............................................................................................................. 71

5 FREEWAY SAFETY PERFORMANCE PART I – CRASH SURROGATES ...................... 73

5.1 Background ........................................................................................................ 73

5.2 The Simplified Crash Surrogate Metric ................................................................ 75
Table of Contents

5.3 Crash Data Processing ........................................................................................................ 78
5.4 Development and Validation of VISSIM Simulation Model ................................. 80
5.5 Preliminary Test .................................................................................................................. 84
5.6 Summary ............................................................................................................................ 85

6 FREEWAY SAFETY PERFORMANCE PART II – BLACK SPOTS IDENTIFICATION......................................................................................................................... 87

6.1 Background .......................................................................................................................... 87
6.2 Site and Data Description ..................................................................................................... 90
6.3 Hotspot Identification Considering Daily Variability of Traffic and Crash Data 92
   6.3.1 Data categorization ........................................................................................................ 92
   6.3.2 EB-based method for morning peak hours ................................................................. 93
   6.3.3 EB-based method for afternoon peak hours .............................................................. 95
   6.3.4 EB-based method for daytime off-peak hours ......................................................... 96
   6.3.5 EB-based method for night off-peak hours ............................................................. 96
   6.3.6 Discussion .................................................................................................................. 97

6.4 Analysis of Identified Hotspots ..................................................................................... 100
6.5 Summary ............................................................................................................................ 102

7 CONCLUSIONS AND FUTURE WORKS ..................................................................... 104

7.1 Conclusions ......................................................................................................................... 104
# Table of Contents

7.2 Future Works ........................................................................................................... 110

7.2.1 The validation for crash surrogate metrics ......................................................... 110

7.2.2 The contributing factors of travel time in the road segment with ramp metering .................................................................................................................. 111

REFERENCES ................................................................................................................. 112

APPENDIX 1: ESTIMATION OF HEAVY VEHICLE PASSENGER CAR EQUIVALENTS FOR ON-RAMP ADJACENT ZONES UNDER DIFFERENT TRAFFIC VOLUMES: A CASE STUDY .......................................................................... 132

PUBLICATION LIST ........................................................................................................ 145

Refereed Journals........................................................................................................... 145

Refereed Conferences.................................................................................................... 145
SUMMARY

The whole research program aimed to improve operation, sustainability and safety of ramp areas. For this purpose, I first calculated passenger car equivalents (PCE) for a specific type of heavy vehicles (HVs) on the on-ramp through various different PCE methods. Through this study, I concluded that 1) homogenization based method (HM) cannot properly predict the variation trend of PCE values over traffic volume due to the low sensitivity of the speed to the change in traffic volume; 2) both time headway based method (THM) and traffic flow based method (TFM) can derive the results which are relatively consistent with outcome from simulation model. As this study is not relevant with the overall aim of the research program, it will be presented in Appendix 1.

The areas adjacent to ramps have always been regarded as traffic bottlenecks during peak hours because the frequent interactions between the merging and diverging traffic and the through traffic contribute to the loss in travel time. Currently, there is few literature to explore the impact of on-ramp lane configurations on travel time of through traffic. In this study, I comparatively analyzed the impact of freeway mainline traffic flow and proportion of mainline heavy goods vehicles (HGVs) on the average travel time of the road segment fitted with two types of on-ramp lane arrangements. The mainline traffic volumes vary from 800 to 2200 and the proportions of mainline HGVs range from 0 to 12%. The calibrated and validated simulation models were used to generate the average travel time under different traffic scenarios. Through comparative analyses, the following conclusions can be drawn. 1) For the impact of HGVs on travel time, when the mainline traffic flow is below 1200 vehs/hr/ln, the performance in travel
time of the road segment fitted with zip merging outperforms that fitted with added lane; when the mainline traffic volume is 1400 vehs/hr/ln, through traffic, starting from 10% of HGVs, spends less travel time on the road segment equipped with added lane; when the mainline traffic flow reaches 2200 vehs/hr/ln, the road segment fitted with added lane roundly performs better than that fitted with zip merging in term of travel time. 2) For the impact of traffic volume on travel time, although the proportion of mainline HGVs is 0, the road segment equipped with added lane starts to outperform that equipped with zip merging when traffic flow is approximately 2200 vehs/hr/ln; when the proportion of mainline HGVs is 12%, through traffic spends less travel time on the road segment fitted with added lane once the mainline traffic flow exceeds 1200 vehs/hr/ln. The abovementioned conclusions come from a case study. Currently, I cannot ensure they apply to other closely spaced on- and off-ramp areas. Further study will be conducted in future works.

As traffic operation has a close connection with environmental sustainability, the assessment of carbon dioxide emissions (CO$_2$) was also the key point of the research program. Areas adjacent to ramps have been viewed as zones with high emissions due to more traffic stops. Currently, many researchers have deemed that proper traffic control and the improvements in geometry can reduce CO$_2$ emissions in such areas. Few research have assessed the impact of on-ramp lane configurations on sustainability. In this study, I used the improved comprehensive modal emissions model (CMEM) to quantitatively evaluate the impact of mainline traffic volume and percentages of mainline HGVs on CO$_2$ emitted on the road segment fitted with two on-ramp lane arrangements. Traffic volumes range from 800 to 1800 vehs/hr/ln with an increment of 200 vehs/hr/ln and the proportions of HGVs vary from 2% to 10% with an increment of
The results show that 1) For the impact of HGVs on CO₂ emissions, when traffic flow is 800 vehs/hr/ln, through traffic on the road segment fitted with added lane can obtain a better performance in CO₂ emissions after the percentage of mainline HGVs exceeds 8%; when traffic flow varies from 1000 to 1800 vehs/hr/ln, through traffic generates less CO₂ emissions on the road segment equipped with added lane under the effect of any percentage of HGVs; 2) For the impact of traffic volume on CO₂ emissions, when the proportion of HGVs is 2%, less CO₂ is emitted on the road segment fitted with added lane after mainline traffic flow reaches 1000 vehs/hr/ln; when the proportion of HGVs reaches 10%, the performance of added lane on CO₂ emissions is completely superior to that of zip merging. In addition, two-factor-based CO₂ emissions contour charts were depicted. They could assist traffic engineers in selecting an appropriate combination of traffic volume and percentage of HGVs in order to achieve control of emissions.

The poor performance in traffic operation may contribute to more traffic conflicts. My research direction thus turned to safety assessment for on-ramps. Nowadays, many crash surrogate metrics have been proposed and designed for predicting the rear-end crash risks for basic freeway sections, including the time to collision (TTC), the deceleration rate to avoid crash (DRAC), the crash potential index (CPI) and the aggregated crash index (ACI). However, they might not be applicable to assess crash risks for on-ramps. As a consequence, I proposed the simplified crash surrogate metric (SCSM) to predict the rear-end crash risks for on-ramps. A one-lane on-ramp of Pacific Motorway, Australia was selected to validate the proposed surrogate metric. Another two surrogate measures (TTC and ACI) were compared with the SCSM through a simple proportional relationship between the societal risk index and crash rates.
Through this study, I conclude that 1) as an upgraded version of the TTC, the SCSM not only features the same straightforward closed form as the traditional TTC, but also makes up for the shortcoming of the TTC that is unable to accurately assess crash risks in saturated traffic flow; 2) the TTC based surrogate metric performed the worst; 3) the performance of the SCSM is more or less similar to that of the ACI. But considering the ability to resolve practical engineering issues, the SCSM is superior to the ACI.

Hotspots identification (HSID), a reactive crash prediction based on the historical crash counts, is crucial to transport authorities for evaluating the risk level of the object road sites. Many researchers have focused on improving the accuracy of HSID, namely to identify those un-identified hotspots that should have been treated. In practice, several conventional HSID approaches have been developed and applied for decades, but they fail to take the daily variability of traffic flow and crash record into account. To address it, four novel Empirical Bayesian (EB) based methods (for (1) morning and (2) afternoon peak hours, and (3) daytime and (4) night off-peak hours) were proposed to screen hotspots in the Pacific Motorway Southeast Queensland section linking Brisbane to Gold Coast. The detailed six-year crash records were used. I further analyzed the applicability of four proposed EB-based methods and three traditional HSID methods: (5) crash frequency method (CFM), (6) societal risk-based method (SRCM), and (7) Empirical Bayesian method (EB) in regard to freeway main carriageways, on-ramps and off-ramps through two consistency tests. Through this study, the following conclusions were drawn. 1) The EB-based methods considering the effect of daily variability outperform other approaches in the HSID for freeway main carriageways. 2) The performances in proposed methods are inferior to those in the EB and the CFM in the
HSID for on- and off-ramps. 3) The conventional EB method possess the best performance in the HSID for on- and off-ramps.
LIST OF FIGURES

Figure 2.1. One-lane On-ramp type A (Austroads, 2009) .......................................................... 12
Figure 2.2. One-lane On-ramp type B (Austroads, 2009) .......................................................... 13
Figure 2.3. One-lane on-ramp type C (Austroads, 2009) .......................................................... 13
Figure 2.4. Two-lane on-ramp type A (Austroads, 2009) .......................................................... 14
Figure 2.5. Two-lane on-ramp type B (Austroads, 2009) .......................................................... 14
Figure 2.6. One-lane off-ramp type A (Austroads, 2009) .......................................................... 14
Figure 2.7. One-lane off-ramp type B (Austroads, 2009) .......................................................... 15
Figure 2.8. One-lane off-ramp type C (Austroads, 2009) .......................................................... 15
Figure 2.9. Two-lane off-ramp type A (Austroads, 2009) .......................................................... 15
Figure 2.10. Two-lane off-ramp type B (Austroads, 2009) ......................................................... 16
Figure 2.11. Two-lane off-ramp type C (Austroads, 2009) ......................................................... 16
Figure 2.12. TTC notion represented by vehicle trajectory (Hayward, 1972) ......................... 28
Figure 2.13. Concept of TIT (Minderhoud and Bovy, 2001) ..................................................... 29
Figure 3.1. The investigated road segment fitted with two on-ramp lane arrangements 39
Figure 3.2. The layout of the investigated site ............................................................................. 41
Figure 3.3. Cumulative distribution of free flow speed ............................................................... 42
Figure 3.4. Average speed comparison between observed data, calibrated simulation data, and default simulation data ......................................................................................... 45
Figure 3.5. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 800 vehs/hr/ln .................................. 48
Figure 3.6. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1000 vehs/hr/ln ............................ 48
List of Figures

Figure 3.7. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1200 vehs/hr/ln........................................ 49

Figure 3.8. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1400 vehs/hr/ln........................................ 49

Figure 3.9. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1600 vehs/hr/ln........................................ 50

Figure 3.10. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1800 vehs/hr/ln........................................ 50

Figure 3.11. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 2000 vehs/hr/ln........................................ 51

Figure 3.12. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 2200 vehs/hr/ln........................................ 51

Figure 3.13. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 0.............................................................. 53

Figure 3.14. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 2%.......................................................... 54

Figure 3.15. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 4%.......................................................... 54

Figure 3.16. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 6%.......................................................... 55

Figure 3.17. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 8%.......................................................... 55

Figure 3.18. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 10%....................................................... 56
Figure 3.19. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 12% .................................................. 56
Figure 4.1. An observation point across Pacific Motorway .............................................. 61
Figure 4.2. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 800 vehs/hr/ln .............................. 63
Figure 4.3. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1000 vehs/hr/ln .......................... 63
Figure 4.4. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1200 vehs/hr/ln .......................... 64
Figure 4.5. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1400 vehs/hr/ln .......................... 64
Figure 4.6. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1600 vehs/hr/ln .......................... 65
Figure 4.7. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1800 vehs/hr/ln .......................... 65
Figure 4.8. The relationship between CO$_2$ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 2% .............................................. 66
Figure 4.9. The relationship between CO$_2$ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 4% .............................................. 67
Figure 4.10. The relationship between CO$_2$ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 6% .............................................. 67
Figure 4.11. The relationship between CO$_2$ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 8% .............................................. 68
Figure 4.12. The relationship between CO$_2$ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 10% .............................................. 68
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.13</td>
<td>Two-factor-based impact analysis procedure</td>
<td>69</td>
</tr>
<tr>
<td>4.14</td>
<td>CO\textsubscript{2} emissions contour chart for the added lane configuration</td>
<td>70</td>
</tr>
<tr>
<td>4.15</td>
<td>CO\textsubscript{2} emissions contour chart for the zip merging configuration</td>
<td>71</td>
</tr>
<tr>
<td>5.1</td>
<td>The sketch map of the research area</td>
<td>81</td>
</tr>
<tr>
<td>6.1</td>
<td>Traffic flow and crash records fluctuation</td>
<td>89</td>
</tr>
<tr>
<td>6.2</td>
<td>The research segment M1 and M3</td>
<td>92</td>
</tr>
<tr>
<td>6.3</td>
<td>The periodic unbalance of northbound and southbound traffic flow</td>
<td>95</td>
</tr>
<tr>
<td>1</td>
<td>The location of data collection point and study site</td>
<td>139</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

Table 2.1. The tree-structured crash model with eight nodes ........................................ 32
Table 3.1. Real-time traffic data from different time periods ........................................ 42
Table 3.2. Calibrated parameters for each traffic flow rate ........................................... 44
Table 3.3. GEH for different simulated scenarios ......................................................... 46
Table 3.4. The extremum comparison under various traffic flow (Added Lane) .......... 52
Table 3.5. The extremum comparison under various traffic flow (Zip Merging) ......... 52
Table 3.6. The extremum comparison under various percentages of HGVs (Added Lane) .................................................................................................................. 57
Table 3.7. The extremum comparison under various percentages of HGVs (Zip Merging) .................................................................................................................. 57
Table 5.1. 24-hour based crash counts on the study on-ramp from Year 2005 to 2013. 79
Table 5.2. Crash rate in the past nine years under the corresponding LOS .............. 79
Table 5.3. The traffic flow configuration for each on-ramp and off-ramp ................. 80
Table 5.4. Error tests of speeds ....................................................................................... 83
Table 5.5. Societal based risks assessed by three surrogate metrics under four LOS ... 85
Table 6.1. Crash distribution for freeway components .................................................. 93
Table 6.2. The summary of consistency test for freeway main carriageways .......... 98
Table 6.3. The summary of consistency test for on-ramps ........................................... 99
Table 6.4. The summary of consistency test for off-ramps .......................................... 99
Table 6.5. The hotspot aggregation based on the proposed and conventional EB estimates .................................................................................................................. 101
Table 1. The parameters used for HM ........................................................................... 140
List of Tables

Table 2. The parameters used for THM ................................................................. 141
Table 3. The parameters used for TFM ................................................................. 142
Table 4. The parameter used for MLRM ............................................................... 142
Table 5. The preliminary results for different PCE methods .............................. 143
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACI</td>
<td>Aggregated Crash Index</td>
</tr>
<tr>
<td>AC</td>
<td>Air conditioning</td>
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<tr>
<td>BITRE</td>
<td>Bureau of Infrastructure, Transport and Regional Economics</td>
</tr>
<tr>
<td>BRAD</td>
<td>Brake rate to accommodate disturbance</td>
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<tr>
<td>CBD</td>
<td>Central Business District</td>
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<tr>
<td>CDIAC</td>
<td>Cruise-deceleration-idle-acceleration-cruise cycle</td>
</tr>
<tr>
<td>CFM</td>
<td>Crash Frequency Method</td>
</tr>
<tr>
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<td>Comprehensive Modal Emission Model</td>
</tr>
<tr>
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</tr>
<tr>
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</tr>
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</tr>
<tr>
<td>EB</td>
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</tr>
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<td>FHWA</td>
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<td>GHG</td>
<td>Greenhouse gas</td>
</tr>
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<td>HCM</td>
<td>Highway Capacity Manual</td>
</tr>
<tr>
<td>HGVs</td>
<td>Heavy goods vehicles</td>
</tr>
<tr>
<td>HM</td>
<td>Homogenization based method</td>
</tr>
<tr>
<td>HSID</td>
<td>Hotspot identification</td>
</tr>
<tr>
<td>HVs</td>
<td>Heavy vehicles</td>
</tr>
<tr>
<td>Acronym</td>
<td>Definition</td>
</tr>
<tr>
<td>---------</td>
<td>------------</td>
</tr>
<tr>
<td>IR</td>
<td>Individual risk</td>
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<tr>
<td>LOS</td>
<td>Level of service</td>
</tr>
<tr>
<td>LUMS</td>
<td>Lane use management systems</td>
</tr>
<tr>
<td>MADR</td>
<td>Maximum available deceleration rate</td>
</tr>
<tr>
<td>MCM</td>
<td>Monte Carlo method</td>
</tr>
<tr>
<td>MCT</td>
<td>Method consistency test</td>
</tr>
<tr>
<td>MLRM</td>
<td>Multiple linear regression model</td>
</tr>
<tr>
<td>MPE</td>
<td>Mean percentage error</td>
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<td>NSC</td>
<td>National Safety Council</td>
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<tr>
<td>PCs</td>
<td>Passenger cars</td>
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<tr>
<td>PCE</td>
<td>Passenger car equivalents</td>
</tr>
<tr>
<td>PCU</td>
<td>Passenger car units</td>
</tr>
<tr>
<td>PDO</td>
<td>Property damage only</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
</tr>
<tr>
<td>RMSPE</td>
<td>Root mean square percentage error</td>
</tr>
<tr>
<td>SCSM</td>
<td>Simplified Crash Surrogate Metric</td>
</tr>
<tr>
<td>SM</td>
<td>Simulation method</td>
</tr>
<tr>
<td>SR</td>
<td>Societal risk</td>
</tr>
<tr>
<td>SRCM</td>
<td>Societal Risk-based Crash Method</td>
</tr>
<tr>
<td>SSAMs</td>
<td>Surrogate safety assessment models</td>
</tr>
<tr>
<td>TFM</td>
<td>Traffic flow based method</td>
</tr>
<tr>
<td>THM</td>
<td>Time headway based method</td>
</tr>
<tr>
<td>Acronym</td>
<td>Definition</td>
</tr>
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<td>------------</td>
</tr>
<tr>
<td>TIT</td>
<td>Time integrated time to collision</td>
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<td>TTC</td>
<td>Time to collision</td>
</tr>
<tr>
<td>TTC*</td>
<td>Threshold value of TTC</td>
</tr>
<tr>
<td>TRB</td>
<td>Transportation Research Board</td>
</tr>
<tr>
<td>TRDT</td>
<td>Total rank differences test</td>
</tr>
<tr>
<td>U</td>
<td>Theil’s inequality coefficient</td>
</tr>
<tr>
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<td>United States Department of Transportation</td>
</tr>
<tr>
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<td>Variable message signs</td>
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<tr>
<td>VSL</td>
<td>Variable speed limits</td>
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<td>WTO</td>
<td>World Health Organization</td>
</tr>
</tbody>
</table>
NOTATION

\[ a \] — Instantaneous acceleration rate

\[ A \] — Function parameters corresponding to \( \beta_1 \) and \( b_1 \)

\[ A_f \] — Vehicle frontal area

\[ A_r (C) \] — Atomic weight of carbon (=12)

\[ A_r (CO) \] — Atomic weight of carbon monoxide (=28)

\[ A_r (CO_2) \] — Atomic weight of carbon dioxide (=44)

\[ b \] — Regression coefficient

\[ b_1 \] — Drag force related to rolling resistance

\[ b_2 \] — Drag force related to aerodynamic resistance

\[ B \] — Function parameters corresponding to \( \beta_1 \) and \( b_2 \)

\[ c \] — Regression coefficient

\[ c_1 \] — Constant (=0.01)

\[ c_2 \] — Constant (=44.73 m/s)

\[ c_4 \] — Constant

\[ c_5 \] — Constant (=0.4074)

\[ c_6 \] — Constant (=0.1174)

\[ c_7 \] — Constant (=0.01)

\[ c_8 \] — Constant (=0.0049 g/s)
<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_r$</td>
<td>Speed-dependent rolling resistance coefficient</td>
</tr>
<tr>
<td>$C_d$</td>
<td>Aerodynamic drag coefficient (=0.3)</td>
</tr>
<tr>
<td>$d$</td>
<td>Diameter of the vehicle’s driving wheel (=0.4064 m)</td>
</tr>
<tr>
<td>$d_i$</td>
<td>Deceleration rate of leading vehicle</td>
</tr>
<tr>
<td>$D_{i-f}$</td>
<td>Distance gap between leading and following vehicle</td>
</tr>
<tr>
<td>$D_{i-f}(R)$</td>
<td>Distance gap between leading and following vehicle at time $R$</td>
</tr>
<tr>
<td>$D_{i-f}(0)$</td>
<td>Initial distance gap between leading and following vehicle</td>
</tr>
<tr>
<td>$e_0$</td>
<td>Mass factor accounting for the inertial of rotating part</td>
</tr>
<tr>
<td>$E_k$</td>
<td>The change in kinetic energy</td>
</tr>
<tr>
<td>$E_R$</td>
<td>Passenger car equivalents for creational vehicles</td>
</tr>
<tr>
<td>$E_T$</td>
<td>Passenger car equivalents for trucks</td>
</tr>
<tr>
<td>$E_{CO_2}(v,a)$</td>
<td>CO₂ emissions in unit distance</td>
</tr>
<tr>
<td>$E(\lambda)$</td>
<td>Predicted crash density</td>
</tr>
<tr>
<td>$f_i$</td>
<td>Idle fuel rate in mL/h</td>
</tr>
<tr>
<td>$f_{ij}$</td>
<td>The number of crash type $j$ occurring on segment $i$</td>
</tr>
<tr>
<td>$f_i$</td>
<td>Fuel consumption per unit time</td>
</tr>
<tr>
<td>$f_x$</td>
<td>Fuel consumption per unit distance</td>
</tr>
<tr>
<td>$f_{hv}$</td>
<td>Heavy vehicle adjustment factor</td>
</tr>
<tr>
<td>$F_a$</td>
<td>Acceleration fuel consumption</td>
</tr>
<tr>
<td>$F_c$</td>
<td>Cruise fuel consumption</td>
</tr>
<tr>
<td>Notation</td>
<td>Description</td>
</tr>
<tr>
<td>----------</td>
<td>-------------</td>
</tr>
<tr>
<td>$F_d$</td>
<td>Deceleration fuel consumption</td>
</tr>
<tr>
<td>$F_i$</td>
<td>Fuel consumption while idle</td>
</tr>
<tr>
<td>$F_r$</td>
<td>Integral of fuel consumption on investigated time $t$</td>
</tr>
<tr>
<td>$F_x$</td>
<td>Integral of fuel consumption on investigated distance $x$</td>
</tr>
<tr>
<td>$F_{re}$</td>
<td>Running speed fuel consumption</td>
</tr>
<tr>
<td>$F_{xv}$</td>
<td>Average travel speed fuel consumption</td>
</tr>
<tr>
<td>$F(v,a)$</td>
<td>Fuel consumption in unit distance</td>
</tr>
<tr>
<td>$G$</td>
<td>Percent grade</td>
</tr>
<tr>
<td>$j$</td>
<td>Drive axle slippage ($=0.04$) of HSID method</td>
</tr>
<tr>
<td>$k_1$</td>
<td>Integration coefficient related to $v_i$ and $v_f$</td>
</tr>
<tr>
<td>$k_2$</td>
<td>Integration coefficient related to $v_i$ and $v_f$</td>
</tr>
<tr>
<td>$k_a$</td>
<td>Energy parameter related to $k_x$</td>
</tr>
<tr>
<td>$k_x$</td>
<td>Energy parameter related to $M$, $v_i$ and $v_f$</td>
</tr>
<tr>
<td>$k_y$</td>
<td>Energy parameter related to $k_x$</td>
</tr>
<tr>
<td>$k_{E1}$</td>
<td>Calibration parameter</td>
</tr>
<tr>
<td>$k_{E2}$</td>
<td>Calibration parameter</td>
</tr>
<tr>
<td>$k_G$</td>
<td>Calibration parameter</td>
</tr>
<tr>
<td>$K_0$</td>
<td>Constant ($=200$J/rev/l)</td>
</tr>
<tr>
<td>$m_j$</td>
<td>Socially economic loss of crash type $j$</td>
</tr>
<tr>
<td>$M$</td>
<td>Weight of vehicle</td>
</tr>
</tbody>
</table>
### Notation

- $n$: Top $n$ risky sites
- $N$: The number of time interval/the total number of segments being identified
- $P$: Total engine power
- $P_a$: Auxiliary power
- $P_t$: Tractive power
- $P_w$: Power wasted in engine friction
- $P_p$: The percentage of creational vehicles
- $P_r$: The percentage of trucks
- $r$: Overall gear reduction ratio
- $\bar{r}$: Highest value of gear reduction ratio ($=10$)
- $\underline{r}$: Lowest value of gear reduction ratio ($=2$)
- $R$: Reaction time
- $R_i$: Annual monetary loss caused by crashes on road segment $i$
- $R_T$: Tractive force
- $R(k_{j,i})$: The rank of site $k$ identified by method $j$ in period $i$
- $t_a$: Acceleration time
- $t_d$: Deceleration time
- $t_i$: Idle time
- $t_s$: Travel time along investigated road segment/total travel time
- $T$: Investigated time period
### Notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$TTC(R)$</td>
<td>TTC at time $R$</td>
</tr>
<tr>
<td>$T_1$</td>
<td>Stopping time of leading vehicle</td>
</tr>
<tr>
<td>$v$</td>
<td>Instantaneous speed</td>
</tr>
<tr>
<td>$v_c$</td>
<td>Average cruise speed</td>
</tr>
<tr>
<td>$v_f$</td>
<td>Final speed/following vehicle’s speed</td>
</tr>
<tr>
<td>$v_f(R)$</td>
<td>Following vehicle’s speed at time $R$</td>
</tr>
<tr>
<td>$v_f(0)$</td>
<td>Initial speed of following vehicle</td>
</tr>
<tr>
<td>$v_h$</td>
<td>high end of the vehicle’s cruising speed range</td>
</tr>
<tr>
<td>$v_i$</td>
<td>Initial speed</td>
</tr>
<tr>
<td>$v_l$</td>
<td>Leading vehicle’s speed</td>
</tr>
<tr>
<td>$v_l(R)$</td>
<td>leading vehicle’s speed at time $R$</td>
</tr>
<tr>
<td>$v_l(0)$</td>
<td>Initial speed of leading vehicle</td>
</tr>
<tr>
<td>$v_r$</td>
<td>Average running speed</td>
</tr>
<tr>
<td>$v_s$</td>
<td>Average travel speed</td>
</tr>
<tr>
<td>$V$</td>
<td>Engine displacement</td>
</tr>
<tr>
<td>$Var(\lambda)$</td>
<td>Corresponding variance</td>
</tr>
<tr>
<td>$x_a$</td>
<td>Acceleration distance</td>
</tr>
<tr>
<td>$x_c$</td>
<td>Cruise distance</td>
</tr>
<tr>
<td>$x_d$</td>
<td>Deceleration distance</td>
</tr>
<tr>
<td>$x_i$</td>
<td>Observed crash density for segment $i$</td>
</tr>
</tbody>
</table>
Notation

\( x_s \) — Length of investigated road segment/ total travel distance

\( \alpha \) — Constant idle fuel rate in mL/s

\( \beta_i \) — Fuel consumption per unit of energy

\( \beta_2 \) — Fuel consumption per unit of energy-acceleration

\( \varepsilon \) — Drivetrain efficiency (=0.85)

\( \phi \) — Fuel-air ratio

\( \eta \) — Engine efficiency (=0.4)

\( \lambda \) — Lower heating value (=44000 J/g)

\( \lambda_i \) — EB-estimated crash density for segment \( i \)

\( \mu \) — Hydrogen-to-carbon ratio of fuel (=1.85)

\( \rho \) — Air density (=1.247 kg/m³)

\( \Delta t \) — Duration of time interval

\( \Delta v(R) \) — Speed difference between leading and following vehicle at time \( R \)

\( \Delta v(0) \) — Initial speed difference between leading and following vehicle

\( \sum E \) — Summation of carbon dioxide in the investigated road segment
1 INTRODUCTION

1.1 Background

Freeways have been serving as an increasingly significant role in carrying vehicles safely and efficiently and sustaining traffic at consistently high speeds in the urban transport system (Qu et al., 2015&2017). Not only are they key contributors in connecting intra- and inter-urban transportation network, but also in saving travel time spent on roads (Austroads, 2009). However, with the extensive utilization of freeways, traffic delays frequently occur, particularly at freeway recurrent bottleneck areas. Traffic delays arising from frequent vehicular interaction, even traffic crashes, lead to a large number of lost hours to travel time, and high emissions of greenhouse gases (Cheevarunothai et al., 2012; Li et al., 2014; Tavassoli Hojati et al., 2014; Xu et al., 2018). Therefore, addressing excessive travel time and environmental pollution due to traffic delays is of the utmost concern to traffic agencies (Bigazzi et al., 2015; Chang et al., 2016; Dahlgren, 1998; Heinrich, 2004; Stevanovic et al., 2005; Zhou et al., 2017; Kuang et al., 2015; Easa et al., 2017). On- and off-ramps, as vital infrastructures connecting city traffic networks to freeways, may be prone to relatively greater traffic delays than other sections of freeways from the perspective of traffic operation (Mergia et al., 2013; Wang et al., 2009; Qu and Wang, 2015). This is because motorists face a high intensity of competition for merging and diverging space in such areas. Many vehicles cannot merge into freeways due to the lack of acceptable gap of outermost carriageways, which leads to a decline in traffic efficiency. A well-designed ramp
should permit vehicles to merge into the major stream or to diverge from the main route safely and efficiently. In this regard, applying microscopic models to optimize existing ramp lane arrangements could be a good attempt to solve the abovementioned issue.

Apart from a concern to microscopic traffic operation and sustainability, I still dedicate myself to safety analysis and ex-post treatment to motorway ramps. According to the World Health Organization (WTO, 2013), approximately 1.24 million people died and over 50 million were injured in road crashes all over the world. More importantly, road crashes have been the leading cause of death for young people aged 15-29 years. In Australia, the social cost of road crashes has been estimated as a devastating AU$27 billion per annum (Department of Infrastructure and Regional Development, 2013). It has been well recognized that freeway crashes are much more dangerous than those on urban streets due to their severity (Austroads, 2009; US DOT, 2005). According to the crash records on Pacific Motorway southeast Queensland section from Year 2005 to 2013, there were 2149 and 843 crashes occurred on the areas adjacent to on- and off-ramps and freeway main carriageway, respectively. Areas adjacent to ramps, as turbulence areas of merging and diverging vehicles, are dominating incident sites on freeways. Due to the frequent weaving manoeuvres between motor vehicles, even a minor interrupt can lead to rear-end crashes or even chain crashes. However, the truth is that because of the unsoundness of crash records on ramps, considerable research have focused on safety evaluation on down- and up-stream main carriageways of ramps or weaving zones. Only several outdated or unsophisticated surrogate safety assessment models (SSAMs) can be used to evaluate potential crash risks on ramps. In this regard,
capable solutions need to be sought in order to proactively assess or predict ramp crashes.

As outlined in the above, the incompletion of historical crash records drives the progress of SSAMs. They make the most of the observable macroscopic and simulative microscopic traffic data to proactively estimate traffic conflicts. By contrast, freeway agencies are more prone to reduce crashes through hotspot identification. Crash hotspots, also known as sites with promise, black spots, or accident-prone locations, are defined as road sites at which crashes more frequently occur than other similar road sites as a result of local risk factors and to which ought to be given priority (Elvik, 2007). Crash hotspot identification results in a list of sites that are prioritized for detailed engineering studies that can identify crash patterns, contributing factors, and potential countermeasures (Hauer et al., 2002, 2004; Qu et al., 2014; Kuang et al., 2014). Identifying hotspots, namely network screening, is regarded as a reactive crash treatment scheme and is the first step of the freeway safety management process. It is thus of vital importance to transport authorities for enhancing the safety of freeways (PIARC, 2007; Qu and Meng, 2014; Da Costa et al., 2015). The data from BITRE (2016) revealed that, although crash counts on freeways declined year by year, the expenditure of the accident prevention of freeways sustains increased. This mainly arises from a mass of false positives (safe sites mistakenly identified as unsafe) and false negatives (truly hazardous sites wrongly viewed as safe) in the course of crash localizations so that the limited resource applied to safety improvement fail to be efficiently used (Cheng and Washington, 2005; Huang et al., 2009; Vadlamani et al., 2011; Washington et al., 2014). Accordingly, accurate localizations of accident sites are
of great value to the decision makers executing cost effective tasks (Montella, 2001, 2005; Haque et al., 2012; Sze et al., 2014; Yang et al., 2014; Pei et al., 2016).

1.2 Objectives

During the doctoral career, I have been focusing on improving the level and quality of traffic management of Pacific Motorway ramps in Southeast Queensland, from perspectives of traffic operation, sustainability and safety. There were five research involved in the thesis. The doctoral research started with the estimation of passenger car equivalents (PCE) for heavy vehicles in on-ramp adjacent zones. Through this simple study, I was conscious that the changes in the percentage of heavy goods vehicles (HGVs) and the traffic volume on the freeway main line significantly impact traffic efficiency and environment in closely spaced on- and off-ramp zones. As a consequence, I sought a better on-ramp lane arrangements to reduce traffic delays and emissions in such area. Afterwards, more attention was paid to safety evaluation for ramps. For this purpose, I proposed a novel crash surrogate metric to proactively assess crash risks on freeway on-ramps. Furthermore, the Empirical Bayesian methods considering daily volume/crash variability were proposed in order to improve the accuracy of hotspot identification. The specific objectives of each research are given as follows.

Due to the difference in traffic characteristic, it is hard to lump normal passenger vehicles and heavy vehicles (HVs) together in traffic capacity analysis for on-ramps. Consequently, I determined to find out the best estimation of PCE for HVs in the study on-ramp area. Its results should better reflect the variation trend of PCE over the
increase in traffic volumes and be more consistent with the results obtained from a control group. As this research may not be very relevant to the subject of the thesis, it will be presented in Appendix 1.

The second research aimed to assess traffic operation with regard to two on-ramp lane arrangements by considering the impact of the variation in traffic volume and the percentage of HGVs. The average travel time that the mainline traffic pass through the research road segment fitted with both on-ramp lane configurations was viewed as an important index to select a proper on-ramp lane arrangement.

Built on the second research, I assessed the performance in carbon dioxide emissions with regard to two on-ramp lane arrangements with the improved Comprehensive Modal Emission Model (CMEM). Besides, the CO₂ emissions contour charts considering the impact of traffic volume and percentage of HGVs were expected to propose.

Except for efforts I have done in the assessment of traffic operation and sustainability, I also concerned safety analysis on ramps. In the fourth study, my objective was to propose the simplified crash surrogate metric (SCSM) based on the concept of traffic state vulnerability and to validate that the proposed metric is more suitable to assess crash risks on on-ramps compared with two existing surrogate metrics.

While crash surrogate measures possess a congenital advantage in the risk assessment, most transport authorities still used reactive methods based on historical crash records
to predict the occurrence of crashes. The reactive methods are widely used in Hotspot identification (HSID). In the fifth research, I expected to improve the accuracy of the conventional HSID methods in the freeway safety management process, namely to re-identify those hotspots that should have been treated but fail to be given sufficient concerns. For this purpose, my objective was to optimize the existing empirical Bayesian method.

1.3 Contributions

Because there was few research focusing on the estimation of PCE for HVs on the on-ramp, this may contribute to an inaccurate analysis in on-ramp capacity. Hence, the contributions of the first study lie in that it found out the best PCE estimation method for an appointed type of HVs on the study on-ramp, which will improve the accuracy in on-ramp capacity analysis.

Few research have explored the impact of the on-ramp lane arrangement on the average travel time of the vehicles on the freeway road segment. The second study made up for literature vacancy and could assist traffic engineers in selecting the appropriate on-ramp lane configuration for the study road segment.

The contribution of the third study was the proposal of the dual factor-based CO₂ emissions contour charts. They could assist traffic engineers in selecting an appropriate combination of traffic volume and percentage of HGVs in order to achieve control of emissions.
I also focused on Safety analysis of on-ramps. The simplified crash surrogate metric (SCSM) with a closed form was proposed in this study, which advanced the methodological developments. In addition, the SCSM not only enables traffic engineers to get rid of the complex calculation of probabilistic causal models but also makes up for the deficiencies of the conventional Time to Collision (TTC) based method.

The contributions of the fifth study were that I proposed four time interval-based HSID methods on the basis of empirical Bayesian method. By using them, transport engineers could accurately extract the top high-risk road sites from various time periods of the day. The identification of these high-risk road segments enables traffic engineers to further analyze major causal factors of crashes in the corresponding time periods and to give the appropriate countermeasures.

1.4 Thesis Outline

Eight chapters constitute this thesis. Chapter 1 introduces the background, intent, objectives and contributions of each research in my Ph.D. candidate period.

Chapter 2 focuses on a literature review of previous studies, incorporating Australia road standard, the applicability of on-ramp lane arrangements, the impacts of HGVs on different freeway components, the basic concepts of CMEM model, existing safety surrogate measures, hotspot identification methods based on different indicators, and test criteria for HISD approaches.
Chapter 3 describes the investigated road segments and data collection process in the assessment of traffic operation, presents the development of simulation models, and respectively analyzes the travel time spent on two different on-ramp lane arrangements under different combinations of traffic volume and percentage of HGVs.

Chapter 4 comparatively analyzes the performances in emissions for both on-ramp lane arrangements under various traffic conditions based on 24-hour simulation data. The CO₂ emission contour charts for both on-ramp lane arrangements are also proposed for practical engineering applications.

Chapter 5 presents a new proposed crash surrogate metric based on the concept of traffic state vulnerability, and further demonstrates the applicability of the new approach to on-ramps through a comparison with the ACI and the TTC based method.

Chapter 6 formulates the four new Empirical Bayesian (EB) based methods considering daily variability of traffic volumes and crash records, for research road segments in Queensland, Australia and compares the performances of different HSID methods through consistency tests. The application of the new methods is also presented.

Chapter 7 integrally discusses the results from different studies in order to achieve the overall aim of the research program.
Chapter 8 concludes, summarizes the contributions of each research, and makes a preliminary plan for future research work.
Chapter Two: Literature Review

2 LITERATURE REVIEW

In this chapter, literature associated with chapter 3-6 was reviewed. They will supply theoretical basis with the subsequent studies. Australia Road Standard (Austroads) and Highway Capacity Manual (HCM) were first reviewed, which sped up the understanding of the research topics. More attention was paid to treatment schemes resolving traffic operational and safety issues. Secondly, Queensland based ramps were categorized according to Austroads and HCM. Thirdly, five existing vehicle emission models were reviewed in a chronological order. The merits, demerits and applicability of each emission model was understood. Fourthly, five existing crash surrogate measures were referred to, which aided me in proposing a new crash surrogate metric. Fifthly, three hotspot identification (HSID) methods and two consistency test criteria were reviewed.

2.1 Review of Australia Road Standard

Freeways act as a significant role in the urban transportation system. However, with the increase of demands on freeway infrastructure, the conventional freeways may not sustain this daily increased demand. This is because conventional freeways are less capable of preventing traffic congestion and breakdown under some specific traffic conditions. Any triggers described below can all result in flow breakdown.

- Traffic flow in main stream in excess of its capacity
- Lack of logical control signals from on-ramps to freeways
- Insufficient off-ramp accommodation capacity
- Undisciplined driving behaviours
Chapter Two: Literature Review

- Unreasonable ramps’ geometric design

Three out of the above five triggers directly correlate with ramps. It is obvious that the operational performance of ramps can to a great extent impact the efficiency of freeways. To improve transport efficiency, traffic agents have done abundant researches on traffic delay occurred in areas adjacent to on- and off-ramps and dissipation time of traffic conflict or congestion under different traffic scenarios, and given several constructive suggestions. Among them, the most commonly used solution is to re-design the geometry of ramps, which contains the following schemes. Firstly, increasing the number of lanes on entry-ramps and exit-ramps can accommodate more vehicles entering and exiting mainline to prevent them from spilling over to intersections and freeway main carriageways. Secondly, lengthening of acceleration or deceleration lanes, or replacing them with auxiliary lanes is also recommended in order to increase the probability of merging and diverging (e.g. Bonneson et al., 2004; Bared et al., 1999; Chen et al., 2014). When auxiliary lanes are provided, freeway mainline can accommodate a greater percentage of HGVs (Fitzpatrick et al., 2003). However, these geometric alterations are subject to sufficient space and funding.

An alternative treatment scheme is to implement traffic control. Many researchers recommended that ramp metering should be installed to control the rate where traffic enters the freeway so that entering traffic stream lowers the impact on mainstream (e.g. Austroads, 2009; Louah et al., 2011; Neudorff et al., 2006; Jacobson et al., 2006). This management mechanism is based on the real-time data in mainline, which are collected by some intrusive sensors (e.g. wireless vehicle detectors, inductive loop detectors), to macroscopically control the release rate of on-ramps signals and enable up- and down-stream flow of ramps to maintain at a dynamically balanced situation. Apart from
benefits of traffic operation, managed ramps can also improve safety and environmental issues of regional transport network. Data collected in eight cities show that crash rate reduced by 24-50%, and throughput on freeway main lanes achieved an increase of 5-10% due to the implementation of ramp metering. A case study from America also found that two-lane on-ramps with ramp signals can assist motorists in saving 2-55% of fuel under different traffic scenarios (MacCubbin et al., 2005). Generally, ramp signals are applied in conjunction with bypass lanes which enable priority vehicles to bypass the metering. Besides, to obtain more efficient ramps, the lane use management systems (LUMS) including variable speed limits (VSL) and traveler information system with variable message signs (VMS) are also recommended to use.

### 2.2 Queensland Based Ramp Categorization

As high-risk-prone zones, on- and off-ramps have been given a sufficient concern. To better assess the operation and safety performances of ramps, with the assistance of Austroads, Highway Capacity Manual (HCM) 2010 and ArcGIS, all on-ramps in Queensland are classified based on the number of lanes and their functions. For one-lane on-ramps, they are generally constructed according to the following three configurations.

---

![Figure 2.1. One-lane On-ramp type A (Austroads, 2009)](image)

---
One-lane on-ramps with direct tapered merge, shown in Figure 2.1, are mostly observed at regional areas where traffic volumes on through lanes and on-ramps are fairly low. For areas near the downtown, on-ramp configurations shown in Figure 2.2 and Figure 2.3 are commonly used. One-lane on-ramps combined with partial acceleration lane are also found on uphill terrain in order to make entering vehicles approaching to the desirable operating speed on through lanes. One-lane on-ramps combined with added/auxiliary lane are provided where level of service and safety are main concerns and entry and exit ramps are in close proximity to each other.
Figure 2.4. Two-lane on-ramp type A (Austroads, 2009)

Two-lane on-ramps can be classified into two groups shown in Figure 2.4 and Figure 2.5. They both have an auxiliary lane linking the upstream on-ramp to the downstream off-ramp. These two on-ramp configurations are generally constructed in urban region of freeways. I also observed multi-lane on-ramps in Queensland, but their usage rate only occupies less than 1%. Multiple lanes generally merge into two lanes prior to the end of gore area. I stipulate that the base length of an on-ramp is the distance from the signal controlled (e.g. signalized intersections) or non-signal controlled junctions (e.g. roundabouts or the converge point of two roads) to the left end point of gore area.

The categorization of off-ramps is very similar to that of on-ramps. Their base length can be also measured from the right end point of gore area to the signal or non-signal controlled junctions.

Figure 2.5. Two-lane on-ramp type B (Austroads, 2009)

Figure 2.6. One-lane off-ramp type A (Austroads, 2009)
In addition, two-lane off-ramps have three variants. Figure 2.9 shows the most commonly used one connecting to the downstream major intersections and they are highly restricted by the geometry of freeways.
2.3 Vehicle Emission Models

Australia’s greenhouse gas (GHG) emissions have risen steadily from 419.5 megatonnes in 1991 to 576.2 megatonnes in 2008 (Aph.gov.au, 2017). Energy consumption and CO$_2$ emissions (the major component of GHG emissions) in transportation activities respectively accounts for 28% of the United States’ total energy use and 33.4% of carbon dioxide production (Davis et al., 2015; EPA, 2015). As the largest emitter of CO$_2$ (42.7%) in the transportation sector, passenger cars have been given a sufficient concern in the past decade, and reduction in fuel consumption and emission levels have been achieved through rigorous regulations and technical solutions (Wang and Rakha, 2017). Levels of CO$_2$ can be also reduced through a better traffic planning associated with operational level, which generally requires accurate and
efficient emission models to derive robust emission estimates (Demir et al., 2011). In this subsection, several vehicle emission models are reviewed.

### 2.3.1 Instantaneous fuel consumption model

The instantaneous fuel consumption model, or instantaneous model for short, is actually an extension of the power model developed by Kent et al. (1982) and had been calibrated through data from special on-road experiments in Melbourne (Biggs and Akcelic, 1983) and extensive on-road driving data collected in Sydney (Tomlin et al., 1983), so it is applicable to Australian context. It applied vehicle characteristics such as mass, grade, efficiency parameters and drag force parameters associated mainly to aerodynamic and rolling resistance as input parameters to estimate the fuel consumption per second. The model for fuel consumption per unit time can be expressed as:

\[
f_t = \begin{cases} 
\alpha + \beta_1 R_T v + \left( \beta_2 Ma^2 \nu / 1000 \right) & \text{for } R_T > 0 \\
\alpha & \text{for } R_T \leq 0
\end{cases}
\]  

(1)

where \( R_T \) is

\[
R_T = b_1 + b_2 v^2 + Ma \times 10^{-3} + 9.81 \times 10^{-7} MG
\]

(2)

\( f_t \) is the fuel consumption per unit time in mL/s, \( \alpha \) is the constant idle fuel rate in mL/s (default value is 0.444, which is not applicable to some particular vehicle models), \( \beta_1 \) is the fuel consumption per unit of energy in mL/kJ (0.09 as default value), \( \beta_2 \) is the fuel consumption per unit of energy-acceleration in mL/(kJ m/s) (0.045 as default value). In addition, \( R_T \) is the tractive force required to drive the vehicle, which is the sum of drag
force, inertia force and grade force in kN. $b_1$ and $b_2$, two important parameter in the calculation of $R_f$, respectively denote drag force related mainly to rolling resistance (0.333 as default value) and aerodynamic resistance (0.00108 as default value). Moreover, $M$ is the weight of vehicle in kg, $G$ is the percent grade, $a$ is the instantaneous acceleration in m/s$^2$ and $v$ is the instantaneous speed in m/s. Finally, the total amount of fuel consumption for an investigated time period can be calculated as:

$$ F_t = \int_0^T f_i dt $$

(3)

Similarly, fuel consumption per unit distance and total consumption are expressed as:

$$ f_x = \begin{cases} 
\alpha / v + \beta_1 R_f + (\beta_2 M a^2 / 1000) & \text{for } R_f > 0 \\
\alpha / v & \text{for } R_f \leq 0 
\end{cases} \quad (4) $$

$$ F_x = \int_0^x f_x dx \quad (5) $$

The instantaneous fuel consumption model is convenient to calculate and can operate very well at a microscopic level. However, it cannot predict on-road fuel consumption very accurately over short time intervals and does not predict cruise fuel consumption well at low speeds according to Biggs and Akcelik (1983), which means that it may not estimate the fuel consumption accurately when traffic congestions occur.

### 2.3.2  Four-mode elemental fuel consumption model

Bowyer et al. (1985) developed the four-mode elemental fuel consumption model on the basis of Akcelick (1982)’s fuel consumption models for four modes of driving (namely idle, cruise, acceleration and deceleration). They were derived from the instantaneous
model, so the same vehicle associated parameters apply. The prerequisite for application of this model is data relevant to road segment total distance, cruise speed, stopped time and average grade must be obtainable. For more accurate estimations, the initial and final speeds for each acceleration and deceleration need to be known. In order to estimate fuel consumption in idle mode, the definition of a stop is very essential. Generally, we assume that when a vehicle’s speed falls below 20 km/h, it is deemed to be in idle mode.

- Acceleration fuel consumption

The following equation can be used to approximate fuel consumed during an acceleration phase from an initial velocity $v_i$ to a final velocity $v_f$.

$$F_a = \max \left\{ \alpha t_a + \left[ A + k_1 B (v_i^2 + v_f^2) + k_2 \beta ME \right] x_a, \alpha t_a \right\}$$

(6)

where $\alpha, \beta_1, \beta_2, M, G$ have been defined in the instantaneous model. $A$ and $B$ are function parameters corresponding to $\beta_1, b_1$ and $b_2$, which can be calculated as $A = \beta_1 b_1$ and $B = \beta_2 b_2$. $k_1$ and $k_2$ are integration coefficients given by $k_1 = 0.616 + 0.000544v_f - 0.0171\sqrt{v_i}$ and $k_2 = 1.376 + 0.00205v_f - 0.00538v_i$. When the acceleration distance $x_a$ and time $t_a$ are unknown, they can be estimated as $x_a = m_a (v_i + v_f) t_a / 3600$ where $m_a = 0.467 + 0.00200v_f - 0.00210v_i$ and $t_a = (v_f - v_i) / (2.08 + 0.127\sqrt{v_f - v_i} - 0.0182v_i)$. $E_k$ is the change in kinetic energy per unit mass per unit distance during acceleration course and given by $E_k = 0.3858 \times 10^{-4} (v_f^2 - v_i^2) / x_a$.

- Deceleration fuel consumption
The following equation can be used to calculate fuel consumption during a deceleration phase from an initial velocity $v_i$ to a final velocity $v_f$.

$$F_d = \max \left\{a \alpha_d + \left[k_z A + k_y k_1 B (v_i^2 + v_f^2) + k_2 \beta_i ME_k + 0.0981 k_\beta MG \right] x_d, \alpha_t \right\} \quad (7)$$

where three energy related parameters are estimated as $k_z = 0.046 + 100/M + 0.00421 v_i + 0.00260 v_f + 0.0544 G$, $k_y = k^0.75_x$, $k_a = k^{3.81}_x \left(2 - k^{3.81}_x \right)$. The integration coefficient $k_i$ is given by $k_i = 0.621 + 0.000777 v_i - 0.0189 \sqrt{v_f}$. The deceleration distance $x_d$ and time $t_d$ can be estimated as follows when necessary, $x_d = m_d (v_i + v_f) t_d / 3600$ where $m_d = 0.473 + 0.00155 v_i - 0.00137 v_f$ and $t_d = (v_i - v_f) / \left[1.71 + 0.238 \sqrt{v_i - v_f} - 0.0090 v_f \right]$. $E_k$ is the change (decrease) in kinetic energy per unit mass per unit distance during deceleration manoeuvre, $E_k = 0.3858 \times 10^{-4} \left( v_f^2 - v_i^2 \right) / x_d$.

- **Cruise fuel consumption**

Cruise mode is defined as travel from the end of acceleration to the start of the next deceleration where a stop arises. A stop can be thus identified once the speed is less than 20 km/h. The following equation is used to calculate fuel loss during cruise phase allowing for speed fluctuations.

$$F_c = \max \left\{(f_i I v_c + A + B v_c^2 + k_{E_1} \beta_i ME_k + k_{E_2} \beta_i ME_k^2 + 0.0981 k_\beta MG) x_c, f_i x_c / v_c \right\} \quad (8)$$

where $f_i$ is the idle fuel rate in mL/h (1600 as default value), $v_c$ is the average cruise speed in km/h, $x_c$ is cruise distance in km. The calibration parameters can be estimated as $k_{E_1} = \min \left\{12.5 / v_c + 0.000013 v_c^2, 0.63 \right\}$, $k_{E_2} = 3.17$, $k_G = 1 - 2.1 E_k$, for $G < 0$, and
Chapter Two: Literature Review

1−0.3E_{k+} \text{ for } G > 0. The change in kinetic energy due to speed fluctuations is given as

\[ E_{k+} = \max \{0.258−0.0018v_{c}, 0.10\} \, . \]

- Fuel consumption while stopped (idle)

When the vehicle is stopped, the fuel consumption can be approximated as follows.

\[ F_i = a t_i \quad (9) \]

where \( t_i \) is the stopped time in s.

The total fuel consumption during a cruise-deceleration-idle-acceleration-cruise cycle (CDIAC) can be finally estimated as:

\[ F_i = \int_0^{t_c} F_a \, dt + \int_0^{t_d} F_d \, dt + \int_0^{t_c} F_c \, dt + \int_0^{t_a} F_a \, dt \quad (10) \]

The four-mode elemental model is more appropriate to assessment of fuel consumption for a short road segment. Thanks to consideration of four driving modes, it provides abundant driving information, which ensures the minimum loss of accuracy in consumption estimates. However, the CDIAC cycle increases difficulty in data collection, and a large number of parameters in each mode makes it difficult to calculate.

According to Bowyer et al. (1985)’s comparative analysis of first two models, the elemental model can evaluate fuel loss with a 1% error margin. It can obtain more accurate fuel consumption, which is very similar to predicted results of the instantaneous model, if the initial and final speeds are known.
2.3.3 Running speed fuel consumption model

Bowyer et al. (1985) proposed the running speed model, as the aggregated version of the elemental model, to estimate fuel consumption when a vehicle is running or stopped. This model is given as:

\[
F_R = \max \{ \alpha t_i + (f/i) v_r + A + B v_r^2 + k_{E_1} \beta_1 M E_{k^+} + k_{E_2} \beta_2 M E_{k^+}^2 + 0.0981 k_G \beta M G \} x_i, \alpha t_i \}
\] (11)

where \( x_i \) is the length of investigated road segment in km. \( t_i \) and \( t_s \) denote idle time and travel time along segment in s. \( v_r \) is average running speed in km/h and can be calculated as \( v_r = \frac{3600 x_i}{(t_s - t_i)} \). \( E_{k^+} = \max \{ 0.35 - 0.0025 v_r , 0.15 \} \), \( k_G = 1 - 1.33 E_{k^+} \) for \( G < 0 \) or \( 0.9 \) for \( G > 0 \), \( k_{E_1} = \max \{ 0.675 - 1.22 / v_r , 0.5 \} \), \( k_{E_2} = 2.78 + 0.0178 v_r \). In this model, the acceleration, deceleration and cruise phases are lumped together. It can be used to estimate fuel consumption under various traffic contexts, ranging from short to long segments.

2.3.4 Average travel speed fuel consumption model

This model, due to its straightforward and aggregate form, has been widely used in real world for decades. It estimates fuel consumption only based on average travel speed rather than some driving behaviour related microscopic parameters (e.g. instantaneous acceleration and deceleration) and terrain associated parameters (e.g. grade). Therefore, it is more appropriate to approximate fuel consumption at a traffic network level rather than short road segments. The model is given as follow.

\[
F_X = \left( b / v_r + c \right) x_i
\] (12)
where $b$ and $c$ are regression coefficients related to the vehicle parameters $M$, $\beta_1$, $\beta_2$, etc. as well as the driving environment. $v_s$ is average travel speed in km/h and calculated as $v_s = \frac{3600x_s}{t_s}$ where $x_s$ and $t_s$ are total travel distance in km and travel time including any stopped time in s.

### 2.3.5 Comprehensive modal emission model

The comprehensive modal emission model (CMEM) was developed by Barth et al. (1996, 2000). Similar to the abovementioned emission methodologies, it creates an analytical link between an individual vehicle’s characteristics (mass, speed, acceleration etc.) to second-by-second fuel consumption rates (Nie and Li, 2013). In addition, it further approximates the power consumption due to engine friction and air conditioning (AC), which fails to be considered in other methods. Finally, the fuel rates can be derived according to a total engine power conversion equation. Once the fuel consumption rates are known, they are used for estimating CO$_2$ emissions based on carbon balance and the empirical relationships between CO/HC emissions and fuel consumption (Nam, 2003). The estimation of engine output power can be calculated through the following equations.

- The tractive power

$$P_t = Mv\left[ a(1+e_0) + 9.81(G + C_r) \right] + 0.5\rho C_d A_f v^3$$  \hspace{1cm} (13)

where $e_0$ is the mass factor accounting for the inertia of rotating part, which approximately equals 0.1 (Nam, 2003). $C_r$ is speed-dependent rolling resistance coefficient, which can be defined as $C_r = c_1\left(1 + \frac{v}{c_2}\right)$, where $c_1$ and $c_2$ are constants.
(0.01 and 44.73 as default values according to Mannering et al. (2005)). $\rho$ is air density in kg/m$^3$ (1.247 as default value). $C_d$ is the aerodynamic drag coefficient (due to the unavailability of drag coefficient for various vehicle categories, the mean 0.3 is selected as default value in accordance with Mannering et al. (2005)). $A_f$ is the vehicle frontal area in m$^2$ (2 as default value).

- The power tasted in engine friction

$$P_w = \frac{c_4K_0V}{\pi d (1 - j)} \left[ c_3 (v - v_h)^2 + r \right]v$$

where

$$c_3 = \frac{\bar{r} - r}{v_h^2}$$

$$r = c_3 (v - v_h)^2 + \bar{r}$$

where $r$ is the overall gear reduction ratio; $\bar{r}$ and $r$ are the highest and lowest values of gear reduction ratio (10 and 2 as default values, respectively). $v_h$ is the high end of the vehicle’s cruising speed range (35 m/s as default value here). $d$ is the diameter of the vehicle’s driving wheels in meter (0.4064 as default value). $j$ is drive axle slippage (0.04 as default value according to Mannering et al. (2005)). $V$ is engine displacement, which can be obtained through simulated vehicle characteristic data. $K_0$ is a constant in $\text{J/rev/l}$ (200 as default value according to Barth et al. (2000)). $c_4$ is a constant (1.25 as default value according to a simple calculation).

- The auxiliary power
Chapter Two: Literature Review

The auxiliary power is mainly dependent upon the status of AC. When AC is turned off, $P_a$ can be generally viewed as a constant in W (1000 as default value according to Nam (2003)). Finally, the total engine power can be calculated as the weighted sum of the three.

$$P = \frac{P}{\varepsilon \eta} + \frac{P}{\eta} + P_w$$  \hspace{1cm} (17)

where $\varepsilon$ is the drivetrain efficiency, which depends on $v$ and $a$ in a complicated way (Barth et al., 2000). In this study, it is simplified as a constant near the middle of its range (0.85 as default value). $\eta$ is the engine efficiency, which is typically treated as a constant for all vehicles (0.4 as default value according to Barth et al. (2000)).

The total power can be converted into fuel consumption and CO$_2$ emissions in the unit of gram per meter based on Equations 18 and 19.

$$F(v, a) = \frac{\phi P}{\lambda v}$$  \hspace{1cm} (18)

where $\phi$ is the air fuel equivalent ratio. In this study, we stipulate $\phi=1.0$ for regular vehicles and $\phi=1.13$ for HGVs. $\lambda$ is the fuel’s lower heating value in J/g (44000 as default value).

$$E_{CO_2}(v, a) = \gamma_1 F(v, a) + \frac{\gamma_0}{v}$$  \hspace{1cm} (19)

where

$$\gamma_0 = -\frac{A_y(CO_2) \cdot c_8}{A_y(C) + \mu}$$ \hspace{1cm} $$\gamma_1 = A_y(CO_2) \left( \frac{1 - c_7}{A_y(C) + \mu} - \frac{c_5(1 - \phi^{-1}) + c_6}{A_y(CO)} \right)$$
The CO$_2$ emissions in the unit distance can be estimated according to the carbon balance. $\text{A}_r(C)$, $\text{A}_r(CO)$ and $\text{A}_r(CO_2)$ denote the atom weight of carbon, carbon monoxide and carbon dioxide (12, 28 and 44, respectively). $c_3 - c_8$ are parameters fitted from data (0.4074, 0.1174 and 0.01, and 0.0049 g/s as default values, respectively, based on Nam (2003)’s research). $\mu$ is the hydrogen-to-carbon ratio of fuel (1.85 as default value).

The summation of CO$_2$ emissions in the investigated road segment can be estimated as follows.

$$\sum E = \int_0^x E_{CO_2}(v,a)dx$$

(20)

2.4 Crash Surrogate Measures

Due to the enormous losses to society caused by traffic crashes, scholars have been seeking appropriate solutions to improve traffic safety for decades, which contributes to two alternative approaches evaluating traffic safety, namely reactive and proactive evaluation (e.g. Qi et al., 2013; Yannis et al., 2010; Washington et al., 2001). The reactive methods highly rely on historical crash counts. Many count-data regression models were thus proposed by developing the relationship between discrete crash counts and traffic/geometric parameters in a macroscopic manner (e.g. Hauer, 2004; Lord and Persaud, 2000; Lord et al., 2007; Miaou, 1994). However, the abovementioned count models exist some drawbacks and restrictions (Tarko et al., 2009). Firstly, massive time and labour need to be spent on data collection due to the
Chapter Two: Literature Review

low frequency and discreteness of traffic crashes. Secondly, as a passive method based on the past crash counts, they are not appropriate to predict crash risks of those sites where were recently implemented safety countermeasure. Thirdly, they are excessively dependent upon statistical techniques and data so that they lost sight of the crash mechanism. By contrast, the emergence of proactive methods remedies the deficiencies in reactive evaluation (Thorson and Glennon, 1975). They generally take advantage of surrogate events, namely traffic conflicts, to proactively predict traffic crashes (e.g. Chin and Quek, 1997; Ishak et al., 2012; Li et al., 2013; Quenneville and Dunning, 2012; Xu et al., 2012). Tarko et al. (2009) suggested a surrogate event need to meet the following two requirements: 1) a surrogate event should be obtained from observable non-crash events which have high correlations with crashes; 2) the relationship between surrogate events and relevant crash counts can be quantified in the form of linearity or non-linearity. The advantages of crash surrogate events lie in: firstly, they occur much more frequently than crashes and have strong probabilistic characteristics; secondly, as a critical state between safety and crash, surrogate events can reflect the potential crash causality and mechanism; thirdly, their crash risks could be proactively evaluated before crashes occur. In this subchapter, several existing crash surrogate measures are reviewed. The corresponding merits and demerits are discussed as well.

2.4.1 Time to collision

The time to collision (TTC) has become one of the most well-recognized microscopic safety indicators and been widely applied to evaluate the level of safety in different situations of traffic (e.g. Meng and Weng, 2011; Sayed et al., 2013; Qu et al., 2013; Qu et al., 2014; Qu et al., 2015). Similar concepts were also used in marine traffic safety analysis (Qu et al., 2011; Qu and Meng, 2012; Li et al., 2012).
As can be seen in Figure 2.12, the TTC is defined as the time remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained (Hayward, 1972), mathematically,

\[
TTC = \begin{cases} 
\frac{D_{l-f}}{v_f - v_l}, & \text{if } v_f > v_l \\
\infty, & \text{otherwise}
\end{cases}
\] (21)

where \(v_f\) is the speed of follower’s vehicle, \(v_l\) is the speed of leader’s vehicle, and \(D_{l-f}\) is the distance gap between the two vehicles. All TTC values need to compare with an appointed threshold ranging from 1.5 to 4s (Van der Horst, 1991). Only those car-following scenarios with TTC values less than its threshold could be judged as risky.
2.4.2 Time integrated time to collision

Minderhoud and Bovy (2001) developed the time integrated time to collision (TIT) based on the notion of TTC. It was proposed to approximate the difference between time-dependent TTC and its TTC threshold value by using the integral of drivers’ TTC profiles shown in Figure 2.13, mathematically,

\[
TIT = \sum_{i=1}^{N} \int_{t=0}^{T} \left[ TTC^* - TTC_i(t) \right] dt \quad \forall 0 \leq TTC_i(t) \leq TTC^*
\]  

(22)

where \( TTC_i(t) \) is the TTC value of \( i^{th} \) vehicle at discrete time \( t \), \( TTC^* \) is the threshold value of \( TTC \). \( TIT \) is the integral of the domains where \( TTC_i(t) \) is less than \( TTC^* \) over the investigative time for all investigative vehicles (in s\(^2\)), namely the summation of shadow areas. A greater TIT value signifies more time exposed to an unsafe situation. The change in TTC over time is considered in the TIT, but the determination of TTC threshold value still lacks a specific judgement criterion.

Figure 2.13. Concept of TIT (Minderhoud and Bovy, 2001)
2.4.3 Deceleration rate to avoid crash

The deceleration rate to avoid crash (DRAC) is another widely-used safety surrogate measure, which is defined by as the minimum deceleration rate required by the following vehicle in a car-following scenario to exactly avoid a crash (Cooper and Ferguson, 1976), which can be denoted as:

\[
DRAC = \begin{cases} 
\frac{(V_f - V_i)^2}{D_{l-f}}, & \text{if } V_f > V_i \\
0, & \text{otherwise}
\end{cases} \tag{23}
\]

or

\[
DRAC = \frac{(V_f - V_i)}{TTC} \tag{24}
\]

The DRAC has been recognized as an upgraded version of TTC. A higher DRAC value indicates a more dangerous car-following scenario. Similar with the TIT, the DRAC still fails to provide a convincing criterion for boundary settings. In addition, despite it took evasive action (deceleration) into account, drivers’ perception reaction time was still neglected.

2.4.4 Crash potential index

Crash potential index (CPI) was defined by Cunto and Saccomanno (2008) as the probability that a vehicle’s DRAC is greater than its maximum available deceleration rate (MADR) or braking capacity, mathematically,

\[
CPI_t = \frac{\sum_{i=0}^{N} P(DRAC_i(t) > MADR_i) \cdot \Delta t}{T} \tag{25}
\]
where $\Delta t$ and $N$ are the duration and the number of time interval, respectively. $T$ is the investigated time, where $T = N \cdot \Delta t$. $DRAC_i(t)$ and $MADR_i$ stand for the $DRAC$ and $MADR$ for $i^{th}$ car-following scenario at discrete time $t$. As MADR is vehicle and scenario specific, it is generally represented as a truncated normal distribution (e.g. AASHTO, 2004; Cunto and Saccomanno, 2008; Meng and Weng, 2011). The CPI has been widely used to evaluate crash risks in safety analysis (e.g. Guido et al., 2011; Saccomanno et al, 2008). By considering the MADR distribution for various vehicles, the CPI can address the issue of boundary settings, which makes the final results more convincing. Furthermore, the CPI is represented as a ratio, which can intuitively reveal the conflict severity.

2.4.5 Aggregated crash index

Kuang et al. (2015) proposed the aggregated crash index (ACI) which can better assess conflicts occurred on saturated freeways. Based on the notion of probabilistic causal model, they developed a tree-structured crash model with eight nodes, each of which represents a category of traffic conflict and is identified through four successive condition levels shown in Table 2.1. Condition level 1 is the process distinguishing conflict type A from B by comparing the following drivers’ reaction time ($R$) and the stopping time for the leading vehicles ($T_1$). Condition level 2 is used to judge whether a crash occurs during the follower motorist’s reaction time by comparing the reaction time $R$ to $T_A$ or $T_B$. Condition level 3 compares which vehicle stops sooner after the following vehicle takes the evasive action. Condition level 4 is used to compare the difference between deceleration action taken by the follower vehicle and its actual
braking capacity. For the detailed process of the ACI, please refer to Kuang et al.’s paper.

Table 2.1. The tree-structured crash model with eight nodes

<table>
<thead>
<tr>
<th>Node No.</th>
<th>Conflict type</th>
<th>Condition level 1</th>
<th>Condition level 2</th>
<th>Condition level 3</th>
<th>Condition level 4</th>
<th>Leaf node</th>
<th>Probability P(L)</th>
<th>Outcome C_L</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A1</td>
<td>R ≥ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R ≥ T&lt;sub&gt;A&lt;/sub&gt;</td>
<td>_</td>
<td>_</td>
<td>L&lt;sub&gt;1&lt;/sub&gt;</td>
<td>P(L&lt;sub&gt;1&lt;/sub&gt;)</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>B1</td>
<td>R ≤ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R ≥ T&lt;sub&gt;B&lt;/sub&gt;</td>
<td>_</td>
<td>_</td>
<td>L&lt;sub&gt;2&lt;/sub&gt;</td>
<td>P(L&lt;sub&gt;2&lt;/sub&gt;)</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>A211</td>
<td>R ≥ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R &lt; T&lt;sub&gt;A&lt;/sub&gt;</td>
<td>TTC(R) ≥ (T&lt;sub&gt;i&lt;/sub&gt; - R) / 2</td>
<td>BRAD&lt;sub&gt;i&lt;/sub&gt; &gt; MADR</td>
<td>L&lt;sub&gt;3&lt;/sub&gt;</td>
<td>P(L&lt;sub&gt;3&lt;/sub&gt;)</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>A210</td>
<td>R ≥ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R &lt; T&lt;sub&gt;A&lt;/sub&gt;</td>
<td>TTC(R) ≥ (T&lt;sub&gt;i&lt;/sub&gt; - R) / 2</td>
<td>BRAD&lt;sub&gt;i&lt;/sub&gt; ≤ MADR</td>
<td>L&lt;sub&gt;4&lt;/sub&gt;</td>
<td>P(L&lt;sub&gt;4&lt;/sub&gt;)</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>B211</td>
<td>R ≤ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R &lt; T&lt;sub&gt;B&lt;/sub&gt;</td>
<td>TTC(R) ≥ (T&lt;sub&gt;i&lt;/sub&gt; - R) / 2</td>
<td>BRAD&lt;sub&gt;i&lt;/sub&gt; &gt; MADR</td>
<td>L&lt;sub&gt;5&lt;/sub&gt;</td>
<td>P(L&lt;sub&gt;5&lt;/sub&gt;)</td>
<td>1</td>
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<tr>
<td>6</td>
<td>B210</td>
<td>R ≤ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R &lt; T&lt;sub&gt;B&lt;/sub&gt;</td>
<td>TTC(R) ≥ (T&lt;sub&gt;i&lt;/sub&gt; - R) / 2</td>
<td>BRAD&lt;sub&gt;i&lt;/sub&gt; ≤ MADR</td>
<td>L&lt;sub&gt;6&lt;/sub&gt;</td>
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<td>0</td>
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<tr>
<td>7</td>
<td>B220</td>
<td>R ≤ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R &lt; T&lt;sub&gt;B&lt;/sub&gt;</td>
<td>TTC(R) &lt; (T&lt;sub&gt;i&lt;/sub&gt; - R) / 2</td>
<td>BRAD&lt;sub&gt;i&lt;/sub&gt; ≤ MADR</td>
<td>L&lt;sub&gt;7&lt;/sub&gt;</td>
<td>P(L&lt;sub&gt;7&lt;/sub&gt;)</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>B221</td>
<td>R ≤ T&lt;sub&gt;i&lt;/sub&gt;</td>
<td>R &lt; T&lt;sub&gt;B&lt;/sub&gt;</td>
<td>TTC(R) &lt; (T&lt;sub&gt;i&lt;/sub&gt; - R) / 2</td>
<td>BRAD&lt;sub&gt;i&lt;/sub&gt; &gt; MADR</td>
<td>L&lt;sub&gt;8&lt;/sub&gt;</td>
<td>P(L&lt;sub&gt;8&lt;/sub&gt;)</td>
<td>1</td>
</tr>
</tbody>
</table>

The advantages of the ACI lie in 1) it considered the MADRs and drivers’ perception reaction times in the form of a distribution rather than a fixed value, which resolves the issue of boundary settings present in aforementioned safety surrogate indicators; 2) by imposing a hypothetical disturbance to the leading vehicle, eight possible traffic conflicts were proposed in the ACI; 3) it was particularly proposed for risk assessment of saturated freeways. However, the complex representation form and calculation restrict its application and popularization. Accordingly, I have to appeal to the random sampling method to simplify the calculative procedures.

### 2.5 Monte Carlo Method

The Monte Carlo method (MCM), also called as the random sampling method or the statistical testing method, originated from the early mathematical idea that “the frequency approximates the probability”. It is an essential tool in many quantitative investigations, even the only method to estimate certain numerical values associated
with a simulation model. The principle is to repeat random experiments in quantity in order to understand the modelling of a complex system. It has been widely used for sampling, estimation and optimization in traffic and transportation engineering (e.g. Hadachi et al., 2012; Meng and Qu, 2012; Yamamoto and Sakamoto, 2015). In computing probabilistic causal model related to traffic, the MCM, in essence, is the generation of random numbers which follow certain probability distributions. When the solution to a problem is the occurrence probability of a certain event, or is an expected value of any variant, one may make use of a “testing” method to obtain the occurrence frequency of an event or the average value of the variant, and these may be used as the solutions to problems (e.g. Haralambides, 1991; Li and Zhu, 2010; Margellos and Lygeros, 2013). The MCM is a process in which, based on the probability model and in accordance with the process described by this model, simulation test results become approximate solutions (Wang et al., 2010). In this thesis, the MCM is applied to simplify the complicated calculation processes involved in safety surrogate measure ACI.

2.6 Hotspot Identification Methods Based on Different Indicators

2.6.1 Crash frequency method

Crash frequency method (CFM) is the most straightforward and widely used HSID method. The hazardous sites are generally ranked in an ascending order on the basis of the crash counts. To accomplish the homogeneity of different segments, the crash frequency should be divided by the segment length and the time period and represented in the form of crash count per kilometre per year.
2.6.2 Societal risk-based crash method

Combining the crash severity and the societal monetary loss, societal risk-based crash method (SRCM) builds on the premise of “willingness-to-pay” approach estimating the amounts that individuals are prepared to pay to reduce risk to their lives. Its merit lies in that it attempts to capture trade-offs between wealth and small reductions in risk (Qu and Meng, 2014). Many traffic agencies (e.g. National Safety Council (NSC), The Federal Highway Administration (FHWA)) have assessed the economic loss of four types of crash severities: fatal, serious injury, possible injury and property damage only (PDO). All studies about the economic loss reveal the same consistency. The expenditure of different crash severities evaluated by NSC are utilized in this measure. The SRCM can be calculated as follows:

\[ R_i = \sum_{j=1}^{4} (f_{ij}m_j), \quad \forall i \in \{1,2,...,I\} \]  

(26)

where \( f_{ij} \) and \( m_j \) represent the number of crashes of type \( j \) severity occurring on segment \( i \) and the socially economic loss of type \( j \) crash severity, respectively. \( R_i \) is defined as the annual monetary loss caused by crashes on the road segment \( i \).

2.6.3 Empirical Bayesian method

The empirical Bayesian method (EB) integrates a predictive crash model with the recorded crash history to achieve the high consistency of results (Persaud et al., 1999). In the EB procedure, the expected number of crashes that occur on the same road segment but in different time periods is firstly estimated. Secondly, actual crash counts
are obtained from the object road segment. Finally, a better expectation of crash counts is derived as per the following equations, mathematically,

\[ \hat{\lambda}_i = wE(\hat{\lambda}) + (1 - w)x_i \]  \hspace{1cm} (27)

where \( w \) is a weighting factor which can be computed by the following equation:

\[ w = \frac{E(\hat{\lambda})}{E(\hat{\lambda}) + Var(\hat{\lambda})} \]  \hspace{1cm} (28)

where \( x_i \) is the observed crash density for segment \( i \); \( E(\hat{\lambda}) \) is the predicted crash density; \( Var(\hat{\lambda}) \) is the corresponding variance and \( \hat{\lambda}_i \) is EB-estimated crash density for segment \( i \). It is worthy of noting that in this thesis, the expected number of crashes and actual crash counts are replaced with the expected crash density and actual crash density, in the unit of crash counts per kilometer per lane per year, in order to obtain a better estimated crash density. The EB can minimize the impact of randomly high or low crash density, namely avert the regression-to-the-mean bias present in other HSID methods. However, this method is generally based on the crash records of whole time of the day, which may not be appropriate to identify those road sites with daily variability of crash record.
2.7 **Test Criteria for HISD Methods**

2.7.1 **Method consistency test**

The method consistency test (MCT) was developed to evaluate the performance of various HSID methods by measuring the number of intersection of top \( n \) hotspots identified in two successive time periods. It is assumed that road segments should be in the same or similar underlying operational states and their expected safety performance remains virtually unaltered over the two periods (Cheng and Washington, 2008). With the homogeneity assumption, the greater the number is, the more consistent the HSID method performs. The test statistic is given as:

\[
MCT_j = \{k_{N-n+1}, k_{N-n}, \ldots, k_N\}_{j,j} \cap \{k_{N-n+1}, k_{N-n}, \ldots, k_N\}_{j,j+1}
\]  

(29)

where \( j \) is the type of HSID method; \( N \) and \( n \) denote the total number of segments being identified and the top \( n \) risky sites, respectively.

2.7.2 **Total rank differences test**

The total rank differences test (TRDT) measures the consistency of HSID methods by calculating the summation of the total ranking differences of each hotspot identified across consecutive two periods (Montella, 2010). It is based on the same premise as the MCT. Although the MCT can explicitly reveal the consistency performance of various HSID approaches, it fails to discover the variation of ranking occurred on hotspots. By contrast, the TRDT remedy its defect, but a relatively complex calculation is required. Accordingly, the combination of the MCT and TRDT can better investigate the reliability of various HSID methods. The smaller the summation of total rank
differences is, the more consistent is the HSID approach is. The test criteria can be denoted as follows:

\[
TRDT_j = \sum_{k=N-n+1}^{N} \left| R(k_{j,i}) - R(k_{j,i+1}) \right|
\]  

(30)

where \( R(k_{j,i}) \) is the rank of site \( k \) identified by method \( j \) in period \( i \).
Chapter Three: Freeway Ramp Configuration Part I – Travel Time Analysis

3 FREEWAY RAMP CONFIGURATION PART I – TRAVEL TIME ANALYSIS

3.1 Background

On uninterrupted flow facilities like freeways, the cause of traffic congestion is basically because the amount of traffic exceeds the capacity of a road segment. The sites adjacent to ramps have always been viewed as bottlenecks. An inappropriate ramp lane arrangement may lead to recurring breakdowns in peak times. Therefore, the selection of freeway ramp configuration is of utmost importance to mitigate traffic delays and congestion in the phase of traffic planning. Travel time has been identified by Austroads as an important system performance measure and travel time surveys are regularly carried out by state road authorities (Austroads, 1997). Travel time may be simply influenced by traffic volume, traffic composition and road geometric design (e.g. Jie et al., 2013; Kim et al., 2014; Zhu et al., 2014; Ren et al., 2016). In this research, I respectively evaluated travel time passing through the road segment fitted with two kinds of on-ramp lane arrangements under various mainline traffic volumes and proportions of mainline heavy goods vehicles (HGVs). Therefore, my main task was to calculate the average travel time that through traffic pass through the shadow area shown in Figure 3.1. The two on-ramp lane arrangements illustrated in Figure 3.1 were used for a comparative study. The investigated freeway section is a typical weaving zone where a one-lane on-ramp is closely followed by a one-lane off-ramp, with two connected by a continuous added/auxiliary lane. By means of added lane, entering vehicles can directly pull out of the freeway without lane changing actions. In addition, added lane is able to enhance traffic operation and efficiency, particularly at urban
expressways with closely spaced on- and off-ramps. However, the construction of added lane generally requires more space and funding compared to its alternative, zip merging. Furthermore, the weaving zone with more one lane incorporates more crossing or weaving behaviour, which may increase potential crash risks in peak hours.

Figure 3.1. The investigated road segment fitted with two on-ramp lane arrangements

In view of the abovementioned issues, I started to imagine whether zip merging performs as good as added lane and saves limited budget at the same time. After all, zip merging is the most commonly used on-ramp lane configuration form in Queensland, Australia. It is able to sustain mainline traffic operation under both congested and uncongested conditions (Styles and Luk, 2006). For example, traffic on the outer through lane never needs to do lane-changing prior to the next exit. Nevertheless, zip merging has some disadvantages. Firstly, merging stream generates a potential impact
on main stream, as the mainline traffic generally slows down and changes lane to elude the interference of merging traffic. Secondly, it is relatively difficult for vehicles to merge into the saturated freeway. Only those vehicles meeting acceptable gap can enter the freeway.

In this research, I applied micro-traffic simulation software, VISSIM, to quantitatively evaluate travel time for both on-ramp lane arrangements.

### 3.2 Site Description and Data Collection

The weaving zone located in the northbound direction of Pacific motorway (M1) between Nerang Broadbeach Road and Nerang Connection Road was modelled as a case study. The layout of the investigated weaving segment is shown in Figure 3.2. It is a 4-lane road segment on M1, connecting Brisbane and Gold Coast, with closely spaced on- and -off-ramps. It is adjacent to the plaza ‘My Centre Nerang’ and has a length of 800m. The road segment was selected because there are an overhead pedestrian bridge across the freeway and a roadside observation point at the exit ramp, make video recording of traffic trajectories possible in the absence of loop detectors. By means of video technique, I obtained real-time traffic data including volumes and vehicle composition under varying eight time periods shown in Table 3.1.
Traffic videos of different time periods were observed to compute the relative flow rates of through, merging and diverging traffic. For example, when traffic volume is about 800 vehs/hr/ln, 80 percent of vehicles from the on-ramp merge onto the freeway, and the rest of them diverge to Nerang Connection Road. More than 90 percent of vehicles on the freeway represent through traffic flow, only 9 percent of them exit the freeway along the off-ramp. A similar procedure was applied for estimating the vehicle composition. Vehicles were divided into passenger cars and heavy goods vehicles (trunks and buses) in this study. As can be seen in Table 3.1, trucks and buses account for 6.4 percent of the total traffic on the freeway mainline from 19:00 to 20:00.

The desired speed distribution was developed based on the free flow speeds. According to the HCM 2010, as long as traffic flow is less than 1000 vehs/hr/ln, then it can be regarded as a free flow. Accordingly, I randomly selected 400 vehicles and retrieved their speeds from the video recorded from 19:00 to 20:00. Finally, the cumulative
desired speed distribution curve for the 400 vehicles was derived and shown in Figure 3.3, which is an important input used in VISSIM for desired speed.

Table 3.1. Real-time traffic data from different time periods

<table>
<thead>
<tr>
<th>Time periods</th>
<th>Traffic flow (vehs/hr/ln)</th>
<th>Percent HVs (%)</th>
<th>$V_{FF}$ (%)</th>
<th>$V_{FR}$ (%)</th>
<th>$V_{RF}$ (%)</th>
<th>$V_{RR}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>05:00-06:00</td>
<td>1221</td>
<td>7.0</td>
<td>89</td>
<td>11</td>
<td>85</td>
<td>15</td>
</tr>
<tr>
<td>06:00-07:00</td>
<td>2016</td>
<td>7.9</td>
<td>85</td>
<td>15</td>
<td>91</td>
<td>9</td>
</tr>
<tr>
<td>07:00-08:00</td>
<td>2235</td>
<td>8.2</td>
<td>87</td>
<td>13</td>
<td>90</td>
<td>10</td>
</tr>
<tr>
<td>09:00-10:00</td>
<td>1610</td>
<td>7.5</td>
<td>90</td>
<td>10</td>
<td>84</td>
<td>16</td>
</tr>
<tr>
<td>12:00-13:00</td>
<td>1008</td>
<td>7.1</td>
<td>91</td>
<td>9</td>
<td>83</td>
<td>17</td>
</tr>
<tr>
<td>16:00-17:00</td>
<td>1389</td>
<td>7.3</td>
<td>80</td>
<td>20</td>
<td>87</td>
<td>13</td>
</tr>
<tr>
<td>17:00-18:00</td>
<td>1793</td>
<td>7.0</td>
<td>83</td>
<td>17</td>
<td>89</td>
<td>11</td>
</tr>
<tr>
<td>19:00-20:00</td>
<td>786</td>
<td>6.4</td>
<td>91</td>
<td>9</td>
<td>80</td>
<td>20</td>
</tr>
</tbody>
</table>

Figure 3.3. Cumulative distribution of free flow speed
3.3 Calibration and Validation of VISSIM Simulation Model

VISSIM is a microscopic, time-stepping, stochastic simulation model for traffic system operation analysis. It uses the psycho-physical driver behaviour model developed by Wiedemann, which can properly simulate car-following behaviour and the interaction between vehicles. VISSIM version 7.0 was used in this study. The geometric characteristics of the study site, including the number of lanes, lane widths, link lengths, and levels were coded in the simulation model by using Google Earth Pro. The data described in Section 3.2, as input parameters, was also used for the development of simulation model. Besides, in order to achieve realistic outputs, the simulation model was extended to one kilometre north and one kilometre south of the investigated road segment.

The calibration of parameters in a simulation model has always been a prerequisite to obtain accurate outcomes (Jie et al., 2013). But in the practical cases, most users generally applied the default values provided by the software for these parameters instead of modifying them according to the actual circumstances, which may lead to a significant difference between simulated and observed results. To reduce the errors of simulated results, a series of sensitivity analyses has been conducted on driving behaviour parameters in the Wiedemann (1999) model in VISSIM (Dong et al., 2015; Tettamanti et al., 2015). Among them, the average desired distance between stopped cars (CC0), the distance in seconds that a driver wants to keep at a certain speed (CC1), and the distance exceeding the desired safety distance a driver allows before he intentionally moves closer to the car in front (CC2) are the main factors affecting simulation precision. Changing the values of CC3 through CC9 does not
generate a significant difference in traffic capacity analysis. Therefore, these less affected values were set as defaults in the calibration process. Besides, according to the simulation animation in VISSIM, drivers’ lane-changing behaviour fails to reflect the real world situation. For example, some simulated vehicles may change lanes from the innermost lane to exit the freeway at the very last minute, which causes traffic congestion not seen in the field observation. To solve this issue, the desired lane change distance (DLCD) in connector settings was calibrated as well. In this study, genetic algorithm (GA) was used for the calibration in order to find out the best set of values for abovementioned parameters. Compared with other optimization methods, it can search the whole value space. By using GA, the best fitted values for these four parameters under eight different traffic volumes can be obtained and compared with the default values. Table 3.2 shows the best fitted parameter set for each traffic volume.

<table>
<thead>
<tr>
<th>Time periods</th>
<th>Traffic flow (vehs/hr/ln)</th>
<th>CC0 (m)</th>
<th>CC1 (s)</th>
<th>CC2 (m)</th>
<th>DLCD (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>19:00-20:00</td>
<td>786</td>
<td>2.0</td>
<td>2.1</td>
<td>5.0</td>
<td>200.0</td>
</tr>
<tr>
<td>12:00-13:00</td>
<td>1008</td>
<td>2.0</td>
<td>1.9</td>
<td>5.0</td>
<td>200.0</td>
</tr>
<tr>
<td>05:00-06:00</td>
<td>1221</td>
<td>2.0</td>
<td>1.6</td>
<td>4.6</td>
<td>200.0</td>
</tr>
<tr>
<td>16:00-17:00</td>
<td>1389</td>
<td>1.8</td>
<td>1.0</td>
<td>4.1</td>
<td>250.0</td>
</tr>
<tr>
<td>09:00-10:00</td>
<td>1610</td>
<td>1.6</td>
<td>1.0</td>
<td>4.0</td>
<td>400.0</td>
</tr>
<tr>
<td>17:00-18:00</td>
<td>1793</td>
<td>1.5</td>
<td>0.9</td>
<td>4.0</td>
<td>500.0</td>
</tr>
<tr>
<td>06:00-07:00</td>
<td>2016</td>
<td>1.3</td>
<td>0.8</td>
<td>3.7</td>
<td>600.0</td>
</tr>
<tr>
<td>07:00-08:00</td>
<td>2235</td>
<td>1.3</td>
<td>0.7</td>
<td>3.5</td>
<td>800.0</td>
</tr>
<tr>
<td>Default values</td>
<td>1.5</td>
<td>0.9</td>
<td>4.0</td>
<td>200.0</td>
<td></td>
</tr>
</tbody>
</table>

To validate calibrated parameters better reproducing the real-world traffic situations, the relationships between the average speeds and traffic flow rates were compared between the observed data, calibrated simulation data, and default simulation data. To obtain
observed average speed, the speeds for 200 vehicles were randomly retrieved from each of the eight traffic scenarios and averaged. The average speeds for default simulation and calibrated simulation were automatically derived through loop detectors set in VISSIM model. However, for sake of simulation precision, one-hour warm-up period is required (30 minutes were respectively set before and after data collection). Then, ten simulation runs were performed for each scenario using random seeds from 55 to 100 with a five-unit increment. By averaging results of the ten simulation runs, the simulated average speed can be obtained. As can be seen in Figure 3.4, when traffic volume is less than 1100 vehs/hr/ln, both default and calibrated simulation data can match with observed data. Default simulation underestimates average speed at high traffic volume. By contrast, calibrated simulation data can better fit with observed average speed curve. In other word, in any traffic scenario, calibrated parameters can simulate more real traffic conditions compared to default parameters.

![Average speed comparison between observed data, calibrated simulation data, and default simulation data](image)

Figure 3.4. Average speed comparison between observed data, calibrated simulation data, and default simulation data
Chapter Three: Freeway Ramp Configuration Part I – Travel Time Analysis

To compare simulation inputs and outputs, the GEH formula was applied to evaluate fitting degree between volume input and output.

\[
GEH = \sqrt{\frac{2(m-c)^2}{m+c}}
\]  

(31)

where \( m \) and \( c \) are output and input traffic volume in vehs/hr, respectively. According to Table 3.3, all GEH values were calculated less than 1, which are in the acceptable range. This indicates traffic volume input and output do not have a significant difference for simulation models with calibrated parameters.

To sum up, the calibrated VISSIM simulation model can realistically reproduce the down-to-earth traffic stream situation including car-following behavior, the selection of desired lane change distance, and the interaction between vehicles. Therefore, VISSIM was used to quantitatively assess the performance of traffic operation for two freeway on-ramp lane arrangements under different scenarios.

<table>
<thead>
<tr>
<th>c</th>
<th>m</th>
<th>GEH</th>
</tr>
</thead>
<tbody>
<tr>
<td>786</td>
<td>795</td>
<td>0.32</td>
</tr>
<tr>
<td>1008</td>
<td>1023</td>
<td>0.47</td>
</tr>
<tr>
<td>1221</td>
<td>1203</td>
<td>0.52</td>
</tr>
<tr>
<td>1389</td>
<td>1411</td>
<td>0.59</td>
</tr>
<tr>
<td>1610</td>
<td>1598</td>
<td>0.30</td>
</tr>
<tr>
<td>1793</td>
<td>1784</td>
<td>0.21</td>
</tr>
<tr>
<td>2016</td>
<td>1989</td>
<td>0.60</td>
</tr>
<tr>
<td>2235</td>
<td>2197</td>
<td>0.81</td>
</tr>
</tbody>
</table>
3.4 Impact of HGVs

In this subchapter, I analysed the impact of different percentages of HGVs on average travel time for two freeway on-ramp configurations, under various scenarios of traffic volumes from 800 to 2200 vehs/hr/ln with a step of 200 vehs/hr/ln. The average travel time of through traffic passing through the study site can be obtained through loop detectors installed at the upstream investigated road segment close to the on-ramp and the downstream investigated road segment close to the off-ramp. The magnitude of average travel time can reflect the potential impacts of merging stream, diverging stream, and weaving stream on through traffic. As can be seen in Figure 3.5 and Figure 3.6, when traffic flow is 800 or 1000 vehs/hr/ln, a rise in the proportion of HGVs fails to generate a remarkable impact on operational performance for both lane arrangements. Table 3.4 and Table 3.5 show that travel time gaps for added lane and zip merging are 2.95 and 2.35 seconds at traffic volume of 800 vehs/hr/ln; 3.15 and 3.90 seconds at traffic volume of 1000 vehs/hr/ln. Zip merging on-ramp outweighs added lane under both scenarios. When traffic flow increases to 1200 vehs/hr/ln, growth rate of travel time for zip merging gradually surpasses that for added lane, and average travel time for zip merging starts to exceed that for added lane when the number of HGVs accounts for approximately 12% of mainline traffic. When traffic flow rate varies from 1400 to 2000 vehs/hr/ln, the intersection of both curves tends to move leftward. This means that with an increase in traffic volume, a smaller proportion of HGVs can result in the same average travel time for both on-ramp configurations. The performance of added lane is never overwhelmingly superior to that of zip merging until traffic volume reaches 2200 vehs/hr/ln.
Chapter Three: Freeway Ramp Configuration Part I – Travel Time Analysis

Figure 3.5. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 800 vehs/hr/ln

Figure 3.6. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1000 vehs/hr/ln
Figure 3.7. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1200 vehs/hr/ln

Figure 3.8. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1400 vehs/hr/ln
Figure 3.9. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1600 vehs/hr/ln.

Figure 3.10. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 1800 vehs/hr/ln.
Chapter Three: Freeway Ramp Configuration Part I – Travel Time Analysis

Figure 3.11. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 2000 vehs/hr/ln

Figure 3.12. The relationship between average travel time and the percentage of HGVs for both on-ramp configurations when traffic volume is 2200 vehs/hr/ln
Table 3.4. The extremum comparison under various traffic flow (Added Lane)

<table>
<thead>
<tr>
<th>Traffic flow (vehs/hr/ln)</th>
<th>The minimum travel time (s)</th>
<th>The maximum travel time (s)</th>
<th>Gap (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>800</td>
<td>42.30</td>
<td>45.25</td>
<td>2.95</td>
</tr>
<tr>
<td>1000</td>
<td>43.10</td>
<td>46.25</td>
<td>3.15</td>
</tr>
<tr>
<td>1200</td>
<td>43.80</td>
<td>47.90</td>
<td>4.10</td>
</tr>
<tr>
<td>1400</td>
<td>45.00</td>
<td>50.15</td>
<td>5.15</td>
</tr>
<tr>
<td>1600</td>
<td>46.45</td>
<td>53.00</td>
<td>6.55</td>
</tr>
<tr>
<td>1800</td>
<td>48.15</td>
<td>56.15</td>
<td>8.00</td>
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<tr>
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<td>50.00</td>
<td>59.75</td>
<td>9.75</td>
</tr>
<tr>
<td>2200</td>
<td>52.10</td>
<td>67.05</td>
<td>14.95</td>
</tr>
</tbody>
</table>

Table 3.5. The extremum comparison under various traffic flow (Zip Merging)

<table>
<thead>
<tr>
<th>Traffic flow (vehs/hr/ln)</th>
<th>The minimum travel time (s)</th>
<th>The maximum travel time (s)</th>
<th>Gap (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>800</td>
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<tr>
<td>1200</td>
<td>42.40</td>
<td>47.95</td>
<td>5.55</td>
</tr>
<tr>
<td>1400</td>
<td>43.65</td>
<td>50.75</td>
<td>7.10</td>
</tr>
<tr>
<td>1600</td>
<td>44.90</td>
<td>54.35</td>
<td>9.45</td>
</tr>
<tr>
<td>1800</td>
<td>46.85</td>
<td>59.45</td>
<td>12.60</td>
</tr>
<tr>
<td>2000</td>
<td>49.25</td>
<td>65.35</td>
<td>16.10</td>
</tr>
<tr>
<td>2200</td>
<td>52.25</td>
<td>72.45</td>
<td>20.20</td>
</tr>
</tbody>
</table>

3.5 Impact of Traffic Volume

I also analysed the impact of traffic volume on average travel time under varying percentages of HGVs. When passenger cars account for 100% of the total number of mainline traffic, the operational performance of zip merging is always better than that of added lane under any traffic volumes. However, a slight increase in percent HGVs may
result in the significant variation in average travel time. According to Figure 3.14 through Figure 3.19, the intersection of two curves moves from traffic scenario of 2100 vehs/hr/ln with 2 percent of HGVs to that of about 1250 vehs/hr/ln with 12 percent of HGVs. A larger percentage of HGVs contributes to that added lane outperforms zip merging under a lower traffic volume. It is noteworthy that the growth rate of average travel time for zip merging is faster than that for added lane at higher traffic flow under the effect of any percent of HGVs, and the average travel gap for zip merging is always greater than that for added lane in accordance with Table 3.6 and Table 3.7. This illustrates that high traffic volume and large percentage of HGVs give rise to relatively less impact on the operational performance for added lane.

Figure 3.13. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 0
Figure 3.14. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 2%

Figure 3.15. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 4%
Figure 3.16. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 6%.

Figure 3.17. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 8%.
Figure 3.18. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 10%.

Figure 3.19. The relationship between average travel time and traffic volume for both on-ramp configurations when the proportion of HGVs is 12%.
Table 3.6. The extremum comparison under various percentages of HGVs (Added Lane)

<table>
<thead>
<tr>
<th>The percentage of HGVs (%)</th>
<th>The minimum travel time (s)</th>
<th>The maximum travel time (s)</th>
<th>Gap (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
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<td>52.10</td>
<td>9.80</td>
</tr>
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<td>2</td>
<td>42.60</td>
<td>53.20</td>
<td>10.60</td>
</tr>
<tr>
<td>4</td>
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<td>54.75</td>
<td>11.70</td>
</tr>
<tr>
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<td>43.45</td>
<td>56.80</td>
<td>13.35</td>
</tr>
<tr>
<td>8</td>
<td>43.95</td>
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<td>16.00</td>
</tr>
<tr>
<td>10</td>
<td>44.55</td>
<td>63.25</td>
<td>18.70</td>
</tr>
<tr>
<td>12</td>
<td>45.25</td>
<td>67.05</td>
<td>21.80</td>
</tr>
</tbody>
</table>

Table 3.7. The extremum comparison under various percentages of HGVs (Zip Merging)

<table>
<thead>
<tr>
<th>The percentage of HGVs (%)</th>
<th>The minimum travel time (s)</th>
<th>The maximum travel time (s)</th>
<th>Gap (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>41.10</td>
<td>52.25</td>
<td>11.15</td>
</tr>
<tr>
<td>2</td>
<td>41.20</td>
<td>54.15</td>
<td>12.95</td>
</tr>
<tr>
<td>4</td>
<td>41.50</td>
<td>56.45</td>
<td>14.95</td>
</tr>
<tr>
<td>6</td>
<td>41.85</td>
<td>59.35</td>
<td>17.50</td>
</tr>
<tr>
<td>8</td>
<td>42.25</td>
<td>62.65</td>
<td>20.40</td>
</tr>
<tr>
<td>10</td>
<td>42.75</td>
<td>66.30</td>
<td>23.55</td>
</tr>
<tr>
<td>12</td>
<td>43.45</td>
<td>72.45</td>
<td>29.00</td>
</tr>
</tbody>
</table>

3.6 Summary

In this chapter, my main objective was to quantitatively assess the operational performances for two on-ramp lane configurations. To this end, the study site with closely-spaced on- and off-ramps was applied for a case study. Because the reference index, average travel time for through traffic, is difficult to collect in the real world, I assessed it by means of VISSIM micro-simulation models. The simulation models were calibrated with geometric characteristics of the study site, car-following behaviour and
desired lane change distance prior to use. It was found that the calibrated simulation model can better reproduce realistic traffic conditions. Afterwards, the impacts of percent HGVs on travel time for two on-ramp lane arrangements were analyzed under seven traffic scenarios with the proportion of HGVs from 0 to 12% with a 2% increment. At low traffic volume, an increase in percent HGVs does not change final results that zip merging always outperforms added lane. While with the increase in traffic volume, the impact of percent HGVs emerges. A smaller proportion of HGVs can lead to that the operational performance for added lane is superior to that for zip merging. In addition, I analyzed the effect of mainline traffic flow on travel time for the two on-ramp lane arrangements under scenarios with traffic volumes from 800 to 2200 vehs/hr/ln with a 200-unit increment. The results show that zip merging can accommodate a lower traffic flow with a smaller percentage of HGVs and perform better than added lane. But in the increase in traffic volumes and percent HGVs, added lane is better.

It should be pointed out that the assessment of average travel time for both on-ramp lane arrangements is only based on an investigated road segment in Queensland, Australia. More data need to be collected at some similar freeway segments, to validate my conclusions.
4 FREEWAY RAMP CONFIGURATION PART II – EMISSION ANALYSIS

4.1 Background

In designing a management scheme, the traffic manager may be required to consider objectives related to air pollution, energy consumption, safety and traffic performance. Transportation activities account for 28% of the total U.S. energy use and 33.4% of carbon dioxide (CO₂, the major component of greenhouse gas (GHC) emissions) production (Davis et al., 2015; EPA, 2015). Consequently, there is a need to reduce transportation-related energy and GHC emissions in response to global energy and environmental issues. Researchers have devoted themselves to the estimation of fuel consumption and emissions in order to develop eco-routing and eco-driving systems and green logistics. There are currently two primary means of deriving estimates of CO₂ emissions in urban traffic management. They are on-road measurement of emissions and the use of emission prediction models. For some traffic management tasks and in some traffic systems, on-road measurement can be more cost-effective. It is often used for post-implementation assessment of a particular scheme. However, for the planning phrase of a particular sustainable management scheme, emission model may be the only practical means for emission prediction. Currently, the main emission treatment scheme is by traffic control (e.g. ramp metering for on-ramp and variable speed limits for basic freeway mainline) to minimize traffic delay and then to achieve the reduction in emissions. Very few scholars have concentrated on the impact of on-ramp lane configuration on sustainability. Therefore, I conducted a comparative analysis on
emission for two on-ramp lane arrangements: added lane and zip merging. I used microscopic traffic simulation model, along with the improved comprehensive modal emission model (CMEM), to quantitatively evaluate the effect of traffic volumes and percent heavy goods vehicles (HGVs) on sustainability for two types of on-ramps. The contributions of this study are 1) all speeds and acceleration related to emission calculation were derived through calibrated and validated VISSIM simulation models; 2) the two contributing factors-based CO$_2$ emission contour chars for both on-ramp lane configurations were proposed, which could assist traffic engineers in determining an appropriate on-ramp lane arrangements from the perspective of sustainability. The remainder of this Chapter is organized as follows. Section 4.2 describes the study site and the development of simulation models. Section 4.3 compares the impact of HGVs on emissions under scenarios with six traffic volumes and the impact of traffic flow rates on emissions under 5 types of percent HGVs. The contour charts are presented in Section 4.5. Section 4.6 summarizes.

4.2 Site Description and Development of Simulation Model

The same study site as Chapter 3 was selected in this Chapter, and parameter calibration also abides by the procedures described in Chapter 3. The layout of an observation point is shown in Figure 4.1. To assess the variation in CO$_2$ emissions for both on-ramp lane configurations, the development of the study on-ramp lane is of the utmost importance. As the on-ramp lane in the study site is added lane, it can be built based on Google Earth Pro. While for zip merging, I need to refer to the Australia Road Planning and Design Manual (ARPDM) to determine its lane geometrical parameters. The lengths of diverging taper (DT) and merging taper (MT) for zip merging should be sufficient to
accommodate free diverging and merging behavior of traffic in most cases. They should meet the following requirements.

\[
DT = \frac{V_{85\%} W_{\text{off}}}{3.6}
\]

\[
MT = \frac{V_{85\%} W_{\text{on}}}{2.16}
\]

where \( V_{85\%} \) is the 85th percentile of the approaching speed, and \( W_{\text{off}} \) and \( W_{\text{on}} \) represent the widths of the off-ramp and on-ramp, respectively.

Figure 4.1. An observation point across Pacific Motorway

4.3 Impact of HGVs

The CMEM method relies on vehicles’ acceleration rates and instantaneous speeds, along with microscopic traffic data, to assess fuel consumption and CO\(_2\) emissions.
However, the acceleration rates and speeds vary from vehicle to vehicle, which increases the difficulty of calculating emissions. To overcome it, the investigated road segment in VISSIM was equally divided into as many sections as possible, so that every vehicle’s speed and acceleration in any small sections are regarded as instantaneous speed and acceleration. In this study, there were 800 small sections involved in the 800-meter investigated road segment. Every data collection point was set up in the middle of every small section. Finally, the CO₂ emissions of any vehicle in any section were calculated using the CMEM method and then all the emissions were accumulated together. The impact of percent HGVs on sustainability was analysed under scenarios with traffic volumes from 800 to 1800 vehs/hr/ln with a 200-unit increment. As can be seen in Figure 4.2 through Figure 4.7, when traffic volume is relatively low, the changing curves of emissions are almost the same. For the traffic flow of 800 vehs/hr/ln with 2-8 percent HGVs, the performance of zip merging is more or less better than that of added lane. But when the percentage of HGVs exceeds 8 percent, added lane is slightly better. For the scenario with 1000 vehs/hr/ln, added lane can contribute to relatively less emissions under any percent HGVs. For the scenarios with traffic volumes from 1200 to 1800 vehs/hr/ln, when percent HGVs is greater than 4%, the implementation of zip merging leads to a larger increase rate of CO₂ emissions which tends to be approximately exponential growth, while added lane can keep a linear increase. Moreover, the gap of emissions for two different on-ramp lane configuration-based freeway segments tends to be greater.
Figure 4.2. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 800 vehs/hr/ln

Figure 4.3. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1000 vehs/hr/ln
Figure 4.4. The relationship between CO2 emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1200 vehs/hr/ln

Figure 4.5. The relationship between CO2 emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1400 vehs/hr/ln
Figure 4.6. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1600 vehs/hr/ln

Figure 4.7. The relationship between CO$_2$ emissions and the percentage of HGVs for both on-ramp configurations when traffic volume is 1800 vehs/hr/ln
4.4 Impact of Traffic Volume

According to Figure 4.8 through Figure 4.12, I can conclude that with an increase in traffic flow, CO₂ emissions for the zip merging present an exponential increasing tendency, and the difference in CO₂ emissions between the two on-ramp lane arrangements becomes greater. Under the scenarios with 2 percent HGVs, when traffic volume is smaller than 1000 vehs/hr/ln, zip merging can obtain a better sustainable performance. While traffic volume is greater than 1000 vehs/hr/ln, added lane outperforms than zip merging. Under the scenarios with 4 percent HGVs, the critical point decreases from 1000 to 900 vehs/hr/ln. Starting from traffic stream with 6 percent, the performance of added lane is completely superior to that of zip merging at any traffic flow rate.

![Figure 4.8. The relationship between CO₂ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 2%](image-url)
Figure 4.9. The relationship between CO₂ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 4%.

Figure 4.10. The relationship between CO₂ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 6%.
Figure 4.11. The relationship between CO$_2$ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 8%.

Figure 4.12. The relationship between CO$_2$ emissions and traffic volume for both on-ramp configurations when the proportion of HGVs is 10%.
In this section, the impact analyses of two relevant factors, traffic volume and percentage of HGVs, on CO₂ emissions were carried by means of VISSIM and CMEM. To this end, the impact analysis procedure is summarized as follows. First, the ranges of traffic volumes \( (T_i) \) and the percentage of HGVs \( (H_j) \) are determined and discretised. The traffic volume ranges from 800 to 1800 vehs/hr/lane in accordance with real-life observations, and the step is taken to be 200 vehs/hr/lane based on previous research (Meng et al., 2011). The proportion of HGVs is assumed to range from 2% to 10% and a 2% step is adopted. Therefore, the typical traffic volumes and percentages of HGVs
are respectively taken to be 800, 1000, 1200, 1400, 1600 and 1800 vehs/hr/lane, and 2%, 4%, 6%, 8% and 10%. Then, all possible combinations of the two contributing factors were utilized to evaluate CO₂ emissions for the two on-ramp lane configurations. The instantaneous speed and acceleration of each vehicle in each small section in each combination can be obtained from VISSIM and the CO₂ emissions can then be calculated using Equation 18 and 19. Figure 4.13 shows the two-factor-based impact analysis procedure.

Figure 4.14. CO₂ emissions contour chart for the added lane configuration

Based on the abovementioned procedure, the CO₂ emission contour charts for the two on-ramp lane arrangements were developed in order to demonstrate the changing pattern of CO₂ emissions. 30 possible combinations of the two factors were taken into
account. All points that emit the same quantity of greenhouse gases were plotted and connected using a smooth line. Figure 4.14 and Figure 4.15 present CO₂ emissions contour charts for the added land and the zip merging, respectively. Overall, CO₂ emissions grow with the increase in traffic volumes and the proportion of HGVs. These two CO₂ emissions contour charts could help traffic engineers to determine CO₂ emissions per second per vehicle under any possible combination of the percentage of HGVs and traffic volumes.

![Diagram](image)

Figure 4.15. CO₂ emissions contour chart for the zip merging configuration

### 4.6 Summary

In this research, I compared the performances of CO₂ emissions for two on-ramp lane arrangements (zip merging and added lane) in a selected freeway segment in order to...
assist traffic engineers in choosing the appropriate on-ramp configuration. To this end, I first recorded the real traffic trajectory at the selected site and utilized them to calibrate and validate VISSIM simulation models. Second, the CMEM, depending upon two variables, instantaneous speed and acceleration, was applied to calculate CO₂ emissions. Third, I evaluated the relationships between CO₂ emissions and percent HGVs for two on-ramp lane arrangements under scenarios with traffic volumes from 800 to 1800 vehs/hr/lane with a step of 200. In most cases, the performance of added lane is superior to that of zip merging lane. Besides, the relationships between CO₂ emissions and traffic volumes under scenarios with 2%, 4%, 6%, 8% and 10% of HGVs were also compared. I concluded that the added lane outperforms zip merging in most cases from the perspective of environmental sustainability. Fourth, I developed a couple of emissions contour charts for two on-ramp lane configurations to assist transport agencies in determining CO₂ emissions under the target percentage of HGVs and the target traffic volumes.
5 FREEWAY SAFETY PERFORMANCE PART I – CRASH SURROGATES

5.1 Background

Considerable research efforts have been carried out over the past fifty years on developing count-data regression models to predict crash frequency (Lee et al., 2002; Brijs et al., 2008; Wu et al., 2014), most of which are purely dependent on statistical techniques. These count-data regression models, in accordance to distinct statistical assumptions, represent the relationship between number of crashes and its contributing factors which have little, if not none, consideration of traffic flow dynamics (Lord et al., 2008; Park and Lord, 2009). Since 1970s, some researchers began to use crash surrogate measure to evaluate road safety (e.g., Chin and Quek, 1997; Gettman and Head, 2003; Tarko, 2012; Xu et al., 2012). Only recently has a consensus emerged concerning the definition of a crash surrogate, which is defined based on the relationship (Hauer, 1982; Tarko et al., 2009; Wu and Jovanis, 2012): the number of crashes expected to occur on an entity during a certain period of time ($\lambda$) = the number of crash surrogates occurring on an entity in that time ($\pi$) * crash-to-surrogate ratio for that entity ($c$), mathematically,

$$\lambda = \pi \cdot c$$  \hspace{1cm} (34)

A few crash surrogate metrics have been proposed and designed (Minderhoud and Bovy, 2001; Tarko, 2012; Wang and Stamatiadis, 2013, 2014; Wu and Jovanis, 2013), including time to collision (TTC), deceleration rate to avoid crash (DRAC) and crash potential index (CPI). However, as proposed by Kuang et al. (2015), these models are
incapable of representing crash surrogates on freeways, especially saturated freeways where a minor disturbance can result in a rear-end crash due to very high speeds and small headways. For example, if the time headway between two consecutive vehicles on a freeway is 0.5 second and their speeds are equal at 110 km/hr, all these crash surrogate metrics will identify it as a safe scenario. In other words, the above-mentioned crash surrogate metrics fail to assess crash risks of this particular car following scenario, which may lead to erroneous judgement. In this regard, Kuang et al. (2015) proposed a tree structured crash surrogate metric by imposing a hypothetical disturbance to the leading vehicle. An aggregated crash index (ACI) was proposed to combine eight possible scenarios caused by the imposed hypothetical disturbance. According to the validation, the ACI outperforms the traditional TTC based surrogate metrics in representing freeway rear-end crash risks.

The biggest disadvantage of this tree structured crash surrogate metric is that a closed form is not available due to this rather complicated tree structure. It, unfortunately, limits the metric’s applicability to deal with real-world problem. For example, the model is naturally applicable to optimize the traffic operations of connected and automated vehicles in order to achieve the highest safety level. Unfortunately, as there is no closed form for ACI, the traditional optimization models cannot be used and only simulation based optimization models can be considered as an alternative. As such, it is difficult to analyze the analytical properties of the optimization results.

In this Chapter, I proposed a new concept of traffic state vulnerability to develop a simplified crash surrogate metric (SCSM). Traffic state vulnerability is defined as the maximum disturbance that a car following scenario can accommodate. With this new
concept, the SCSM with a closed form was proposed. I further compared the performances of this new surrogate metric, ACI and the conventional TTC based surrogate metrics on on-ramps. According to the comparative analysis, although SCSM has a much simpler form, it has more or less similar performance compared to ACI, which outperforms the TTC. The rest of the Chapter is organized as follows. Section 5.2 introduces the SCSM. Crash data process is presented in Section 5.3. Section 5.4 demonstrates the development and validation of VISSIM simulation models. A comparative analysis is carried out in Section 5.5. Section 5.6 summarizes this study and points out some future research directions and possible application of the new metric.

5.2 The Simplified Crash Surrogate Metric

The ACI adequately considered crash mechanism and the corresponding evasive actions taken by following vehicles, which remedies the drawbacks present in the TTC, DRAC and CPI. However, some deficiencies still exist in the ACI. Firstly, traffic data used to calculate the ACI is hard to collect in the real world, so the ACI more relies on simulated data rather than observed data. Secondly, the complicated calculation process of the ACI let Monte Carlo method (MCM) be the only solution to deal with it. Thirdly, the ACI was initially proposed to assess crash risks of the car-following events in saturated traffic flows. In view of the above issues, I determined to develop a novel crash surrogate measure with a closed form which is technically designed for car-following crashes on on-ramps.
Chapter Five: Freeway Safety Performance Part I – Crash Surrogates

Based on the notion of traffic state vulnerability, a new simplified crash surrogate metric (SCSM) was proposed. It is defined as the maximum disturbance that a traffic state could accommodate, namely the ultimate capacity that a car following scenario can avoid a collision. It can be categorized into two scenarios based on the occurrence probability of a crash.

**Scenario I**

A crash will not occur under the condition that

\[ v_f \leq v_i - \delta \]  \hspace{1cm} (35)

That is,

\[ \delta \leq v_i - v_f \]  \hspace{1cm} (36)

where \( \delta \) is the maximum interference that a traffic state can withstand.

**Scenario II**

A crash is possible to occur under the condition that

\[ v_f > v_i - \delta \]  \hspace{1cm} (37)

That is,

\[ \delta > v_i - v_f \]  \hspace{1cm} (38)

Apparently, as \( v_f \) is greater than \( v_i - \delta \), a crash will occur if both vehicles maintain the same speed. In other words, the modified time to collision with respect to disturbance \( \delta \) can be calculated as,
To further evaluate the crash risks of a car following state, I need to compare the predicted remaining time to crash and the threshold of time to collision. If Equation (47) holds, the following vehicle is able to timely decelerate and a crash could be avoided. Otherwise, a crash will occur. The TTC is a significant index highly relying on drivers’ perception reaction time. Its threshold is hard to be collected and calibrated in the real world. According to the previous researchers’ experience (Van der Horst, 1991; Qu et al., 2013 and 2014), 3s as the critical value could be suitable to assess crash risks on freeways with saturated flow.

\[
\frac{d_{v-f}}{v_f - (v_i - \delta)} \geq \tau \tag{40}
\]

As \( d_{v-f} \) can be estimated by

\[
d_{v-f} \approx v_f h - L_i \tag{41}
\]

where \( h \) is the time headway of this car following scenario and \( L_i \) is the length of the leading vehicle. By substituting Equation (48) to Equation (47), I have

\[
\frac{v_f h - L_i}{v_f - (v_i - \delta)} \geq \tau \tag{42}
\]

As \( v_f - (v_i - \delta) > 0 \), Equation (49) is equivalent to
In other words, as long as a disturbance satisfies Equation (50), a crash is avoidable; otherwise, a crash will occur. By combining the conditions for Scenarios I and II, I can conclude that a crash will not occur if

\[ 0 \leq \delta \leq (v_i - v_f) + \frac{v_j h - L_i}{\tau} \]  

(44)

Namely, \((v_i - v_f) + \frac{v_j h - L_i}{\tau}\) is the maximum disturbance that a car following scenario is able to accommodate. The greater \(\delta\) is, the larger disturbance a traffic state can accommodate, namely a car-following scenario have better capacity to resist the occurrence of a rear-end crash on on-ramp.

5.3 Crash Data Processing

In this study, crash data were provided by Department of Transport and Main Roads (DTMR) and compiled based on annual daily hourly crash counts. They also offer some detailed information including crash coordinates, the occurrence time of a crash and crash type (e.g. rear-end, sideslipping and lane-changing). By means of crash coordinates, all rear-end crashes occurred on the study on-ramp from Year 2005 to 2013 were extracted and listed in Table 5.1. For example, there was only one rear-end crash occurred in the time period from 1:00 to 2:00 am from Year 2005 to 2013. Due to the lack of crash data, I determined to merge current crash counts based on levels of service.
(LOS). For this purpose, each time period in the 24 hours was marked with LOS based on the hourly traffic flow rate provided by DTMR from 15 to 19 April, 2013 (5 workdays). Four groups of LOS were considered in this study: A&B, C, D and E. According to HCM 2010, the determination of LOS highly depends on traffic volumes and capacity. Accordingly, LOS acted as an important role in this research. Based on the processed data, crash rates under the corresponding LOS from Year 2005 to 2013 can be calculated and presented in Table 5.2.

Table 5.1. 24-hour based crash counts on the study on-ramp from Year 2005 to 2013

<table>
<thead>
<tr>
<th>Time period</th>
<th>LOS</th>
<th>Crash counts</th>
<th>Time period</th>
<th>LOS</th>
<th>Crash counts</th>
<th>Time period</th>
<th>LOS</th>
<th>Crash counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>00:00-01:00</td>
<td>A &amp; B</td>
<td>0</td>
<td>08:00-09:00</td>
<td>D</td>
<td>1</td>
<td>16:00-17:00</td>
<td>D</td>
<td>2</td>
</tr>
<tr>
<td>01:00-02:00</td>
<td>A &amp; B</td>
<td>1</td>
<td>09:00-10:00</td>
<td>D</td>
<td>1</td>
<td>17:00-18:00</td>
<td>E</td>
<td>3</td>
</tr>
<tr>
<td>02:00-03:00</td>
<td>A &amp; B</td>
<td>1</td>
<td>10:00-11:00</td>
<td>C</td>
<td>0</td>
<td>18:00-19:00</td>
<td>D</td>
<td>1</td>
</tr>
<tr>
<td>03:00-04:00</td>
<td>A &amp; B</td>
<td>0</td>
<td>11:00-12:00</td>
<td>C</td>
<td>1</td>
<td>19:00-20:00</td>
<td>C</td>
<td>1</td>
</tr>
<tr>
<td>04:00-05:00</td>
<td>A &amp; B</td>
<td>0</td>
<td>12:00-13:00</td>
<td>C</td>
<td>1</td>
<td>20:00-21:00</td>
<td>C</td>
<td>0</td>
</tr>
<tr>
<td>05:00-06:00</td>
<td>D</td>
<td>1</td>
<td>13:00-14:00</td>
<td>C</td>
<td>0</td>
<td>21:00-22:00</td>
<td>A &amp; B</td>
<td>1</td>
</tr>
<tr>
<td>06:00-07:00</td>
<td>E</td>
<td>2</td>
<td>14:00-15:00</td>
<td>C</td>
<td>2</td>
<td>22:00-23:00</td>
<td>A &amp; B</td>
<td>0</td>
</tr>
<tr>
<td>07:00-08:00</td>
<td>E</td>
<td>3</td>
<td>15:00-16:00</td>
<td>D</td>
<td>2</td>
<td>23:00-00:00</td>
<td>A &amp; B</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 5.2. Crash rate in the past nine years under the corresponding LOS

<table>
<thead>
<tr>
<th>LOS</th>
<th>The number of time periods</th>
<th>Crash counts</th>
<th>Crash rate (counts/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A &amp; B</td>
<td>8</td>
<td>3</td>
<td>0.38</td>
</tr>
<tr>
<td>C</td>
<td>7</td>
<td>5</td>
<td>0.71</td>
</tr>
<tr>
<td>D</td>
<td>6</td>
<td>8</td>
<td>1.33</td>
</tr>
<tr>
<td>E</td>
<td>3</td>
<td>8</td>
<td>2.67</td>
</tr>
</tbody>
</table>
Chapter Five: Freeway Safety Performance Part I – Crash Surrogates

In addition, according to the existing data, the average traffic flow rates under four different LOS can be derived through loop detectors set up at upstream 200 metres of off-ramp 1, which was used as traffic volume input in VISSIM. Similarly, the average number of merging traffic, diverging traffic for each on-ramp and off-ramp can also be obtained and shown in Table 5.3.

Take traffic scenario 1 as an example. The traffic volume input for on-ramp 1, 2, 3, 5 and the study on-ramp account for 7.1%, 6.5%, 4.6%, 4.1% and 7.5% of their corresponding mainline traffic, respectively. Similarly, there are 5.4%, 5.3%, 7.2%, 6.3% and 6.8% of mainline traffic diverging into off-ramp 1, 2, 3, 4 and 5.

Table 5.3. The traffic flow configuration for each on-ramp and off-ramp

<table>
<thead>
<tr>
<th>Traffic scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOS</td>
<td>A&amp;B</td>
<td>C</td>
<td>D</td>
<td>E</td>
</tr>
<tr>
<td>Freeway input (vehs/hr)</td>
<td>1830</td>
<td>3960</td>
<td>5220</td>
<td>6360</td>
</tr>
<tr>
<td>Off-ramp 1 output (vehs/hr)</td>
<td>99 (5.4%)</td>
<td>245 (6.1%)</td>
<td>298 (5.7%)</td>
<td>426 (6.7%)</td>
</tr>
<tr>
<td>On-ramp 1 input (vehs/hr)</td>
<td>123 (7.1%)</td>
<td>238 (6.4%)</td>
<td>315 (6.4%)</td>
<td>362 (6.1%)</td>
</tr>
<tr>
<td>Off-ramp 2 output (vehs/hr)</td>
<td>98 (5.3%)</td>
<td>233 (5.9%)</td>
<td>346 (6.6%)</td>
<td>384 (6.1%)</td>
</tr>
<tr>
<td>On-ramp 2 input (vehs/hr)</td>
<td>114 (6.5%)</td>
<td>223 (6.0%)</td>
<td>303 (6.2%)</td>
<td>414 (7.0%)</td>
</tr>
<tr>
<td>Off-ramp 3 output (vehs/hr)</td>
<td>135 (7.2%)</td>
<td>334 (7.7%)</td>
<td>441 (8.5%)</td>
<td>512 (8.1%)</td>
</tr>
<tr>
<td>On-ramp 3 input (vehs/hr)</td>
<td>80 (4.6%)</td>
<td>189 (5.2%)</td>
<td>304 (6.4%)</td>
<td>401 (6.9%)</td>
</tr>
<tr>
<td>Study on-ramp input (vehs/hr)</td>
<td>136 (7.5%)</td>
<td>291 (7.6%)</td>
<td>405 (8.0%)</td>
<td>466 (7.5%)</td>
</tr>
<tr>
<td>Off-ramp 4 output (vehs/hr)</td>
<td>123 (6.3%)</td>
<td>276 (6.7%)</td>
<td>364 (5.2%)</td>
<td>488 (7.3%)</td>
</tr>
<tr>
<td>On-ramp 5 input (vehs/hr)</td>
<td>75 (4.1%)</td>
<td>165 (4.3%)</td>
<td>190 (3.9%)</td>
<td>279 (4.5%)</td>
</tr>
<tr>
<td>Off-ramp 5 output (vehs/hr)</td>
<td>130 (6.8%)</td>
<td>281 (7.0%)</td>
<td>329 (6.5%)</td>
<td>466 (7.2%)</td>
</tr>
</tbody>
</table>

5.4 Development and Validation of VISSIM Simulation Model

In this research, VISSIM was used to simulate and reproduce down-to-earth traffic scenarios of the research segment (Fan et al., 2013; Huang et al., 2013). An on-ramp of
northbound Pacific Motorway, Queensland, adjacent to the largest shopping centre of suburb Nerang, was chosen as the research site, as it involves slight traffic delay and relatively many weaving manoeuvres during rush hours and has always been regarded as a bottleneck by Gold Coast City Council (GCCC). There are 36 data collection points set up on the 360-metre on-ramp with a spacing of 10 metres. To reproduce the impact of the up- and down-stream traffic flow on the research on-ramp, the simulation model was extended to a length of 10 kilometres. Additional 4 on-ramps and 5 off-ramps were involved within 10 kilometres. The sketch map of the research area is shown in Figure 5.1. There was no accident occurred during the data collection process and no major modification of the research on-ramp and its circumambient ramps from Year 2005 to 2013. All settings associated with geometrical characteristics need to be coded based on Google Earth Pro and behavioural parameters in the Wiedemann 99 model need to be calibrated with the real situations as per the procedures described in Chapter 3.

Figure 5.1. The sketch map of the research area
Chapter Five: Freeway Safety Performance Part I – Crash Surrogates

To validate the effectiveness of VISSIM in generating dynamic vehicle behaviour, a bottleneck on the freeway closed to the study on-ramp was identified and used for video recording. Four videos need to be recorded. However, they should meet the following criterion: the traffic volumes in the four videos are as close as possible to those generated by simulation models at the same location. Then, the traffic trajectories for 20 random consecutive vehicles in each video were extracted and compared with those generated from simulation models. Four error tests were herein carried out to evaluate the differences between the simulated results and the observed data (Jin et al., 2015a&b): (1) root mean square error (RMSE), (2) root mean square percentage error (RMSPE), (3) mean percentage error (MPE), and (4) Theil’s inequality coefficient (U), mathematically represented as

\[ RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (y_n^s - y_n^0)^2} \]  \hspace{1cm} (45)  

\[ RMSPE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left( \frac{y_n^s - y_n^0}{y_n^0} \right)^2} \]  \hspace{1cm} (46)  

\[ MPE = \frac{1}{N} \sum_{n=1}^{N} \left( \frac{y_n^s - y_n^0}{y_n^0} \right) \]  \hspace{1cm} (47)  

\[ U = \frac{\sqrt{\frac{1}{N} \sum_{n=1}^{N} (y_n^s - y_n^0)^2}}{\sqrt{\frac{1}{N} \sum_{n=1}^{N} (y_n^s)^2} + \sqrt{\frac{1}{N} \sum_{n=1}^{N} (y_n^0)^2}} \]  \hspace{1cm} (48)
where \( y_n^s \) is the simulation value (speed) of the \( n^{th} \) vehicle, \( y_n^0 \) is the field value (speed) of the \( n^{th} \) vehicle, and \( N_0 \) is the number of vehicles observed or simulated. The error tests of speeds were shown in Table 5.4.

### Table 5.4. Error tests of speeds

<table>
<thead>
<tr>
<th>LOS group</th>
<th>RMSE (m/s)</th>
<th>RMSPE (%)</th>
<th>MPE (%)</th>
<th>U (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A&amp;B</td>
<td>3.37</td>
<td>14.19</td>
<td>7.69</td>
<td>0.28</td>
</tr>
<tr>
<td>C</td>
<td>3.28</td>
<td>13.73</td>
<td>6.67</td>
<td>0.26</td>
</tr>
<tr>
<td>D</td>
<td>2.64</td>
<td>11.86</td>
<td>5.75</td>
<td>0.23</td>
</tr>
<tr>
<td>E</td>
<td>2.68</td>
<td>11.51</td>
<td>5.51</td>
<td>0.24</td>
</tr>
</tbody>
</table>

For any error tests, the difference between simulated speeds and observed speeds is the greatest under LOS A&B, as the speeds for vehicles in the traffic flows close to free speeds are difficult to capture. Besides, the selection of driving speeds is highly free, which is less impacted by HGVs and traffic volumes. As a result, a larger difference is inevitable. For a speed limit of 110 km/hr (30.56 m/s), an error of 3.37 m/s is in the acceptable range. The values for RMSPE are less than 15% across all groups. The largest value for MPE is positive 7.69%, which indicates that the simulated speeds are slightly over-estimated by VISSIM compared with real speeds. Furthermore, U values are close enough to zero. The closer to zero the coefficient is, the smaller the difference in speeds is. Accordingly, I can conclude that VISSIM is able to well simulate a real traffic situation in terms of microscopic level.
5.5 Preliminary Test

The individual risk (IR) is defined as the crash threat to an individual motorist, which is regarded as the likelihood of collision occurring to an individual traveller. The ACI, SCSM and the difference between TTC and its threshold (if TTC is less than its threshold) all can be viewed as the IR. To assess the crash risks of all vehicles on the research on-ramp under four different LOS, the concept of societal risk (SR) was introduced. SR refers to the integrated risk of all individual risks to all of the affected drivers on the on-ramp with length \( L \) measured by surrogate metric \( j \), mathematically,

\[
SR_j = \sum_{i=1}^{M} \int_0^L IR_j(l)dl \approx \sum_{i=1}^{M} \sum_{l=0}^{N} IR_j(l) \times i_{dc}
\]  

where \( IR_j(l) \) represents the individual risk of the discrete scenario \( i \) at discrete length \( l \) measured by surrogate \( j \), \( i_{dc} \) is the interval of two consecutive data collection points, there are a total of \( N \) collection points in length \( L \). In this study, 36 data collection points evenly spread on the 360-metre research on-ramp. Due to the calculation complexity of the ACI, the Monte Carlo method (MCM) was used to calculate the crash probability. 10,000 random drivers’ reaction times and MADRs were generated by MCM in each car-following scenario. To make the numerical values more readable, I applied normalization method to process the results of SCSM. Table 5.5 presents the SR represented by the TTC, ACI and SCSM for four varying LOS. As crash data are limited, I cannot conclude which metric has a better ability to predict risks for the study on-ramp through a linear model. However, according to the proportional relation between SR and crash rate, the performance of the SCSM is superior to others indeed,
Chapter Five: Freeway Safety Performance Part I – Crash Surrogates

followed by the ACI and TTC. For the TTC, I generally compared the difference between the leading vehicle’s speed and the following vehicle’s speed to judge a car-following scenario safe or risky. This judgement criterion is obviously unreasonable for assessing crash risks for on-ramps, since the speeds of leading vehicles in the merging traffic are larger than those of following vehicles in most cases. However, in a saturated merging traffic stream with smaller time headways and higher driving speeds, even though the abovementioned condition is met, a crash may occur. Accordingly, the traditional TTC is inappropriate for risk assessment for on-ramps. For the ACI, a robust probabilistic causal model enables it to capture any potential car-following risks on the on-ramp. However, its complex calculation restricts its applicability in the real world. With the simplified calculation procedure and more or less similar performance to the ACI, the SCSM stand out of these three surrogate measures.

Table 5.5. Societal based risks assessed by three surrogate metrics under four LOS

<table>
<thead>
<tr>
<th>LOS</th>
<th>Crash counts</th>
<th>Crash rate (counts/hr)</th>
<th>SR represented by surrogate metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>TTC</td>
</tr>
<tr>
<td>A &amp; B</td>
<td>3</td>
<td>0.38</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>5</td>
<td>0.71</td>
<td>5.52</td>
</tr>
<tr>
<td>D</td>
<td>8</td>
<td>1.33</td>
<td>15.91</td>
</tr>
<tr>
<td>E</td>
<td>8</td>
<td>2.67</td>
<td>19.23</td>
</tr>
</tbody>
</table>

5.6 Summary

Aiming at rear-end crashes occurred on on-ramps, in this Chapter I proposed a new concept of traffic state vulnerability in order to develop and assess the simplified crash surrogate metric (SCSM). As an upgraded version of the traditional time to collision
(TTC), the SCSM not only features the same straightforward closed form as the traditional TTC, but also makes up for the shortcoming of the TTC that is unable to accurately assess crash risks in saturated traffic flow. In this study, I used it and another two surrogate measures, aggregated crash index (ACI) and TTC, to predict the crash risks for an on-ramp on Pacific Motorway in Queensland, Australia. Based on a comparative analysis, the TTC based surrogate metric performed the worst, as it made a concession to limited historical crash counts and boundary condition. Moreover, it was assessed based on that the speeds for leading and following vehicles are invariable during the collision course, which is inconsistent with the real world. When the following vehicle takes necessary evasive actions to avoid a crash, the change in deceleration rates taken by the following vehicle is hard to capture. The SCSM tactfully takes advantage of the concept, the maximum disturbance that a traffic state could accommodate, thereby effectively evading the consideration for the complicated evasive actions involved in a car-following scenario. In general, as a variation of the traditional TTC, the SCSM can better assess crash risks in the context of urban environment. The performance of the SCSM is more or less similar to that of the ACI. But considering the ability to resolve practical engineering issues, the SCSM is superior to the ACI. It can assist traffic agents in efficiently and precisely assessing rear-end crash risks for on-ramps.

The limitations, such as the lack of validation for crash surrogate metrics, still exist in the research, but they will be resolved in the future works.
6 FREEWAY SAFETY PERFORMANCE PART II – BLACK SPOTS IDENTIFICATION

6.1 Background

Currently, there is a relatively abundant literature focused on different hotspot identification (HSID) approaches (e.g. Monsere, 2006; Montella, 2010; Oh et al., 2010; Yu et al., 2014). Among them, the crash frequency method (CFM) has been widely used by many highway agencies in different countries, although some scholars have complained about their ineffectiveness (Elvik, 2008). Afterwards, an approach taking both the frequency and crash severity into account was proposed (PIARC, 2004). However, it only considered the severe consequence of crashes and sometimes did not apply to the real world (Wang and Abdel-Aty, 2008; Li et al., 2012). For example, some road sites with low crash frequency may be mistakenly judged as hotspots due to several severe crashes. Considering the impacts of crashes on the societal monetary loss, Qu and Meng (2014) developed a societal risk-based crash Method (SRCM) by converting crashes into their corresponding economical loss. To control the random fluctuations during the observation period, the empirical Bayesian method (EB) has always been used for addressing the regression-to-the-mean effect of crashes (Hauer, 1997; Saccomanno et al., 2001; Persaud and Lyon, 2007; Liu et al., 2013). It takes not only the historical crash record of the research road segments but also their expected crash counts into account.
Chapter Six: Freeway Safety Performance Part II – Black Spots Identification

The objective of HSID is to find the segments that need to be treated either by traffic control (usually during peak hours) or by geometric re-design (usually during non-peak hours). In view of this, it is important to take into account the daily volume/crash variability in the HSID process. Let me use two cases in the Pacific Motorway to further illustrate my point. For the first case, the road section Nm12 linking to Logan City on-ramp has been believed to be a crash-prone location during peak hours, and ramp metering is currently implemented to improve its safety level. However, according to the traditional methods, it is not evaluated as a hotspot. As the traffic control strategies (e.g. ramp metering) is usually implemented during peak hours, it is important to understand which spots are more dangerous during peak hours. For the second case, while the road section Sm26 (through suburb Yatala) fitted with slippery road warning signs and lower speed limit (for improving safety) is not considered as a hotspot according to the traditional methods, they are indeed high-risk spots during off peak hours due to the geometric characteristics. According to the record, road warning sign and lower speed limit can indeed reduce the number of crashes during off-peak hours. However, these effective measures will not be performed if I use the traditional methods to identify hotspots. In this regard, it is essential to take into account the daily crash/volume variability in the HSID process. As can be seen in Figure 6.1, the traffic flow gathered by loop detectors set on the freeway mainline and crash counts for two representative road sites fluctuate over hours of the day. The causations of crashes are significantly different under distinct traffic scenarios. During peak hours, traffic flow stability and geometric design defects may jointly contribute to traffic crashes. While during non-peak hours, as traffic flow is less complicated, the deficiency in geometric design may be the main contributing factor leading to the occurrence of crashes.
According to Gold Coast City Transport Strategy (2013), the daily 24-hour period was decomposed into four time groups. Among analysing my detailed crash data, in the morning (from 6:00am till 9:00am) and afternoon peak times (from 3:00pm till 7:00pm), as the speeds were usually not high and drivers had a relatively high level of concentration, the crashes were usually resulted from traffic flow stability (or disturbance propagation) as well as geometric design defects. In contrast, the occurrence of traffic crashes was more random in the daytime off-peak times (from 9am till 3:00pm), mainly caused by the issue of geometry limitations such as stopping sight distance or alignment. As for the night off-peak times (from 7:00pm till the next 6:00am), visibility played a key role for crashes. In this regard, I categorized the whole time of the day into four groups: morning peak hours, afternoon peak hours, daytime off-peak hours and night off-peak hours.
Chapter Six: Freeway Safety Performance Part II – Black Spots Identification

The objective of this Chapter was to improve the accuracy of HSID, namely to identify those un-identified hotspots that should have been treated. To achieve it, I compared the differences in the proposed HSID methods and the conventional HSID approaches with respect to freeway main carriageways, on-ramps and off-ramps. Six years of crash records from the Pacific Motorway from Gold Coast to Brisbane were applied in the research. The remainder of this paper is presented as follow. Section 6.2 describes the research segment and the procedure of the data collection. Section 6.3 formulates four EB-based methods focusing on different time periods of the day and discusses the comparative results of HSID methods. Section 6.4 explains a comparative study. Section 6.5 concludes.

6.2 Site and Data Description

In this study, the Pacific Motorway Southeast Queensland section connecting Brisbane Central Business District (CBD) to the major tourist region of Gold Coast via M1 and M3 (from the data collection point at William Jolly Bridge, Brisbane to the data collection point at Stewart Road, Currumbin Waters), with 94.7 km in length, was selected as the research segment. M1 and M3 are linked by interchange of Eight Miles Plains. The segment truly reflects the current traffic dilemma in Australia, since the increasing vehicles commuting between the two satellite cities (North-South) swarm into this important inter-city motorway, which inevitably leads to more potential hotspots, even more severe traffic crashes. Besides, it involves different geographical environment features (e.g. plain, rural, urban, etc.). To examine the applicability of various HSID methods to the different freeway components, the research objects were classified into freeway main carriageways, on-ramps and off-ramps. Freeway main
carriageways were divided into 50 sections due to the heterogeneity of the number of lanes. With the help of highway capacity manual (HCM) and ArcGIS, one on-ramp can be identified as the lane from the signal or non-signal controlled junction to the edge point of highway entrance gore. Similarly, the length of an off-ramp is the distance from the edge point of highway exit gore to the signal or non-signal controlled junction. There are 78 on-ramps and 82 off-ramps spreading over Northbound and Southbound directions.

The crashes occurred in the research segment from Year 2005 to 2010 were recorded by Queensland police and compiled by Department of Transport and Main Roads (DTMR) of Queensland that supplied crash records used in this study. The crash records elaborate the time of crash, the detailed latitudes and longitudes of crash sites, the crash severity (e.g. fatality, hospitalization, medical treatment, minor injury, etc.), the crash description (e.g. lane changes, rear-end, off carriageway on straight/ curve hit object, etc.), the crash atmospheric and lighting conditions. The coordinates of crashes were imported into ArcGIS in order to identify incident sites. To summarize, there were 2978 crashes in the research segment from 2005 to 2010. Among them, 2078 and 900 crashes occurred in M1 and M3, respectively. Unfortunately, Queensland traffic safety standard lacks a specific division of crash severity. I thus utilized the rule from NSC in this study. The fatal, serious injured, possible injured and PDO crashes in quantity respectively occupied 229, 424, 857 and 1468.
6.3 Hotspot Identification Considering Daily Variability of Traffic and Crash Data

6.3.1 Data categorization

I categorized the six years of crash records occurred on freeway main carriageways, on-ramps and off-ramps into four types of time periods, which is shown in Table 6.1. The new EB-based approaches were proposed on the basis of the four clusters. In general, the number of crashes occurred in morning peak hours from Year 2005 to 2010 was relatively low due to a short reference time. Afternoon peak hours, by contrast, led to more crashes. Under the two scenarios, HSID is susceptible to traffic flow and geometric design. Because of the differences in crash counts under both scenarios, I separated them into two groups. In addition, HSID in daytime and night off-peak hours
tends to be influenced by the road geometry and visibility issues, respectively. Accordingly, there is a need to consider four different time periods when identifying hotspots.

Table 6.1. Crash distribution for freeway components

<table>
<thead>
<tr>
<th>The crash distribution for main carriageways</th>
<th>The crash distribution for on-ramps</th>
</tr>
</thead>
<tbody>
<tr>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Morning peak-based crash counts</td>
<td>80</td>
</tr>
<tr>
<td>Afternoon peak-based crash counts</td>
<td>110</td>
</tr>
<tr>
<td>Daytime off-peak-based crash counts</td>
<td>103</td>
</tr>
<tr>
<td>Night off-peak-based crash counts</td>
<td>91</td>
</tr>
<tr>
<td>Sum</td>
<td>384</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The crash distribution for off-ramps</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>Morning peak-based crash counts</td>
</tr>
<tr>
<td>Afternoon peak-based crash counts</td>
</tr>
<tr>
<td>Daytime off-peak-based crash counts</td>
</tr>
<tr>
<td>Night off-peak-based crash counts</td>
</tr>
<tr>
<td>Sum</td>
</tr>
</tbody>
</table>

6.3.2 EB-based method for morning peak hours

As per the investigation, the north-south Pacific Motorway involves an unbalanced traffic flow problem. Northbound vehicles dominate in the morning peak hours, since the motorists commute from Gold Coast to Brisbane. In this situation, the occurrence of crashes is highly related to the interaction of traffic flow stability and road geometric characteristics because of relatively high traffic volumes and low speeds on freeways. Based on the proposed methodology, crashes occurred in morning peak times from Year
2005 to 2010 were firstly extracted and were then converted into the EB-based crash density through the following equation in the unit of counts per kilometer per lane per year.

\[
EB_{ij}^{am} = \bar{w}E^{am}(Y_j) + (1 - \bar{w})Y_{ij}^{am}
\]  

(50)

\[
\bar{w} = \frac{E^{am}(Y_j)}{E^{am}(Y_j) + Var^{am}(Y_j)}
\]  

(51)

where \(EB_{ij}^{am}\) is the better estimate of annual crash density for am peak hours in year \(i\) for segment \(j\); \(E^{am}(Y_j)\) is the expected annual crash density for am peak hours for segment \(j\); \(Var^{am}(Y_j)\) is the variance of annual crash density for am peak hours for segment \(j\); \(Y_{ij}^{am}\) is the observed annual crash density for am peak hours in year \(i\) for segment \(j\). The detailed estimation process is illustrated as follows. Firstly, crash occurred in morning peak hours from Year 2005 to 2010 were extracted. Secondly, crash counts for road segment \(j\) in each hour of morning peak times were converted into crash density in the unit of counts per kilometer per lane per hour per year. Thirdly, all these crash densities for segment \(j\) were averaged to obtain the expected crash density for segment \(j\) in morning peak hours. The variance is also estimated based on these crash densities for segment \(j\) in morning peak hours.
6.3.3 EB-based method for afternoon peak hours

Inversely, during afternoon peak hours, more vehicles travel South due to the commuters returning from Brisbane. Figure 6.3 reflects a periodic unbalance of traffic flow. There is thus a need to segment morning and afternoon peak times in order to achieve more precise HSID. The EB estimate building on afternoon peak times can be formulated as follows:

\[
EB^{pm}_j = \bar{w}E^{pm}(Y_j) + (1-\bar{w})Y^{pm}_j
\]  
(52)

\[
\bar{w} = \frac{E^{pm}(Y_j)}{E^{pm}(Y_j) + Var^{pm}(Y_j)}
\]  
(53)

Figure 6.3. The periodic unbalance of northbound and southbound traffic flow
6.3.4 EB-based method for daytime off-peak hours

As a transitional time period between morning and afternoon peak times, crashes are more likely to be impacted by road geometry parameters and random factors. The casualties caused by sideslip and out-of-control tend to be more during daytime off-peak hours. Accordingly, it must be separated for a further discussion. The EB-based method for daytime off-peak hours is expressed as follows:

\[
EB_{ij}^{do} = wE^{do}(Y_j) + (1 - w)Y_{ij}^{do}
\]

\[
\bar{w} = \frac{E^{do}(Y_j)}{E^{do}(Y_j) + Var^{do}(Y_j)}
\]

6.3.5 EB-based method for night off-peak hours

The night-time crashes have little to do with traffic flow due to low traffic volume, but are highly related to visibility problems and the loss of motorists’ concentration. Driving off carriageways and hitting objects are two leading causes bringing about night crashes. The EB-based method considering night visibility and human errors is thus proposed as follows:

\[
EB_{ij}^{no} = \bar{w}E^{no}(Y_j) + (1 - \bar{w})Y_{ij}^{no}
\]

\[
\bar{w} = \frac{E^{no}(Y_j)}{E^{no}(Y_j) + Var^{no}(Y_j)}
\]
6.3.6 Discussion

The main contribution of the research was the proposal of a new assumption that daily variability of traffic volumes and crash record has a high level of impact on HSID. To justify my conception, I proposed four novel EB-based methods for (1) morning peak hours, (2) afternoon peak hours, (3) daytime off-peak hours, and (4) night off-peak hours, and assessed their consistency performance along with (5) crash frequency method (CFM), (6) societal risk-based method (SRM), and (7) conventional empirical Bayesian method (EB) through the method consistency test (MCT) and the total rank differences test (TRDT). To this end, six years of crash records were divided into two time groups: period 1 (from Year 2005 to 2007) and period 2 (from Year 2008 to 2010). The top 5, 10 and 15 high-risk sites identified through these seven HSID methods over two periods were respectively compared in order to spot the HSID method with the highest consistency. Apart from freeway main carriageways, the consistency check was also applied on on-ramps and off-ramps for the purpose of exploring the impact of consistency tests on different freeway components. The test results are summarized in Table 6.2 to Table 6.4.

As can be seen from Table 6.2, the test values (not ranking) associated with the proposed methods are relatively similar with those associated with the conventional EB methods, but they are not the point that I want to focus on. This is because our main purpose is to screen those hotspots that should be treated in peak or non-peak times, but are ignored by the conventional HSID methods. As long as the test values of the proposed approaches, with regard to the same locations, are similar with or more or less superior to those of the conventional HSID methods, then I believe segmentation of
time intervals is valuable to HSID. The test values and rankings also reflect that crashes on freeway main carriageways follow a periodic distribution. Their occurrence heavily depends upon four different time periods I determined. The CFM yields to the random fluctuation of crashes and ranks sixth in the seven approaches. The seventh-placed SRM better represents the perspective of traffic agencies, but it is more susceptible to the low frequency of fatal or serious crashes. Its test values also reflect the occurrence of those severe crashes is more random than that of PDO crashes. In short, the proposed EB-based methods are capable of capturing those un-identified hotspots that should have been treated.

Table 6.2. The summary of consistency test for freeway main carriageways

<table>
<thead>
<tr>
<th>HSID method</th>
<th>Method consistency test</th>
<th>Total rank differences test</th>
<th>Test results for freeways: top 5 of hotspots</th>
</tr>
</thead>
<tbody>
<tr>
<td>FM</td>
<td>Test value 5</td>
<td>13</td>
<td>Test value 6</td>
</tr>
<tr>
<td>SRM</td>
<td>Test value 2</td>
<td>24</td>
<td>Test value 5</td>
</tr>
<tr>
<td>EB for whole day</td>
<td>Test value 7</td>
<td>7</td>
<td>Test value 1</td>
</tr>
<tr>
<td>EB for morning peak</td>
<td>Test value 5</td>
<td>4</td>
<td>Test value 1</td>
</tr>
<tr>
<td>EB for afternoon peak</td>
<td>Test value 5</td>
<td>4</td>
<td>Test value 1</td>
</tr>
<tr>
<td>EB for daytime off-peak</td>
<td>Test value 5</td>
<td>4</td>
<td>Test value 1</td>
</tr>
<tr>
<td>EB for night off-peak</td>
<td>Test value 5</td>
<td>4</td>
<td>Test value 1</td>
</tr>
<tr>
<td></td>
<td>Test ranking 6</td>
<td>6</td>
<td>Test ranking 6</td>
</tr>
<tr>
<td></td>
<td>Test ranking 7</td>
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<td>Test ranking 7</td>
</tr>
<tr>
<td></td>
<td>Test ranking 1</td>
<td>2</td>
<td>Test ranking 1</td>
</tr>
<tr>
<td></td>
<td>Test ranking 1</td>
<td>2</td>
<td>Test ranking 1</td>
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<td>Test ranking 1</td>
</tr>
<tr>
<td></td>
<td>Test ranking 1</td>
<td>2</td>
<td>Test ranking 1</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>HSID method</th>
<th>Method consistency test</th>
<th>Total rank differences test</th>
<th>Test results for freeways: top 10 of hotspots</th>
</tr>
</thead>
<tbody>
<tr>
<td>FM</td>
<td>Test value 14</td>
<td>63</td>
<td>Test value 6</td>
</tr>
<tr>
<td>SRM</td>
<td>Test value 11</td>
<td>112</td>
<td>Test value 6</td>
</tr>
<tr>
<td>EB for whole day</td>
<td>Test value 14</td>
<td>16</td>
<td>Test value 5</td>
</tr>
<tr>
<td>EB for morning peak</td>
<td>Test value 14</td>
<td>16</td>
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</tr>
<tr>
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<tr>
<td>EB for daytime off-peak</td>
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<table>
<thead>
<tr>
<th>HSID method</th>
<th>Method consistency test</th>
<th>Total rank differences test</th>
<th>Test results for freeways: top 15 of hotspots</th>
</tr>
</thead>
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<tr>
<td>FM</td>
<td>Test value 14</td>
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<tr>
<td>SRM</td>
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<td>112</td>
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</tr>
<tr>
<td>EB for whole day</td>
<td>Test value 14</td>
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<td>EB for morning peak</td>
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<td>EB for afternoon peak</td>
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<tr>
<td>EB for daytime off-peak</td>
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### Table 6.3. The summary of consistency test for on-ramps

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<th>HSID method</th>
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</thead>
<tbody>
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<td><strong>SRM</strong></td>
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<td><strong>EB for morning peak</strong></td>
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<tr>
<td><strong>EB for afternoon peak</strong></td>
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<td>2</td>
</tr>
<tr>
<td><strong>EB for night off-peak</strong></td>
<td>Test value 11</td>
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### Table 6.4. The summary of consistency test for off-ramps

<table>
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<th>HSID method</th>
<th>Method consistency test</th>
<th>Total rank differences test</th>
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</thead>
<tbody>
<tr>
<td><strong>FM</strong></td>
<td>Test value 6</td>
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</tr>
<tr>
<td><strong>SRM</strong></td>
<td>Test value 12</td>
<td>4</td>
</tr>
<tr>
<td><strong>EB for whole day</strong></td>
<td>Test value 7</td>
<td>5</td>
</tr>
<tr>
<td><strong>EB for morning peak</strong></td>
<td>Test value 3</td>
<td>3</td>
</tr>
<tr>
<td><strong>EB for afternoon peak</strong></td>
<td>Test value 2</td>
<td>2</td>
</tr>
<tr>
<td><strong>EB for night off-peak</strong></td>
<td>Test value 11</td>
<td>3</td>
</tr>
</tbody>
</table>

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99
Chapter Six: Freeway Safety Performance Part II – Black Spots Identification

According to consistency tests for on- and off-ramps shown in Table 6.3 and Table 6.4, the performances in proposed methods are inferior to those in the EB and the CFM in both test values and rankings. This is because crashes occur too randomly in such areas and crash counts are relatively low. It also reflects the occurrence of crashes does not follow a periodical regularity of traffic flow. The inconsistent performance of the four EB-based methods is compromised by the summation. In brief, there is no need to segment time intervals in HSID for on- and off-ramps. The conventional EB and CFM estimates can perform well.

6.4 Analysis of Identified Hotspots

In the consistency check, the EB-based methods considering four time periods and the conventional EB method based on hours of the day all outperform others in identifying hotspots for freeway main carriageways. As a result, I applied these five methods to do an aggregated view. The top 10 hotspots from Year 2005 to 2010 were identified for further analysis. Among them, some high-risk sites repeatedly arose in the different time periods, which should be regarded as round-the-clock hotspots. They are mutually affected by a set of factors including traffic flow, geometric design characteristics and visibility. For those hotspots that are only identified in a single time period, they may be only influenced by one of factors. In view of this, a simple category analysis based on daily variability can assist traffic agents in not only screening network in different time intervals, but also diagnosing the major cause that leads to those crashes. As per the diagnosis, the appropriate countermeasures can be eventually given.
Table 6.5 demonstrates top 10 hotspots identified through the four proposed EB-based methods and the conventional EB estimate over six years. In summary, the identified black spots prove that there is indeed an unbalanced traffic volume issue present in north and south directions of the research segment. During morning peak hours, the number of northbound hotspots is more than that of southbound hotspots since more motorists commute north to Brisbane, and vice versa. The hotspot distribution of both directions is balanced during daytime and night off-peak hours. Among them, Sm 5 and 12 in red font are the intersections of these five time periods. Both are viewed as really serious hotspots and should be given a high-priority concern at all times.
Chapter Six: Freeway Safety Performance Part II – Black Spots Identification

Only Sm 23 and Nm 1, 12, 17, 18 and 20 in blue font were identified during morning rush times in six consecutive years, which suggest that these sites are more susceptible to the morning peak traffic flow and less dependent upon the afternoon peak traffic flow, random factors and visibility issues. The lane use management systems including variable speed limits are recommended to apply here. When the traffic scenario is in a high demand, they can control traffic speeds and the lane utilization for the sake of improving safety and maintaining stability of traffic flow. Similarly, those hotspots only identified during afternoon rush times should be given the same treatment.

Sm 7 and Nm 11 in green font are the overlap of night off-peak hours and hours of the day. They are prone to be impacted by poor visibility at night. The road authorities can adopt more intensive reflective road markers and increase their quantity at these road sites in order to achieve treatment goals.

Being the only intersection between daytime and night off-peak hours, Sm 26 in yellow font involves not only poor night visibility but also road geometrical problem. To address it, more conspicuous warning signs and road makers should be fitted in such areas.

6.5 Summary

In the course of HSID, I observed two real world special cases. Case 1 is that the road site Nm 12 linking to Logan City on-ramp is screened as a low-risk location through the conventional HSID, although its rush-hour crash rate is considerably high and traffic control is implemented; Case 2 is that the road section Sm 26 (through suburb Yatala) is
fitted with slippery road warning signs and lower speed limit, but it is still considered as a non-hotspot according to the traditional approaches. Both cases prove that the conventional HSID methods are unreasonable and questionable. To address it, I proposed the concept of categorizing time intervals for HSID, namely considering daily variability of traffic flow and crash record in HSID. The results show that the EB-based methods considering the effect of daily variability outperform other approaches in hotspot identification for freeway main carriageways since the crashes occurred on mainlines follow a periodic regularity.
Chapter Seven: Conclusions and Future Works

7 CONCLUSIONS AND FUTURE WORKS

7.1 Conclusions

In the three and half years of PhD career, my research program could mainly be classified into two categories: 1) take advantage of VISSIM traffic simulation models to evaluate the performance in traffic operation and environmental sustainability; 2) apply crash surrogate measures and traffic crash models to conduct safety analyses. Five studies were involved in this thesis. Chapter 1 introduced the overall background of the research program and objectives and contributions of each study. Chapter 2 reviewed Australia road standard, highway capacity manual (HCM), emissions prediction models, crash surrogate measures and existing hotspot identification (HSID) methods. Chapter 3 quantified the impact of mainline traffic volume and percentage of mainline heavy goods vehicles (HGVs) on travel time passing through the road segment fitted with two on-ramp lane arrangements. Chapter 4 assessed the effect of mainline traffic volume and proportion of mainline HGVs on CO2 emitted on the road segment equipped with two on-ramp lane configurations and presented two CO2 emissions contour charts. A new crash surrogate metric was proposed in Chapter 5 and compared with another two crash surrogate measures in order to explore which crash measure performs the best in predicting crash risks for on-ramps. Chapter 6 compared a proposed hotspot identification (HSID) method with the existing ones.

The research program started with the estimation of passenger car equivalents (PCE) for the subject heavy vehicles (HVs) on on-ramps. Various PCE methods were compared in
Chapter Seven: Conclusions and Future Works

In order to find out the best method that can reflect the relationship between PCE values and traffic volumes, we based on data collected from the study site and generated by VISSIM, PCE values were calculated through four existing PCE methods: (1) homogenization based method (HM); (2) time headway based method (THM); (3) traffic flow based method (TFM) and (4) multiple linear regression model (MLRM). The following conclusions can be drawn.

- The HM cannot properly predict the variation trend of PCE values over traffic volume due to the low sensitivity of the speed to the change in traffic volume.
- Both the THM and TFM can derive the results which are relatively consistent with outcome from simulation model. They may be the best PCE calculation methods for the subject HVs on the on-ramp under the premise that there is no new PCE method presented.

As this study may not correlate with the overall aim of the thesis, it was presented in Appendix 1.

Afterwards, I quantitatively assessed the performance in traffic operation for two on-ramp lane configurations (added lane and zip merging) under the impact of different mainline traffic volumes and percentages of mainline HGVs. To this end, one freeway segment with a pair of closely-spaced on- and off-ramps was selected for a case study. The average travel time passing through the study road segment was reviewed as an important indicator to judge goodness and badness of traffic operation. In this study, I took advantage of VISSIM traffic simulation models to automatically generate the average travel time. Prior to the simulation, massive traffic data need to be collected in eight different time periods for the calibration of simulation models. Through previous sensitivity analyses, I found that the average desired distance between stopped cars
(CC0), the distance in seconds that a driver wants to keep at a certain speed (CC1), and
the distance exceeding the desired safety distance a driver allows before
he intentionally moves closer to the car in front (CC2) are the main factors affecting
simulation precision. Moreover, the desired lane change distance (DLCD) in connector
settings also influences simulation results significantly. I used genetic algorithm (GA)
to filter the best sets of values for these four parameters in different time periods. The
final results showed that the simulation using calibrated parameters can better reproduce
a realistic traffic scenario compared with the simulation using default parameters.
Accordingly, VISSIM models must be calibrated before simulation runs. Built on
simulation models, the impact of percentages of mainline HGVs on travel time passing
through the road segment fitted with two on-ramp lane configurations was analysed
under eight traffic volumes scenarios. Through analysis, I drew the following
conclusions.

- For any traffic volume, an increase in percent HGVs resulted in more travel time
  consumed in the road segment equipped with both on-ramp lane configurations.

- For low traffic volume, an increase in percent HGVs did not change the result that
  zip merging outperforms added lane.

- When traffic volume is greater than 1200 vehs/hr/ln, the impact of percent HGVs
  emerges. A smaller proportion of HGVs might lead to that the operational
  performance for added lane is superior to that for zip merging.

In addition, I also analysed the effect of traffic volumes on travel time spent on the road
segment equipped with both on-ramp lane arrangements under eight different percent
HGVs scenarios. The conclusion are shown as follows.
Chapter Seven: Conclusions and Future Works

- For low traffic volume and small percentage of HGVs, the road segment fitted with outperforms that fitted with added lane.

- But with the increase in traffic volumes and percent HGVs, added lane is better.

The performance in sustainability of a road segment may be influenced by its operational performance. In this study, I quantified the performances in CO2 emissions of the road segment equipped with two on-ramp lane arrangements based on simulation models from the last study. The comprehensive modal emissions model (CMEM) was applied to calculate CO2 emissions as it could better capture the changes in instantaneous speeds and accelerations in the study freeway segment. The investigation was conducted on an 800-meter road segment covering 800 small sections, each of which contains one data collection point. Finally, emissions of any vehicle in any small section were calculated using the CMEM and then all the emissions were accumulated together. I first evaluated the impact of percentage of HGVs on CO2 emissions under scenarios of traffic volumes varying from 800 to 1800 vehs/hr/lane with a step of 200 vehs/hr/lane. I drew the following conclusion.

- For most cases, the performance of added lane in the control of CO2 emissions is superior to that of zip merging lane.

Besides, the relationships between CO2 emissions and traffic volumes under scenarios with 2%, 4%, 6%, 8% and 10% of HGVs were also compared. The above-mentioned conclusion can be drawn again. Finally, I developed a pair of emissions contour charts for two on-ramp lane configurations to assist transport agencies in determining CO2 emissions under the target percentage of HGVs and the target traffic volumes.
In the fourth study, I proposed the simplified crash surrogate metric (SCSM) with a closed form which is based on the concept of traffic state vulnerability. I compared the performance in crash risks prediction for the SCSM with another two common surrogate measures, the aggregated crash index (ACI) and time to collision (TTC). Based on a simple proportional relationship between the societal risk index (SR) and crash rates, I drew the following conclusions.

- The TTC-based surrogate metric performed the worst, as it makes a concession to limited historical crash counts and boundary condition.
- The performance of the SCSM is more or less similar to that of ACI. But considering the ability to resolve practical issues and the simple calculation, the SCSM is more appropriate to assess rear-end crash risks for on-ramps.

The limitations still existed in this study. Firstly, due to the restriction of historical crash counts on the research on-ramp, I cannot validate these surrogate metrics by simply developing a linear relationship between the SR and crash counts. I reluctantly displaced crash counts with crash rates under varying LOS. Secondly, the case study was only focus on an on-ramp on Pacific Motorway. In further study, I will apply these three surrogate measures to assess crash risks for other on-ramps on Pacific Motorway.

During the fifth study, I aimed to improve the accuracy of hotspot identification (HSID). I observed two real world special cases. Both cases justified that the conventional HSID methods are unreasonable and questionable. To address it, I proposed the concept of segmenting time intervals for HSID, namely considering daily variability of traffic flow and crash record in HSID. The following efforts have been made. Firstly, I proposed the EB-based methods based on four different time clusters: (1) morning and (2) afternoon peak hours, and (3) daytime and (4) night off-peak hours. Secondly, the partial Pacific
Chapter Seven: Conclusions and Future Works

Motorway M1 and M3 in southeast Queensland were selected as the research segment. Thirdly, the consistency checks were conducted on freeway main carriageways, on-ramps and off-ramps in order to compare the performance of the proposed methods to (5) the conventional empirical Bayesian method (EB), (6) the crash frequency method (CFM) and (7) the societal risk-based method (SRM). The check results are shown below.

- The EB-based methods considering daily variability of traffic flow and crash record outperformed other methods in HSID for freeway main carriageways since the crashes occurred on mainlines follow a periodic regularity.
- The proposed EB-based methods are less applicable to filter black spots for on- and off-ramps, because the occurrence of high-consequence crashes in such areas are highly random and limited by their counts.
- The conventional EB method performed the best in HSID for on- and off-ramps. This is because summation analysis contributes to a more stable hotspot ranking when crashes distribute excessively discrete or are limited by counts.

Finally, I applied the proposed methods and the conventional EB method to do an aggregate analysis to main carriageways of the research segment. The following conclusions could aid traffic engineers in determining the optimal treatment scheme in the stage of network screening.

- If hotspots are only identified in peak hours, both traffic flow stability and geometric design defect may be factors contribute to the occurrence of crashes.
- If hotspots are only identified during off-peak hours, crashes may be caused by road geometric issue or poor visibility.
• If hotspots are identified in multiple time periods, the road sites may be impacted by a set of factors.

### 7.2 Future Works

#### 7.2.1 The validation for crash surrogate metrics

I have been aware that the limitation still existed in the fourth research. For example, there was no validation for various crash surrogate metrics. Due to the restriction of historical crash counts, it is not convincing to only depend on a simple proportional relationship between the societal risk (SR) and crash rates to judge that the SCSM is superior to others. Therefore, I believe the following future works may to some extent make up for the limitation. Firstly, the number of the research on-ramps should be increased. For example, the similar on-ramps identified through VISSIM calibration and validation should be grouped together as the study on-ramps. Secondly, crash counts in each hour occurred on these subject on-ramps need to be extracted from historical crash records. Thirdly, based on the hourly simulation animation for these on-ramps, the results for various surrogate metrics can be obtained. Fourthly, the linear relationships between the SR and crash counts for each surrogate metric can be developed based on 24 points, which will be a sound validation to demonstrate that a certain crash surrogate measure is superior to others.
7.2.2 The contributing factors of travel time in the road segment with ramp metering

In this research, I hope to further optimize traffic operation in the on-ramp adjacent areas. My research objects will turn to on-ramp zones with traffic control. According to daily observations, many factors may affect the average travel time of a certain freeway road segment with ramp metering. Therefore, I will explore the contributing factors affecting travel time and rank these factors according to their impact factors. The number of through lanes, speed limits near ramps, mainline traffic volumes, the percentages of HGVs, and the location and cycle time of ramp metering will be considered as contributing factors presented in this research. The investigation will be conducted on all road segments controlled by ramp metering across Australia. I expected to create a multiple linear regression model between travel time and these factors. This research will aid traffic engineers in seeking out which contributing factor should be prioritized in the traffic management of freeway road segment with ramp metering.
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APPENDIX 1: ESTIMATION OF HEAVY VEHICLE PASSENGER CAR EQUIVALENTS FOR ON-RAMP ADJACENT ZONES UNDER DIFFERENT TRAFFIC VOLUMES: A CASE STUDY

Due to the difference in operational characteristic, heavy vehicles have been viewed as a hindrance in traffic flow and capacity analysis. The emergence of passenger car equivalents (PCE) can assist traffic agencies in better understanding the impact of heavy vehicles on passenger vehicles in the mixed traffic stream, by converting a heavy vehicle of a subject class into the equivalent number of passenger cars. However, according to existing literature, most researchers have devoted to the estimation of PCE for basic freeway sections. Therefore, in this study, I explored the variation of heavy vehicle PCE for on-ramp adjacent zones under varying traffic volume. A one-lane on-ramp in Queensland, Australia, is selected for a case study and four existing PCE approaches are applied in the calculation of PCE. They are homogenization based method, time headway based method, traffic flow based method, and multiple regression method, respectively. The final PCE values are compared to those derived from VISSIM simulation model. The following conclusions are drawn: 1) homogenization based method cannot reveal the variation trend of PCE factors over traffic volume; 2) the results obtained through time headway and traffic flow based methods are more consistent with outcome from simulation model.

A-1 INTRODUCTION
To balance transport costs and time, nowadays increasing motor vehicles have swarmed into freeways. Accordingly, capacity analysis has been of vital importance in planning, design and operation of freeways (Adnan, 2014; Qu et al., 2015 and 2017). However, variations in traffic composition complicate the process. Varying vehicles possess significant differences in size, speed, acceleration and braking capacity, so they cannot be treated as identical. As a result, converting heavy vehicles (HVs) in mixed traffic flow to corresponding number of passenger cars (PCs) is required. The term, passenger car equivalents (PCE) or passenger car units (PCU), was first introduced in the highway capacity manual (HCM) in 1965 and defined as the number of PCs that are displaced by a HV of subject category, under the prevailing roadway and traffic conditions (TRB, 1994). It has been treated as a significant indicator to reveal the adverse impact of HVs on the quality of traffic flow on freeways for several decades (e.g. Adnan, 2014; De Luca and Dell'Acqua, 2013; Elefteriadou et al., 1997; Fan, 1990; Okura and Sthapit, 1995). As per the most recently issued HCM (TRB, 2010), the PCE value was still applied to approximate HV adjustment factors ($f_{HV}$) for basic freeway sections through the following equation:

$$f_{HV} = \frac{1}{1 + P_T (E_T - 1) + P_R (E_R - 1)}$$

(58)

where $P_T$ and $P_R$ are percent trucks and percent creational vehicles. $E_T$ and $E_R$ are PCE values for trucks and creational vehicles, respectively.

According to relatively extensive literature, PCE values are derived from various traffic flow characteristics such as speed, time headway, volume and proportion of HVs as
well as vehicular and freeway characteristics (e.g. Huber, 1982; Jin et al., 2015; Kuang et al., 2015; Qu et al., 2014; Tiwari, 2000; Webster and Elefteriadou, 1999; Meng et al., 2011a&b). They all believe that HVs and PCs should be separately analysed in the vehicle-mixed stream because of the following points: 1) HVs significantly differ from standard PCs in speed and operational characteristics (maneuverability, acceleration, braking, etc.); 2) Compared to PCs, HVs typically need more space and larger time headway to keep safe; 3) the increase in the percentage of HVs in the mixed traffic flow has an effect on traffic operation and efficiency. However, the abovementioned PCE estimates are generally based on homogenous traffic conditions in developed countries and basic freeway sections. There is few research focusing on PCE estimation of HVs on on- and off-ramps and weaving zones. Furthermore, according to Webster and Elefteriadou (1999)’s conclusion, PCE tends to increase with an increase in traffic volume. Therefore, the objective of the paper is to quantify PCE values of HVs on freeway on-ramps. To achieve it, I explored the variation trend in PCE values under varying traffic volume. Five existing methods are applied for the estimation.

The remainder of the paper is organized as follow. Section 2 reviews five existing approaches for PCE factors. Section 3 describes the research segment and the procedure of data collection and processing. Section 4 presents five sets of PCE values and compares them with those provided in HCM (TRB, 2010). Section 5 concludes.

**A-2 EXISTING METHODS FOR PCE ESTIMATES**

This section presents PCE calculation methods which are commonly used by researchers and traffic agents. Among them, time headway based method, traffic flow
based method, multiple regression method, and simulation method are more common (Tiwari et al., 2000).

**A-2.1 Homogenization Based Methods**

The homogenization method (HM) was initially proposed in the 1965 HCM and defined as the ratio of the time spent by the subject HV passing through its own body length to that spent by the PC passing through itself body length. It relies on two variables, the average length and speed of research HVs and standard PCs, mathematically,

\[
PCE_i = \frac{L_i / V_i}{L_c / V_c} = \frac{L_i}{L_c} \times \frac{V_c}{V_i}
\]

where \( L_i \) and \( L_c \) are the mean length of type \( i \) HVs and standard PCs, respectively. \( V_i \) and \( V_c \) are corresponding mean speed. As stated in Chandra and Sikdar (2000), HVs, due to a larger body width, visually squeeze the transverse space of PCs, which psychologically causes drivers’ behavioural characteristics. There is thus a need to consider the width of HVs in the estimation of PCE. They revised the original formula of the HCM by replacing the length of vehicles with the horizontal projected area of vehicles, mathematically,

\[
PCE_i = \frac{A_i / V_i}{A_c / V_c} = \frac{A_i}{A_c} \times \frac{V_c}{V_i}
\]

where \( A_i \) and \( A_c \) are rectangular projected area of type \( i \) HVs and PCs. However, both methods have a limitation in use. They are more appropriate for quantification of PCE for homogeneous traffic in developed countries, as their proposal was based on the traffic conditions of developed countries where the composition of traffic is relatively singularized and most motorists strictly follow the lane discipline of the road.
A-2.2 Time Headway Based Methods

The time headway based methods (THM) have been widely used to calculate PCE values and are built on the notion that HVs following PCs or HVs may have a higher headway compared to the headway between two successive PCs in a saturated and vehicle-mixed flow. It was first proposed by Greenshields et al. (1947) and quantified as a ratio of the average headway for subject HV $i$ to that for standard PC, mathematically

$$PCE_i = \frac{h_i}{h_c}$$ (61)

where $h_i$ is the average time headway for type $i$ HVs, $h_c$ is the average time headway for standard PCs. Time headway, as an essential indicator in traffic flow or capacity analysis, can potentially reflect the temporal space occupied by each vehicle in the longitudinal traffic flow, the variation in traffic volume and driver behaviour (Kimber et al., 1985). However, because of the presence of more than two categories of HVs, the average headways for subject HVs are difficult to obtain from the mixed traffic stream (Yeung et al., 2015). Furthermore, it is more commonly applied in the estimation of PCE for the interrupted flow, namely signalized intersections, according to Marwah and Singh (2000)’s statements.

Krammes and Crowley (1986) further analyzed time headway for four different car-following scenarios in a mixed traffic stream, which reflects headway differences between HVs and PCs. In addition, the effect of non-subject HVs on traffic stream is also taken into account. The revised equation is given as follows,

$$PCE_s = \frac{(1-p)(h_{ps} + h_{sp} - h_{pp}) + ph_{ss}}{h_{pp}}$$ (62)
where $p$ is proportion of HVs in a mixed traffic stream, $h_{pu}$ is mean headway for PCs following HVs of subject class, $h_{ph}$ is mean headway for HVs of subject class following PCs, $h_{pp}$ is mean headway for PCs following PCs, $h_{sh}$ is mean headway for HVs of subject class following HVs of subject class. The data collection needs to focus on four kinds of headways, which may increase the difficulty of using this method.

### A-2.3 Traffic Flow Based Method

Summer et al. (1984) developed the traffic flow based method (TFM) to estimate PCE values based on a flow vs density curve generated by simulation model. In the estimation, it takes into account macroscopic parameters such as traffic flow rate and percent HVs, which reduce the difficulty collecting microscopic parameters such as time headway. The equation is represented as follows,

$$ PCE_s = \frac{1}{\Delta p} \left[ \frac{q_B - q_{B}}{q_s - q_M} \right] + 1 $$

(63)

where $\Delta p$ is the percentage of the subject HVs displacing an equal number of PCs in the mixed traffic flow. Webster and Elefteriadou (1999) recommended it be 5%. $q_B$ is the base vehicle flow rate at a constant traffic density where only PCs are involved. $q_M$ is the mixed vehicle flow rate at a constant traffic density where typical percent HVs are involved. 7.3% of HVs is used in this study. $q_s$ is the subject HV flow rate at a constant traffic density where a certain number of PCs in the mixed traffic stream is replaced with an equal number of the subject PCs. In this case, $q_B$ and $q_s$ are indirectly obtained through flow vs density curve.
**Appendix 1**

**A-2.4 Multiple Linear Regression Model**

The multiple linear regression model (MLRM) has been widely used to calculate PCE factors (Easa et al., 2017; Meng and Qu, 2012; Wang et al., 2013). It was built on the conception that different classes of vehicles in the mixed traffic stream significantly differ in speed reduction potentials. The speed reduction coefficients for different categories of vehicles can be quantified by the relationship between predictor variables (the number of vehicles of different types) and the response variable (the average traffic stream speed under certain traffic volume). MLRM is mathematically given as follows,

$$ MS = u_f + C_1 N_p + C_2 N_h + C_3 N_b + C_4 N_o $$  \hspace{1cm} (64)

where $MS$ is mean traffic stream speed. $u_f$ is free flow speed. $N_p$, $N_h$, $N_b$ and $N_o$ are the number of PCs, HVs, buses and other vehicles in traffic stream, respectively. $C_1$, $C_2$, $C_3$ and $C_4$ are marginal effect of the number of vehicles of different types on mean traffic stream speed. Finally, PCE values for vehicles of type $i$ can be estimated through the following equation.

$$ PCE_i = \frac{C_i}{C_1} $$  \hspace{1cm} (65)

The MLRM is built on premise that the average traffic speed is a linear function of traffic volume. Therefore, it is not appropriate for the estimation of PCE under all traffic scenarios.
A-3 DATA COLLECTION AND PROCESSING

A-3.1 Site Description

The one-hour based traffic data under varying traffic volume is obtained from the zone adjacent to the one-lane zip-merging on-ramp in Queensland, which is shown in Fig. 1.

The study site was selected based on the following criteria:

1. The study site should be in the neighbourhood of on-ramp, which is consistent with my research objective.
2. The vantage point for traffic data recording is required, as some microscopic parameters (e.g. time headway and speed) are retrieved from traffic videos. The quality of videos determines the accuracy of data.
3. The study site ideally has a sound illuminating system, because some data may be collected in the night.
4. The study site should have a wide range of variations in traffic volume.

![Figure 1. The location of data collection point and study site](image-url)
A-3.2 Categorization of Vehicles

Considering the homogeneity of traffic in Queensland, vehicles can be categorized into four groups: 1) trucks with the length of 12.5 meters are viewed as HVs; 2) buses with 12.5 meters are standard buses; 3) 5-meter short cars are regarded as reference PCs; 4) the rest of vehicles in the mixed traffic stream are treated as other vehicles due to the marginal percent composition.

A-3.3 Data Processing

The one-hour based data was collected from nine different time periods, which reflects actual variations in traffic volume. The speeds for 50 HVs and 100 PCs were retrieved from each video and averaged in order to estimate PCE value using HM. HM revised by Chandra and Sikdar (2000) is applied in this study. The parameters for HM are shown in Table 1. THM proposed by Krammes and Crowley (1986) is selected. The proportions of HVs under nine traffic volume were derived from videos. The headways for the following four car-following scenarios were obtained based on 20 corresponding car-following events under each scenario, which is given in Table 2.

<table>
<thead>
<tr>
<th>Traffic flow (vehs/hr/ln)</th>
<th>Time periods</th>
<th>Average speed for HVs (m/s)</th>
<th>Average speed for PCs (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>413</td>
<td>21:00-22:00</td>
<td>26.7</td>
<td>29.8</td>
</tr>
<tr>
<td>609</td>
<td>20:00-21:00</td>
<td>25.0</td>
<td>28.1</td>
</tr>
<tr>
<td>786</td>
<td>19:00-20:00</td>
<td>24.3</td>
<td>27.0</td>
</tr>
<tr>
<td>1008</td>
<td>12:00-13:00</td>
<td>24.0</td>
<td>26.4</td>
</tr>
<tr>
<td>1221</td>
<td>05:00-06:00</td>
<td>23.7</td>
<td>25.9</td>
</tr>
<tr>
<td>1389</td>
<td>16:00-17:00</td>
<td>23.6</td>
<td>25.9</td>
</tr>
<tr>
<td>1610</td>
<td>09:00-10:00</td>
<td>23.5</td>
<td>25.8</td>
</tr>
<tr>
<td>1793</td>
<td>17:00-18:00</td>
<td>23.4</td>
<td>25.8</td>
</tr>
<tr>
<td>2016</td>
<td>06:00-07:00</td>
<td>23.6</td>
<td>25.8</td>
</tr>
</tbody>
</table>
Table 2. The parameters used for THM

<table>
<thead>
<tr>
<th>Traffic flow (vehs/hr/ln)</th>
<th>Proportion of HGVs</th>
<th>Headway for pp (s)</th>
<th>Headway for ss (s)</th>
<th>Headway for sp (s)</th>
<th>Headway for ps (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>413</td>
<td>0.054</td>
<td>6.09</td>
<td>6.28</td>
<td>6.25</td>
<td>6.11</td>
</tr>
<tr>
<td>609</td>
<td>0.063</td>
<td>4.01</td>
<td>4.71</td>
<td>4.45</td>
<td>4.39</td>
</tr>
<tr>
<td>786</td>
<td>0.075</td>
<td>2.93</td>
<td>3.84</td>
<td>3.79</td>
<td>3.41</td>
</tr>
<tr>
<td>1008</td>
<td>0.081</td>
<td>2.28</td>
<td>3.19</td>
<td>3.44</td>
<td>2.89</td>
</tr>
<tr>
<td>1221</td>
<td>0.079</td>
<td>1.80</td>
<td>2.75</td>
<td>2.89</td>
<td>2.46</td>
</tr>
<tr>
<td>1389</td>
<td>0.089</td>
<td>1.54</td>
<td>2.46</td>
<td>2.74</td>
<td>1.99</td>
</tr>
<tr>
<td>1610</td>
<td>0.081</td>
<td>1.20</td>
<td>2.11</td>
<td>2.38</td>
<td>1.59</td>
</tr>
<tr>
<td>1793</td>
<td>0.079</td>
<td>1.08</td>
<td>1.92</td>
<td>2.13</td>
<td>1.46</td>
</tr>
<tr>
<td>2016</td>
<td>0.083</td>
<td>1.06</td>
<td>1.95</td>
<td>2.21</td>
<td>1.39</td>
</tr>
</tbody>
</table>

The parameters in TFM are based on simulation model. In this study, VISSIM was used to simulate and generate three kinds of traffic flow rates, as the dynamics of interaction between PCs and HVs during overtaking and merging and the behaviour of car drivers in the neighbourhood of HVs can be handled internally by VISSIM. It is necessary that VISSIM model need to be calibrated with traffic flow parameters (e.g. time headway, traffic volume, percent HVs, etc.) and be validated with traffic trajectory data extracted from videos recorded on site before use. The parameters used for TFM are shown in Table 3. To estimate PCE values using MLRM, speeds for 100 vehicles were retrieved from each video and averaged. The number of each category of vehicles under nine traffic flow conditions was counted and listed in Table 4.
Table 3. The parameters used for TFM

<table>
<thead>
<tr>
<th>Traffic flow (vehs/hr/ln)</th>
<th>Flow rate for fixed traffic stream (vehs/hr/ln)</th>
<th>Flow rate for base vehicle stream (vehs/hr/ln)</th>
<th>Flow rate for subject HV stream (vehs/hr/ln)</th>
</tr>
</thead>
<tbody>
<tr>
<td>413</td>
<td>421</td>
<td>433</td>
<td>418</td>
</tr>
<tr>
<td>609</td>
<td>611</td>
<td>625</td>
<td>605</td>
</tr>
<tr>
<td>786</td>
<td>795</td>
<td>811</td>
<td>780</td>
</tr>
<tr>
<td>1008</td>
<td>1023</td>
<td>1042</td>
<td>989</td>
</tr>
<tr>
<td>1221</td>
<td>1203</td>
<td>1229</td>
<td>1150</td>
</tr>
<tr>
<td>1389</td>
<td>1411</td>
<td>1446</td>
<td>1322</td>
</tr>
<tr>
<td>1610</td>
<td>1598</td>
<td>1635</td>
<td>1490</td>
</tr>
<tr>
<td>1793</td>
<td>1784</td>
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<td>1674</td>
</tr>
<tr>
<td>2016</td>
<td>1989</td>
<td>2035</td>
<td>1837</td>
</tr>
</tbody>
</table>

Table 4. The parameter used for MLRM

<table>
<thead>
<tr>
<th>Traffic flow (vehs/hr/ln)</th>
<th>Average traffic stream speed (km/hr)</th>
<th>No. of PCs</th>
<th>No. of HVs</th>
<th>No. of buses</th>
<th>No. of other vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>413</td>
<td>102.7</td>
<td>391</td>
<td>15</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>609</td>
<td>98.5</td>
<td>571</td>
<td>26</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>786</td>
<td>94.8</td>
<td>727</td>
<td>44</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>1008</td>
<td>91.9</td>
<td>927</td>
<td>61</td>
<td>14</td>
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<td>88.7</td>
<td>1125</td>
<td>81</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>1389</td>
<td>86.6</td>
<td>1266</td>
<td>96</td>
<td>18</td>
<td>9</td>
</tr>
<tr>
<td>1610</td>
<td>85.4</td>
<td>1480</td>
<td>109</td>
<td>11</td>
<td>10</td>
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<tr>
<td>1793</td>
<td>84.6</td>
<td>1652</td>
<td>123</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>2016</td>
<td>83.1</td>
<td>1849</td>
<td>137</td>
<td>19</td>
<td>11</td>
</tr>
</tbody>
</table>

Due to the lack of a judgement criterion for PCE values, simulation method (SM) was used, as a control group, to compare with PCE values derived from other four methods. In this study, VISSIM simulation model was used to estimate PCE values simply based on freeway merging capacity theory. I let two subject HV only and PC only traffic streams respectively merge into the study area. The maximum number of the subject HVs and PCs merging into the freeway mainline under each traffic volume is obtained through multiple simulation runs. The ratio of the maximum number of PCs merging into the freeway to that of the subject HVs is finally viewed as the PCE value.
Appendix 1

A-4 A COMPARATIVE ANALYSIS

The preliminary results for four different PCE estimates and SM are calculated based on data provided in Section 3 and tabulated in Table 5, which reflects the variation trend of PCE values over the increase in traffic volume.

Table 5. The preliminary results for different PCE methods

<table>
<thead>
<tr>
<th>Traffic flow (vehs/hr/ln)</th>
<th>HM</th>
<th>THM</th>
<th>TFM</th>
<th>MLRM</th>
<th>SM</th>
</tr>
</thead>
<tbody>
<tr>
<td>413</td>
<td>2.79</td>
<td>1.03</td>
<td>1.15</td>
<td>1.58</td>
<td>1.20</td>
</tr>
<tr>
<td>609</td>
<td>2.81</td>
<td>1.20</td>
<td>1.20</td>
<td>1.58</td>
<td>1.26</td>
</tr>
<tr>
<td>786</td>
<td>2.78</td>
<td>1.45</td>
<td>1.39</td>
<td>1.58</td>
<td>1.45</td>
</tr>
<tr>
<td>1008</td>
<td>2.75</td>
<td>1.75</td>
<td>1.70</td>
<td>1.58</td>
<td>1.81</td>
</tr>
<tr>
<td>1221</td>
<td>2.73</td>
<td>1.94</td>
<td>1.94</td>
<td>1.58</td>
<td>2.29</td>
</tr>
<tr>
<td>1389</td>
<td>2.74</td>
<td>2.03</td>
<td>2.38</td>
<td>1.58</td>
<td>2.45</td>
</tr>
<tr>
<td>1610</td>
<td>2.74</td>
<td>2.26</td>
<td>2.48</td>
<td>1.58</td>
<td>2.57</td>
</tr>
<tr>
<td>1793</td>
<td>2.76</td>
<td>2.28</td>
<td>2.32</td>
<td>1.58</td>
<td>2.64</td>
</tr>
<tr>
<td>2016</td>
<td>2.73</td>
<td>2.35</td>
<td>2.69</td>
<td>1.58</td>
<td>2.70</td>
</tr>
</tbody>
</table>

As can be seen in Table 5, PCE values calculated by HM slightly fluctuate with the increase in traffic volume. As the projected area for the subject HVs and reference PCs has been fixed, the PCE value in HM only replies on the ratio of average speed for PCs to that for HVs. The final results reflect the speed is less sensitive to the change in traffic volume, which is consistent with other researchers’ conclusions. Accordingly, HM is not a proper indicator to predict the variation in traffic flow. In THM, traffic volume sensitive parameters, time headway and percent HVs, are taken into account. As a result, PCE values estimated by THM are relatively consistent with those derived from SM, but it slightly underestimate PCE values at high traffic volume conditions. The density-flow curve and simulation based TFM performs slightly better than THM, since its predictor variables are exactly three types of traffic stream rates. Therefore, it is an acceptable indicator to predict the variation in PCE values with the increase in traffic.
flow. MLRM requires a mass of data based on different traffic scenarios. Due to the limitation of data, I simply derive a fixed PCE value under nine traffic scenarios.

A-5 CONCLUSION

The objective of this study is to estimate the variation in PCE values of the subject heavy vehicle, with the increase in traffic volume, for on-ramp adjacent zones. To this end, the zone, in the neighbourhood of a one-lane zip-merging on-ramp in Queensland, Australia, is selected as the study site. Based on data collected from the study site and generated by VISSIM, PCE values are calculated through four existing PCE methods: 1) homogenization based method; 2) time headway based method; 3) traffic flow based method; 4) multiple linear regression model. Besides, simulation method is applied to generate a set of PCE reference values which is a criterion to judge the most appropriate PCE method. Through a comparative analysis, the following conclusions can be drawn: 1) homogenization based method cannot properly predict the variation trend of PCE values over traffic volume due to the low sensitivity of the speed to the change in traffic volume; 2) both time headway and traffic flow based methods can derive the results which are relatively consistent with outcome from simulation model. The developed PCE is very useful for further traffic engineering studies with mixed traffic flow (Easa et al., 2017; Wang et al., 2013).
PUBLICATION LIST

Refereed Journals


Refereed Conferences