REAL-TIME SAFETY AND MOBILITY OPTIMIZATION OF TRAFFIC SIGNALS IN
A CONNECTED-VEHICLE ENVIRONMENT

by

Mohamed Essa

M.Sc., The University of British Columbia, 2015
B.Sc., Ain Shams University, 2008

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in
THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES
(Civil Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA
(Vancouver)

November 2020

© Mohamed Essa, 2020
The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation entitled:

**Real-time safety and mobility optimization of traffic signals in a connected-vehicle environment**

submitted by Mohamed Essa in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Civil Engineering

**Examiner Committee:**

Dr. Tarek Sayed, Professor, Department of Civil Engineering, UBC

Dr. Ziad K. Shawwash, Assistant Professor, Department of Civil Engineering, UBC

Dr. Gregory A Lawrence, Professor, Department of Civil Engineering, UBC

Dr. Annalisa Meyboom, Associate Professor, School of Architecture and Landscape Architecture, UBC

Dr. Alfonso Montella, Professor, Department of Civil, Construction and Environmental Engineering, University of Naples Federico II

**Additional Supervisory Committee Members:**

Dr. Alex Bigazzi, Associate Professor, Department of Civil Engineering, UBC

Dr. Paul de Leur, Manager of Road Safety Programs at Insurance Corporation of British Columbia
Abstract

Adaptive traffic signal control (ATSC) strategies are a promising approach to improving the efficiency of signalized intersections, especially in the era of connected vehicles (CVs) where real-time information on vehicle positions and trajectories is available. Recently, numerous ATSC algorithms have been proposed to accommodate real-time traffic conditions and optimize traffic efficiency. The common objective of these algorithms is to minimize total delays or maximize vehicle throughputs. Despite their positive impacts on traffic mobility, existing ATSC algorithms do not consider optimizing traffic safety. This is most likely due to the lack of tools to evaluate the safety of signalized intersections in real time. This thesis presents several advances toward the real-time safety and mobility optimization of traffic signals in a connected-vehicle environment. First, new models for the real-time safety evaluation of signalized intersections were developed and validated, using traffic video-data of six locations in two Canadian cities. The developed models relate the number of rear-end traffic conflicts, as a surrogate safety measure, to dynamic traffic parameters at the signal cycle level. Several traffic conflict indicators and multiple conflict severity levels were considered. The transferability of the developed models was also investigated and confirmed using additional traffic datasets for two corridors in the United States. Second, a new procedure to integrate the developed real-time safety models with traffic microsimulation models was proposed. The procedure was validated using real-world traffic video data of two signalized intersections in British Columbia. The results showed that the proposed models can predict traffic conflicts from traffic simulation with reasonable accuracy and subsequently can be used to investigate the safety impact of various CVs-based applications before field implementation. Third, a novel self-learning ATSC algorithm to optimize traffic safety using real-time CVs data was proposed. The algorithm was developed using the Reinforcement Learning
approach, trained using a microsimulation model, and validated using real-world traffic data of two signalized intersections in British Columbia. Superior to the traditional actuated signal control system, the proposed algorithm showed positive safety and mobility impacts. The proposed ATSC algorithm was also found to be effective and feasible even under low market penetration rates of CVs.
Lay Summary

In the era of connected vehicles (CVs), a considerable amount of high-resolution data on vehicle positions and trajectories will be generated in real time. These data can potentially be used to adapt traffic signals in real time to optimize traffic mobility and safety. Existing research has focused on real-time mobility optimization at signalized intersections, and disregarded the real-time safety optimization despite the potential safety benefits of the CVs technology. This is most likely due to the lack of tools to evaluate traffic safety at signalized intersections in real time. This thesis presents several advances toward the real-time safety and mobility optimization of traffic signals in a connected-vehicle environment. New methods for the real-time safety evaluation of signalized intersections were proposed using real-world traffic data. Then, a novel adaptive signal control algorithm to optimize traffic safety using CVs data was developed using simulation models and artificial intelligence techniques.
Preface

Articles published in refereed journals:

1) Portions of the introductory text in chapter 1, portions of the literature review in chapter 2, and a version of chapter 3 have been published [Essa, M. and Sayed, T. 2018 “Traffic conflict models to evaluate the safety of signalized intersections at the cycle level.” Transportation Research Part C: emerging technologies, 89, pp.289-302]. I was the lead investigator, responsible for conceptualization, data collection and preparation, formal analysis, software coding, visualization, writing, and manuscript composition. Dr. Sayed T. was the supervisory author and was involved in concept formation and manuscript edits.

2) Portions of the introductory text in chapter 1, portions of the literature review in chapter 2, and a version of chapter 4 have been published [Essa, M. and Sayed, T. 2019 “Full Bayesian conflict-based models for real time safety evaluation of signalized intersections.” Accident Analysis and Prevention, 129, pp.367-381]. I was the lead investigator, responsible for conceptualization, data collection and preparation, formal analysis, software coding, visualization, writing, and manuscript composition. Dr. Sayed T. was the supervisory author and was involved in concept formation and manuscript edits.

3) Portions of the introductory text in chapter 1, portions of the literature review in chapter 2, and a version of chapter 5 have been published [Essa, M., Sayed, T. and Reyad, P. 2019 “Transferability of real-time safety performance functions for signalized intersections.” Accident Analysis and Prevention, 129, pp.263-276]. I was the lead investigator, responsible for conceptualization, data collection and preparation, formal analysis, software coding, visualization, writing, and manuscript composition. Dr. Sayed T. was the supervisory author and was involved in concept formation and manuscript edits. Reyad P.
was involved in the early stages of concept formation and contributed to parts of data preparation and analysis.

4) Portions of the introductory text in chapter 1, portions of the literature review in chapter 2, and a version of chapter 6 have been published [Essa, M. and Sayed, T. 2020 “Comparison between surrogate safety assessment model and real-time safety models in predicting field-measured conflicts at signalized intersections.” Transportation research record, 2674(3), pp.100-112]. I was the lead investigator, responsible for conceptualization, data collection and preparation, formal analysis, software coding, visualization, writing, and manuscript composition. Dr. Sayed T. was the supervisory author and was involved in concept formation and manuscript edits.

5) Portions of the introductory text in chapter 1, portions of the literature review in chapter 2, and a version of chapter 7 have been published [Essa, M. and Sayed, T. 2020 “Self-learning adaptive traffic signal control for real-time safety optimization.” Accident Analysis and Prevention, 146, p.105713]. I was the lead investigator, responsible for conceptualization, data collection and preparation, formal analysis, software coding, visualization, writing, and manuscript composition. Dr. Sayed T. was the supervisory author and was involved in concept formation and manuscript edits.
# Table of Contents

Abstract ......................................................................................................................... iii

Lay Summary .................................................................................................................. v

Preface ............................................................................................................................ vi

Table of Contents .......................................................................................................... viii

List of Tables ................................................................................................................. xv

List of Figures ................................................................................................................. xvii

List of Abbreviations ................................................................................................... xx

Acknowledgements ....................................................................................................... xxii

Dedication ..................................................................................................................... xxiii

# Chapter 1: Introduction ............................................................................................ 1

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

1.2 Problem Statement ................................................................................................. 5

1.2.1 Problem One: Real-time Safety Evaluation for Signalized Intersections .......... 6

1.2.2 Problem Two: Incorporating Conflict Severity and Unobserved Heterogeneity .... 7

1.2.3 Problem Three: Transferability of Real-time Safety Evaluation Methods ........... 7

1.2.4 Problem Four: Integration with Traffic Microsimulation .................................... 8

1.2.5 Problem Five: Real-time Safety Optimization of Traffic Signals Using CVs .......... 9

1.3 Contributions .......................................................................................................... 10

1.3.1 Real-time Safety Models for Signalized Intersections ........................................ 10

1.3.2 A Procedure to Integrate Real-time Safety Models with Traffic Microsimulation .. 12

1.3.3 Adaptive Traffic Signal Control Algorithm for Real-time Safety Optimization ..... 12

1.4 Thesis Structure ..................................................................................................... 13
Chapter 2: Literature Review

2.1 Safety Evaluation of Signalized Intersections ............................................................. 16
  2.1.1 Collision-based SPFs at Signalized Intersections ...................................................... 16
  2.1.2 Transferability of Collision-based SPFs ................................................................. 17
  2.1.3 The Traffic Conflict Technique (TCT) .................................................................. 19
    2.1.3.1 Traffic Conflicts Vs Traffic Collisions ................................................................. 19
    2.1.3.2 Safety Continuum and Traffic Conflict Hierarchy ................................................. 21
    2.1.3.3 Traffic Conflict Indicators ................................................................................. 22
      2.1.3.3.1 Time to Collision (TTC) ................................................................................. 22
      2.1.3.3.2 TTC-based Traffic Conflict Indicators .............................................................. 24
      2.1.3.3.3 Post-encroachment Time (PET) ..................................................................... 26
      2.1.3.3.4 Gap Time (GT) .............................................................................................. 26
      2.1.3.3.5 Deceleration to Safety Time (DST) ................................................................. 27
      2.1.3.3.6 Deceleration Rate to Avoid Crash (DRAC) .................................................. 27
  2.1.4 Conflict-based SPFs at Signalized Intersections ......................................................... 27
  2.1.5 Safety of Signalized Intersection Using Microsimulation Models .......................... 29
  2.1.6 Dilemma Zone and Red-light-runner Violations ......................................................... 32
  2.1.7 Real-time Crash Prediction ....................................................................................... 33
  2.2 Connected Vehicles (CVs) Technology ....................................................................... 34
  2.3 Difference between Automated Vehicles (AVs) and Connected Vehicles (CVs) .......... 37
  2.4 Connected Vehicles in Microsimulation Models ......................................................... 40
  2.5 Adaptive Traffic Signal Control (ATSC) ................................................................... 54
    2.5.1 Implemented ATSC Algorithms .............................................................................. 54
Chapter 3: Real-time Safety Models for Signalized Intersections

3.1 Background

3.2 Study Locations and Data Collection

3.3 Methodology

3.3.1 Shock Waves at Signalized Intersections

3.3.2 Video-data Processing

3.3.2.1 Signal Timing Detection

3.3.2.2 Vehicle Trajectories and Space-time Diagram

3.3.2.3 Shock Wave Analysis

3.3.2.4 Traffic Conflicts

3.3.2.5 Platoon Ratio

3.3.2.6 Summary of Video Data Outputs

3.3.3 Conflict-based SPFs at the Cycle Level

3.4 Results and Discussion

3.4.1 Summary of Data Statistics

3.4.2 Conflict-based SPFs at the Cycle Level (Real-time Safety Models)

3.4.3 Space-time Distribution of Traffic Conflicts

3.5 Potential Applications

3.5.1 Safety Evaluation Using Field-observed Data

3.5.2 Calibration of Microsimulation Models for Safety Evaluation

3.5.3 Real-time Safety Optimization of Signalized Intersections
Chapter 4: Full Bayesian Conflict-based Models for Real-time Safety Evaluation of Signalized Intersections

4.1 Background ........................................................................................................... 86

4.2 Study Locations and Video Data Collection......................................................... 87

4.3 Full Bayesian SPF at the Signal Cycle Level......................................................... 87

4.3.1 Traffic Characteristics ..................................................................................... 87

4.3.2 Number of Traffic Conflicts per Cycle (The Model Response) ...................... 88

4.3.2.1 Time to Collision (TTC) ......................................................................... 88

4.3.2.2 Modified Time to Collision (MTTC)....................................................... 89

4.3.2.3 Deceleration Rate to Avoid Crash (DRAC)............................................. 90

4.3.3 Video Analysis.................................................................................................. 91

4.3.4 Summary of Data Statistics............................................................................... 94

4.3.5 Full Bayesian (FB) Analysis............................................................................ 94

4.3.5.1 PLN Models ............................................................................................... 95

4.3.5.2 PLN Models with Random Intercept ....................................................... 96

4.3.5.3 Prior Distributions...................................................................................... 97

4.3.5.4 Full Bayes Estimation.............................................................................. 98

4.3.5.5 Model Comparison and Goodness-of-Fit............................................... 99

4.3.6 Model Estimates............................................................................................... 99

4.4 Conflict Frequency and Severity ........................................................................ 104

4.4.1 Conflict Frequency Distribution .................................................................... 104

4.4.2 Conflict Severity Distribution ....................................................................... 106
4.4.3 Extended Time to Collision Measures ................................................................. 108
4.4.3.1 Time Exposed to Collision (TET)....................................................................... 108
4.4.3.2 Integrated Time to Collision (TIT) ................................................................. 110
4.5 Summary and Conclusion ....................................................................................... 112

Chapter 5: Transferability of Real-time Safety Models for Signalized Intersections .... 115
5.1 Background ............................................................................................................. 115
5.2 Data Preparation ................................................................................................... 116
5.2.1 Base Jurisdiction Dataset .................................................................................. 116
5.2.2 Destination Jurisdiction Datasets ....................................................................... 117
5.3 Base Models (Canada) .......................................................................................... 120
5.4 Transferability Analysis ......................................................................................... 121
5.4.1 Statistical Measures to Test Transferability ...................................................... 121
5.4.2 Transferability Analysis Approaches ............................................................... 125
5.4.2.1 Application-based Approach ....................................................................... 125
5.4.2.2 Estimation-based Approach ......................................................................... 127
5.4.2.2.1 Intercept and Shape Parameter Calibration ............................................. 127
5.4.2.2.2 Full Model Calibration ........................................................................... 129
5.5 Recommended Real-time Safety Evaluation Model ........................................... 132
5.6 Summary and Conclusion ..................................................................................... 134

Chapter 6: Real-time Safety Models in Traffic Microsimulation ............................. 138
6.1 Background ............................................................................................................ 138
6.2 The Proposed Safety Evaluation Procedure ....................................................... 141
6.3 Validation Using Field-measured Traffic Data ..................................................... 144
6.3.1 Study Locations and Video Data ................................................................. 144
6.3.2 Field-Measured Traffic Conflicts .............................................................. 145
6.3.3 Microsimulation Model ............................................................................. 147
6.3.4 Traffic Conflict Estimation from Simulation Models ................................. 149
  6.3.4.1 SSAM .................................................................................................... 149
  6.3.4.2 Real-time Safety Models ...................................................................... 149
6.4 Results and Discussion ............................................................................... 150
6.5 Case Study ................................................................................................... 156
  6.5.1 CTR Signal Control Algorithm ................................................................. 157
  6.5.2 Mobility and Safety Impacts of CTR ....................................................... 157
6.6 Summary and Conclusion ........................................................................... 159

Chapter 7: Self-learning Adaptive Traffic Signal Control for Real-time Safety

Optimization ........................................................................................................... 162

  7.1 Background .................................................................................................. 162

  7.2 The Proposed RS-ATSC Algorithm ............................................................. 165
    7.2.1 Real-time safety models ......................................................................... 165
    7.2.2 Reinforcement Learning ........................................................................ 165
    7.2.3 Q-learning ............................................................................................ 166
    7.2.4 State Representation .............................................................................. 169
    7.2.5 Action Representation .......................................................................... 172
    7.2.6 Reward Representation ......................................................................... 173
    7.2.7 Learning Rate and Discount Rate ......................................................... 174
    7.2.8 Exploration Versus Exploitation ........................................................... 174
7.2.9 Modeling the Environment .................................................................................. 175
7.2.10 Training the Algorithm .................................................................................... 177
7.3 Validation Using Real-world Traffic Data ......................................................... 179
  7.3.1 Real-world Traffic Data .................................................................................. 179
  7.3.2 Calibrated Simulation Models ....................................................................... 180
  7.3.3 Safety and Operational Performance of the Proposed Algorithm .............. 182
  7.3.4 Validation Results ......................................................................................... 183
  7.3.5 Effect of CVs Market Penetration Rate ....................................................... 189
7.4 Summary and Conclusion .................................................................................... 192

Chapter 8: Conclusion and Future Research .......................................................... 196
  8.1 Summary and Conclusions ................................................................................ 196
    8.1.1 Real-time Safety Models for Signalized Intersections ............................ 197
    8.1.2 A Procedure to Integrate Real-time Safety Models with Traffic Microsimulation 199
    8.1.3 Adaptive Traffic Signal Control Algorithm for Real-time Safety Optimization .... 201
  8.2 Study Limitations and Future Research ............................................................. 202

Bibliography ............................................................................................................. 207
**List of Tables**

Table 1.1 Thesis structure .................................................................................................................. 15

Table 2.1 Sample of previous studies that adopted the HSM’s calibration procedure ............. 18

Table 2.2 Summary of previous research on CVs using microsimulation models ....................... 50

Table 2.3 Summary of previous research on CVs using microsimulation models (continued) ... 51

Table 2.4 Summary of previous research on CVs using microsimulation models (continued) ... 52

Table 2.5 Summary of previous research on CVs using microsimulation models (continued) ... 53

Table 3.1 Description of the study locations ....................................................................................... 62

Table 3.2 Summary of data statistics .................................................................................................. 76

Table 3.3 Conflict-based SPFs at the cycle level ............................................................................... 77

Table 4.1 Summary of data statistics .................................................................................................. 94

Table 4.2 PLN Models for different conflict indicators ........................................................................ 101

Table 4.3 PLN models with random intercept (incorporating site effect) for different conflict indicators .................................................................................................................. 102

Table 5.1 Summary of statistics - base jurisdiction dataset (Canada) ............................................ 117

Table 5.2 Location of the two destination jurisdictions ........................................................................ 119

Table 5.3 Summary of statistics - destination jurisdiction datasets (USA) ................................... 120

Table 5.4 Base models developed from the base jurisdiction dataset (Canada) ......................... 121

Table 5.5 Transferring the base SPFs to the destination jurisdictions without calibration .......... 126

Table 5.6 Transferring the base SPFs to the destination jurisdictions with calibration of the model intercept and the shape parameter ............................................................................. 128

Table 5.7 SPFs at the cycle level developed at the destination jurisdictions .............................. 130

Table 5.8 Goodness-of-fit measures of SPFs developed at the destination jurisdictions ....... 132
Table 6.1 Calibrated VISSIM parameters [47] [48] ................................................................. 148
Table 6.2 Mobility and safety impacts of CTR at the selected intersection ......................... 158
Table 7.1 Calibrated VISSIM parameters [47] [48] ................................................................. 181
Table 7.2 Safety optimization results of the proposed RS- ATSC algorithm compared to the ASC .......................................................................................................................... 188
List of Figures

Figure 2.1 The safety pyramid (Source: [86]) ................................................................. 21
Figure 2.2 Automated and connected vehicles (Source: [9]).............................................. 38
Figure 2.3 Automation levels according to SAE J3016 (Source: [140]) ............................. 39
Figure 2.4 Advanced transportation technology (Source: [10]) ......................................... 40
Figure 3.1 Study locations in the city of Edmonton, Alberta ............................................... 60
Figure 3.2 Study locations in the city of Surrey, British Columbia ..................................... 61
Figure 3.3 Theory of shock wave at signalized intersections ............................................. 64
Figure 3.4 Platform of extract vehicle trajectories and plot space-time diagram using video data ........................................................................................................................................... 68
Figure 3.5 Measurements (Outputs) of the video-data analysis process .............................. 72
Figure 3.6 Space-time heat map for rear-end conflicts (TTC < 1.5 seconds) for all studied locations ................................................................................................................................................... 80
Figure 3.7 Space-time heat map for rear-end conflicts (TTC < 3 seconds) for all studied locations ................................................................................................................................................... 80
Figure 4.1 Samples of space-time diagram results (32 traffic signal cycles) ....................... 92
Figure 4.2 Measurements (outputs) of video data analysis process .................................... 93
Figure 4.3 Conflict frequencies (based on different TTC thresholds) versus traffic signal timing ..................................................................................................................................................... 105
Figure 4.4 Minimum TTC values versus traffic signal timing .............................................. 107
Figure 4.5 Severity index values (based on TTC) versus traffic signal timing .................. 107
Figure 4.6 Time exposed to collision (TET) at the signal cycle versus the shock wave area and platoon ratio ........................................................................................................................................ 110
Figure 4.7 Integrated time to collision (TIT) at the signal cycle versus the shock wave area and platoon ratio ................................................................. 112
Figure 5.1 Example of the space-time diagram for one cycle with traffic characteristics selected for the SPFs ........................................................................................................ 116
Figure 5.2 Destination jurisdictions ......................................................................................................................... 118
Figure 6.1 The proposed procedure to predict rear-end conflicts at signalized intersections........ 142
Figure 6.2 Study locations and video scenes ......................................................................................................... 145
Figure 6.3 Computer vision video-analysis process ............................................................................................... 146
Figure 6.4 Field-measured conflicts versus SSAM conflicts and real-time safety models’ conflicts before and after VISSIM calibration..................................................................... 151
Figure 6.5 Cycle parameters (shock wave area and traffic volume) estimated from field-measured trajectories and simulated trajectories (before and after calibration) for 4 hours at the eastbound approach of the first intersection ......................................................... 155
Figure 7.1 The agent–environment interaction in reinforcement learning [54].......................... 166
Figure 7.2 Modelling an isolated signalized intersection with connected-vehicles in a simulation platform for the proposed RS-ATSC algorithm ................................................................. 177
Figure 7.3 Learning progress of the proposed RS-ATSC algorithm .................................................. 179
Figure 7.4 Study locations and video scenes ................................................................................................. 180
Figure 7.5 Traffic conflicts at the selected intersections before and after implementing the RS-ATSC ................................................................................................................................. 184
Figure 7.6 Real-time variation of the conflict rate at each approach of the first intersection (72 Ave and 128 St) before and after implementing the proposed RS-ATSC............................... 185
Figure 7.7 Real-time variation of the conflict rate at each approach of the second intersection (72 Ave and 132 St) before and after implementing the proposed RS-ATSC ................................. 185
Figure 7.8 Cumulative traffic conflicts each approach of the first intersection (72 Ave and 128 St) before and after implementing the proposed RS-ATSC .................................................. 186
Figure 7.9 Cumulative traffic conflicts each approach of the second intersection (72 Ave and 132 St) before and after implementing the proposed RS-ATSC .................................................. 186
Figure 7.10 The effect of the CVs MPR value on the average conflict rate at the selected intersections when implementing the proposed RS-ATSC .................................................. 191
Figure 7.11 The effect of the CVs MPR value on the average delay time at the selected intersections when implementing the proposed RS-ATSC .................................................. 192
# List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AADT</td>
<td>Annual Average Daily Traffic</td>
</tr>
<tr>
<td>ACPM</td>
<td>Aggregated Crash Propensity Metric</td>
</tr>
<tr>
<td>AIC</td>
<td>Akaike’s Information Criterion</td>
</tr>
<tr>
<td>ATSC</td>
<td>Adaptive Traffic Signal Control</td>
</tr>
<tr>
<td>AVs</td>
<td>Automated (Autonomous) Vehicles</td>
</tr>
<tr>
<td>BA</td>
<td>Before-And-After</td>
</tr>
<tr>
<td>BC</td>
<td>British Columbia</td>
</tr>
<tr>
<td>BGR</td>
<td>Brooks–Gelman–Rubin</td>
</tr>
<tr>
<td>BSM</td>
<td>Basic Safety Message</td>
</tr>
<tr>
<td>CAVs</td>
<td>Connected Autonomous Vehicles</td>
</tr>
<tr>
<td>CMEM</td>
<td>Comprehensive Modal Emission Model</td>
</tr>
<tr>
<td>CPI</td>
<td>Crash Potential Index</td>
</tr>
<tr>
<td>CTR</td>
<td>Cumulative Travel-Time Responsive</td>
</tr>
<tr>
<td>CURE</td>
<td>Cumulative Residual</td>
</tr>
<tr>
<td>CVIC</td>
<td>Cooperative Vehicle Intersection Control</td>
</tr>
<tr>
<td>CVs</td>
<td>Connected Vehicles</td>
</tr>
<tr>
<td>DIC</td>
<td>Deviance Information Criterion</td>
</tr>
<tr>
<td>DP</td>
<td>Dynamic Programming</td>
</tr>
<tr>
<td>DQN</td>
<td>Deep Q-Network</td>
</tr>
<tr>
<td>DRAC</td>
<td>Deceleration Rate to Avoid Crash</td>
</tr>
<tr>
<td>DSRC</td>
<td>Dedicated Short Range Communication</td>
</tr>
<tr>
<td>DST</td>
<td>Deceleration to Safety Time</td>
</tr>
<tr>
<td>EB</td>
<td>Empirical Bayes</td>
</tr>
<tr>
<td>FB</td>
<td>Full Bayesian</td>
</tr>
<tr>
<td>FHWA</td>
<td>Federal Highway Administration</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
</tr>
<tr>
<td>GLM</td>
<td>Generalized Linear Models</td>
</tr>
<tr>
<td>GLOSA</td>
<td>Green Light Optimized Speed Advisory</td>
</tr>
<tr>
<td>GOF</td>
<td>Goodness-Of-Fit</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Position System</td>
</tr>
<tr>
<td>GT</td>
<td>Gap Time</td>
</tr>
<tr>
<td>HCM</td>
<td>Highway Capacity Manual</td>
</tr>
<tr>
<td>HSDW</td>
<td>High-Speed Differential Warning</td>
</tr>
<tr>
<td>HSM</td>
<td>Highway Safety Manual</td>
</tr>
<tr>
<td>IDM</td>
<td>Intelligent Driver Model</td>
</tr>
<tr>
<td>MAD</td>
<td>Mean Absolute Deviation</td>
</tr>
<tr>
<td>MAPD</td>
<td>Mean Absolute Percentage Error</td>
</tr>
</tbody>
</table>
Acknowledgements

I would like to express my deepest gratitude to my advisor, Dr. Tarek Sayed, for his excellent guidance, caring, patience, and providing me with an excellent atmosphere for doing research. He has been a tremendous mentor from whom I have learned a lot during my work at UBC. His enthusiasm for research has always kept me inspired. Without his guidance, this thesis would have never been completed. I will always feel fortunate that I had him as my supervisor.

I would like to thank my supervisory committee for their positive feedback and valuable suggestions for my thesis. Special thanks to Dr. Alex Bigazzi, Dr. Paul de Leur, and Dr. Ziad Shawwash for their constructive comments and thoughtful questions. I would also like to thank the professors and instructors in the Civil Engineering Department at UBC who impacted my graduate study throughout the coursework.

I would like to thank my colleagues from the transportation research group for their amazing friendship. Special thanks to Mohamed Zaki, Mohamed Hussein, and Ahmed Tageldin for their help at the beginning in several aspects related to the computer vision video analysis. I would also like to thank Ahmed Osama for his help in the Full Bayesian analysis. Further thanks to Howard Lin, Dina Sayed, Maria Albitar, Payam Nasernejad for their help in the data collection.

Finally, but foremost, I am deeply grateful for my parents, my sister, and my brother who have always been by my side, supporting and encouraging me with their best wishes. I would like to thank my wife, Passant, and my daughter, Judy. They were always there cheering me up and stood by me through the good and bad times.
Dedication

To my parents, Ahmed and Lobna; my wife, Passant; my daughter, Judy; and my twin sons, Ahmed and Omar.
Chapter 1: Introduction

1.1 Background

Road collisions are a major cause of death among all age groups and the leading cause of death for young people aged 5–29 years. According to the World Health Organization (WHO), about 1.3 million people die and 20-50 million are injured every year as a result of road collisions around the world [1]. In Canada, road collisions result in about 1,900 fatalities and 165,000 injuries annually, and the annual cost of road collisions to the Canadian economy is estimated at $CDN 62.7 billion [2]. In many jurisdictions such as British Columbia (BC), insurance premiums are spiraling ever higher as auto insurance companies face considerable losses [3]. Therefore, the importance of research into reducing the social and economic costs of road collisions cannot be overstated.

Approximately 25% of all road collisions in Canada occur at signalized intersections, according to the national collision database (NCDB) provided by Transport Canada [4]. In BC, collisions at intersections constitute 35% of the total number of collisions [5]. For many signalized intersections, especially those among urban corridors, collision frequencies and severities remain high despite the implementation of various geometric and traffic measures. Traffic collisions at signalized intersections can occur for a number of reasons, including stop-and-go conditions, dilemma zones (i.e. when it is difficult for the driver to decide whether to stop or to proceed during the onset of the yellow light), left and right turn movements, red-light violations, and shock waves, among others. In addition to being hazard locations, signalized intersections are also common sites of traffic congestion, possibly due to inadequate traffic capacity or poor signal control. Traffic congestion is a growing problem that affects the quality of life, the environment, and the economy.
According to Transport Canada [6], traffic congestion costs to the Canadian economy range from $3.1 billion nationally, under the 50% threshold (movements at less than 50% of free-flow speeds are considered as congestion), to $3.9 billion under the 60% threshold, and $4.6 billion under the 70% threshold.

One of the promising solutions to improve traffic safety and mobility at signalized intersections is the emerging Connected-Vehicles (CVs) technology. The concept of CVs refers to the capability of various elements of the transportation system (vehicles, bicycles, pedestrians, road infrastructure, traffic control, management centers, etc.) to continuously intercommunicate in real time [7]. Connected vehicles use wireless technology to connect with each other [i.e., vehicle to vehicle communication (V2V)] and/or with transportation infrastructures [i.e., vehicle to infrastructure (V2I)]. The two communication types V2V and V2I are generally denoted as V2X, which means a communication between a connected vehicle and any other device (e.g., vehicle, infrastructure, smartphone, etc.). The V2V connectivity allows vehicles to share their position, speed, brake status, and other information in real time with other similar connected vehicles [8]. Meanwhile, the V2I connectivity allows real-time exchange of information between the connected vehicle and the transportation infrastructures equipped by the CV technology, such as traffic signals, roadway signage, and traffic management centers. Both V2V and V2I communications occur over dedicated short-range communication (DSRC) systems. The DSRC is a wireless technology that allows rapid communications (up to 10 times per second) between connected vehicles within a distance ranges from 150 to 300 meters [7]. The most common data element is called a basic safety message (BSM). The BSM contains a vehicle’s location, speed, direction, brake status, and other information [9] [10].
The CVs technology has recently become an area of increasing interest among researchers and practitioners. This technology is moving rapidly from the experimental phase into real-world applications and is expected to be the next generation of intelligent transportation systems [7]. In the era of CVs, a considerable amount of high-resolution data on vehicle positions and trajectories can be generated in real time. Analyzing such big traffic data in real time has become feasible with the availability of innovative machine learning and artificial intelligence techniques. This enables developing strategies for real-time traffic optimization at signalized intersections. Through real-time connectivity and data transmissions, drivers can be supported with advisories and warnings to avoid collisions or unnecessary delays. In addition, traffic control devices, such as traffic signals and variable message signs, can be adapted in real time to relieve congestion and improve safety. Existing research has demonstrated that CVs can potentially have considerable mobility, safety, and environmental sustainability benefits to road networks (e.g., [10] [11] [12]).

Using real-time CVs data to optimize traffic mobility at signalized intersections has been widely investigated in the literature. Over the past decade, numerous studies have proposed several traffic signal optimization procedures to minimize traffic delays, maximize throughput capacity, and/or minimize queue lengths (e.g., [13] [14] [15] [16] [17] [18] [19]). A few studies have also considered minimizing emissions and fuel consumption as objectives for the real-time signal optimization process to improve the environmental sustainability of signalized intersections (e.g., [20] [21]). However, the real-time safety optimization of traffic signals has generally been disregarded in existing research despite the potential safety benefits of CVs. This is mainly because safety optimization is generally more complicated than mobility optimization. Unlike vehicle delay and travel time, the safety level of signalized intersections cannot be directly estimated in
real time from CVs data. The main challenge is the lack of tools to evaluate the safety of signalized intersections in real time.

Traditionally, the safety of signalized intersections has often been evaluated at an aggregate level using safety performance functions (SPFs) [22]. These SPFs relate historical collision records to the traffic and geometric characteristics of the intersection. Although collision-based SPFs of signalized intersections have been widely developed and calibrated in the literature [22] [23] [24] [25] [26], they cannot be used for evaluating safety in real-time. In fact, relying on collision data in modeling real-time safety is very difficult for several reasons. First, the use of the historical collision data in safety analysis requires collisions to occur and be recorded over an adequately long period (usually years) to conduct a statistically sound safety diagnosis [27] [28]. Second, the use of several years of collisions requires reliance on aggregate exposure measures such as the annual average daily traffic (AADT), which does not explicitly account for the fact that not all vehicles are interacting unsafely and does not represent the variation of traffic flow within shorter periods. Third, important signal cycle-related variables that can affect intersection safety such as the arrival type (i.e., a parameter that describes the quality of vehicle progression at signalized intersections) and the shock wave characteristics are usually omitted due to the traffic data aggregation.

To overcome some of the limitations of collision data, the traffic conflict technique (TCT) has been advocated as a proactive approach to study road safety from a broader perspective than relying only on collision data analysis [28] [27] [29]. A traffic conflict is defined as “an observable situation in which two or more road users approach each other in space and time to such an extent
that there is a risk of collision if their movements remained unchanged" [30]. A number of traffic conflict indicators based on time and space proximity were developed in the literature. The most common indicators are: Time to collision (TTC) [31], Modified time to collision (MTTC) [32], Post-encroachment time (PET) [33], Deceleration to safety time (DST) [34], Deceleration rate to avoid the crash (DRAC) [35] [36], Time exposed time-to-collision (TET) [37], and Time integrated time-to-collision (TIT) [37]. Traffic conflicts are more frequent than collisions, can be clearly observed, and can provide insight into the failure mechanism that leads to collisions. Previous research has shown that reducing traffic conflicts can lead to a reduction in the frequency of road collisions [38] [39]. The use of traffic conflicts for safety diagnosis has recently been accepted among road safety researchers as a surrogate or a complementary approach to the collision data analysis approach. Several studies have attempted to develop SPFs for signalized intersections using traffic conflicts as an alternative to traffic collisions [27] [40] [41]. In these studies, the exposure measure is usually represented by the average hourly traffic volume, while traffic conflicts are usually aggregated to hours (i.e. number of conflicts/hour). However, similar to the collision-based SPFs, due to traffic data aggregation and the lack of including dynamic traffic variables, the conflict-based SPFs still cannot be used for evaluating the safety of signalized intersections in real time.

1.2 Problem Statement

Optimizing traffic signals in real time for mobility and safety performances can be achieved in the era of CVs when real-time information on vehicle positions and trajectories is available. Previous studies have mainly focused on using CVs data for real-time mobility optimization. On the other side, the real-time safety optimization of traffic signals has generally been disregarded, despite the
potential safety benefits of CVs. The main challenge is the lack of tools to evaluate the safety of signalized intersections in real time. Such a challenge suggests the need for more research. In fact, there is a growing need to develop real-time safety evaluation methods for signalized intersections. These methods must consider the effect of various dynamic traffic parameters (e.g., traffic volume, shock waves, etc.) on safety within short time-periods (i.e., a few seconds). Subsequently, these methods would provide insight into how real-time changes in traffic signal design can affect safety. This will pave the way for developing new strategies that utilize CVs data to adapt traffic signals in real time (e.g., adaptive traffic signal control algorithms) to optimize traffic safety and mobility. The overall goal is to maximize the potential benefits of the emerging CVs technology, leading to less congestion and fewer collisions at signalized intersections. Within this overall goal, this thesis presents a number of solutions for several existing research gaps. Specifically, this thesis aims to solve the following research problems:

1.2.1 Problem One: Real-time Safety Evaluation for Signalized Intersections

Collisions at signalized intersections can occur for several reasons including drivers’ behavior in dilemma zones, approach queues, and shock waves [42] [43]. For intersection safety solutions that target these collisions, evaluating safety in real time is essential to understand how real-time changes in traffic parameters and signal control affect safety. The real-time safety evaluation is also a prerequisite for developing new adaptive traffic signal control strategies that utilize real-time CVs data to optimize traffic safety at signalized intersections. Unfortunately, the existing safety evaluation methods cannot evaluate safety in real time, since they aggregate traffic data and disregard dynamic traffic parameters that can affect safety. Therefore, there is a growing need to develop new methods for real-time safety evaluation at signalized intersections. This need lays the ground for the following research problem:
“Develop real-time safety models (i.e., real-time SPFs) for signalized intersections that can be used to evaluate safety in real time based on dynamic traffic variables. The models must be able to predict the safety level of the signalized intersection within a short time-period (i.e., a few seconds). The models should be developed by relating a measure of safety to dynamic traffic parameters (e.g., traffic volume, shock wave characteristics, and platoon ratio), using real-world traffic data. Traffic conflicts are a promising measure of real-time safety since they are more frequent than collisions and can be clearly observed.”

1.2.2 Problem Two: Incorporating Conflict Severity and Unobserved Heterogeneity

Since the aforementioned real-time safety models use traffic conflicts as a measure of safety, it is suggested to incorporate various traffic conflict indicators with different severity levels in the developed models. Moreover, the developed models should account for unobserved heterogeneity and variation of traffic conditions across different sites. This gives the rise for the following research problem:

“Develop real-time safety models for signalized intersections using various traffic conflict indicators and considering different severity levels. In addition, using an advanced statistical approach that can account for the unobserved heterogeneity and site variation is required.”

1.2.3 Problem Three: Transferability of Real-time Safety Evaluation Methods

For a wider application of the developed real-time safety models, their transferability to other jurisdictions needs to be examined. This formulates the following research problem:

“Investigate the transferability of the developed real-time safety models. The transferability analysis should include evaluating the models’ performance at new jurisdictions. The state-of-the-art measures of transferability and goodness-of-fit should be estimated to test the validity of using the developed models for real-time safety evaluation at signalized intersections.”
1.2.4 Problem Four: Integration with Traffic Microsimulation

After developing the real-time safety models and investigating their transferability, it is suggested to integrate them with traffic microsimulation models. This integration will enable evaluating the safety of signalized intersection from simulation results. The importance of such integration comes from the fact that traffic microsimulation models are frequently used to develop and test new applications, especially those related to emerging technologies such as connected and autonomous vehicles.

It should be noted that traffic microsimulation models can be used to evaluate traffic safety by analyzing simulated vehicle trajectories using the Surrogate Safety Assessment Model (SSAM) to estimate the number and severity of traffic conflicts [44]. However, recent research showed that evaluating safety using SSAM is associated with several limitations [45] [46] [47] [48] [49]. First, a rigorous calibration procedure must be applied to the simulation model to obtain reliable conflict results. Second, simulation models, in many cases, do not accurately represent the actual driving behavior. Subsequently, they often fail to capture the actual mechanism generating near misses.

Given the previously mentioned limitations of SSAM, a new alternative procedure for evaluating the safety of signalized intersections is needed. The procedure can combine simulated vehicle trajectories with real-time safety models to evaluate traffic safety. Such a procedure will benefit from the simulation models’ ability to provide reliable estimates of dynamic traffic parameters (such as traffic volume, shockwave characteristics, platoon ratio) and from the real-time safety models’ ability to predict traffic conflicts. Meanwhile, the procedure will avoid some of the SSAM limitations. This leads to the following research problem:
“Develop a new procedure, alternative to SSAM, for evaluating the safety of signalized intersections from traffic simulation. The procedure can combine simulated vehicle trajectories with real-time safety models to predict the number of traffic conflicts. The conflict prediction should be based on dynamic traffic parameters repeatedly measured from simulation over a short time interval (e.g. a few seconds). The proposed procedure must be validated using real-world traffic data.”

1.2.5 Problem Five: Real-time Safety Optimization of Traffic Signals Using CVs

The development of real-time safety models enables developing adaptive traffic signal control (ATSC) strategies for real-time safety optimization. The ATSC is a promising technique to improve the efficiency of signalized intersections, especially in the era of CVs when real-time information on vehicle positions and trajectories is available. Numerous ATSC algorithms have been proposed in the literature to accommodate real-time traffic conditions and optimize traffic efficiency (e.g., [13] [14] [15] [16] [17] [18] [19]). The common objective of these algorithms is to minimize total delay, decrease queue length, or maximize vehicle throughput. Despite their positive impacts on traffic mobility, the existing ATSC algorithms do not consider optimizing traffic safety. This lays the ground for the following research problem:

“Develop an ATSC algorithm that utilizes real-time CVs data to optimize the safety of signalized intersections, without deteriorating mobility. The algorithm can be developed using real-time safety models integrated with a microsimulation platform. The algorithm should be validated using real-world traffic data. The safety and the mobility performance of the algorithm must be compared to the state-of-the-art traffic signal control system. Lastly, the algorithm’s performance should be tested under various market penetration rates (MPRs) of CVs.”
1.3 Contributions

The work provided in this thesis aims to tackle the previously mentioned research problems. The contributions of this thesis represent several advances toward the real-time safety and mobility optimization of traffic signals in a connected-vehicle environment. Specifically, this thesis has three main contributions. First, the thesis advocates new models to evaluate the safety of signalized intersections in real time. The models utilize real-time dynamic traffic parameters to predict the safety level of signalized intersections within a short time-period (i.e., a few seconds). Second, the thesis proposes an approach to integrate the developed real-time safety models with traffic microsimulation models. Third, the thesis presents a novel ATSC algorithm that optimizes traffic safety using real-time CVs data. The following sections provide a detailed description of the thesis contributions.

1.3.1 Real-time Safety Models for Signalized Intersections

a) Real-time safety model (i.e., real-time SPF) for signalized intersections were developed using the state-of-the-art statistical analysis methods in road safety. The models relate the number of rear-end conflicts occurring in each signal cycle to dynamic traffic parameters such as traffic volume, maximum queue length, shock wave characteristics (e.g. shock wave speed and shock wave area), and the platoon ratio. Time to collision (TTC) \[31\] was used as a traffic conflict indicator. The developed models can provide insight into how real-time changes in the signal cycle design affect the safety of signalized intersections.

b) To develop the real-time safety models, real-world traffic video data obtained from several signalized intersections were analyzed. A new video analysis procedure was proposed to precisely collect dynamic traffic parameters and estimate traffic conflicts at the signal cycle level. As such, no hourly aggregation was needed. The proposed video analysis procedure
was applied to create an extensive traffic database that contains detailed vehicle trajectories, dynamic traffic parameters, and signal timing data of approximately 765 signal cycles at 6 signalized intersections in the city of Surrey, British Columbia, and the city of Edmonton, Alberta. This database is being expanded and analyzed in a number of ongoing research projects and is considered as a secondary contribution of this thesis.

c) Conflict heat maps were developed to investigate the spatial and temporal distribution of traffic conflicts.

d) Additional real-time safety models for signalized intersections were also developed to incorporate various traffic conflict indicators, including the Time to collision (TTC) [31], the Modified time to collision (MTTC) [32], and the Deceleration rate to avoid the crash (DRAC) [35] [36]. To account for different severity levels, the models were developed by identifying conflicts at several thresholds of TTC, MTTC, and DRAC. In addition, conflict severity and temporal distributions were investigated. The Severity Index (SI) based on TTC [50], the extended time to collision measures (Time exposed time-to-collision (TET) and Time integrated time-to-collision (TIT) [37]) were investigated.

e) The additional real-time safety models were developed using the Full Bayesian (FB) approach to address the unobserved heterogeneity and the variation among different sites. Two kinds of FB models were developed: (1) Poisson-LogNormal distribution (PLN) models that account for heterogeneity; and (2) PLN models with a random intercept that account for heterogeneity and site effect.

f) The transferability of the developed real-time safety models to new jurisdictions was investigated. Two corridors of signalized intersections in California and Atlanta, USA, were used in the analysis as destination jurisdictions. Detailed vehicle trajectories for these
corridors were obtained from the Next Generation Simulation (NGSIM) data [51]. The state-of-the-art approaches of the transferability analysis were applied. Several goodness-of-fit measures were examined to assess the ability of the developed models to predict traffic conflicts at new jurisdictions.

1.3.2 A Procedure to Integrate Real-time Safety Models with Traffic Microsimulation

a) A new procedure, superior to SSAM, for evaluating the safety of signalized intersections from traffic simulation was proposed. The procedure combines simulated vehicle trajectories with the developed real-time safety models to predict rear-end conflicts at the intersection’s approaches. The conflict prediction is based on dynamic traffic parameters, such as traffic volume and shock wave characteristics, repeatedly measured over a short time interval (e.g. a few seconds). The proposed procedure benefits from the simulation models’ ability to provide reliable estimates of these dynamic parameters.

b) The proposed procedure was validated using real-world traffic conflict data extracted from 54 hours of video recordings at two signalized intersections in the city of Surrey, British Columbia. The procedure’s performance in predicting traffic conflicts was also compared with SSAM.

c) As an illustrative case study, the proposed procedure was applied to evaluate the safety impact of a recently-developed real-time adaptive traffic signal control (ATSC) algorithm [13], which aims to minimize total delays in the CVs environment.

1.3.3 Adaptive Traffic Signal Control Algorithm for Real-time Safety Optimization

a) A novel self-learning ATSC algorithm to optimize the safety of signalized intersections using real-time CVs data was proposed. The algorithm is referred to as RS-ATSC (Real-time Safety-optimized Adaptive Traffic Signal Control). The RS-ATSC algorithm has
several advantages. First, although the algorithm was developed and trained using the simulation platform VISSIM [52], the safety evaluation is not based on simulated conflicts that were shown not to well represent actual-field conflicts and crashes [47] [48] [53]. Rather, the optimization is based on real-time safety models that were originally developed and validated using real-world traffic data. Second, the algorithm was developed using the Reinforcement Learning (RL) technique [54] as an efficient approach to solving the ATSC problem considering real-time and stochastic traffic changes [55] [56] [57]. Third, the algorithm is practical since it respects all traffic signal operation standards, including the phasing sequence, the minimum/maximum green time, and the intersection clearance time. Lastly, to the best of the author’s knowledge, this is the first self-learning ATSC algorithm that optimizes traffic safety in real time (i.e., safety is evaluated and optimized over a very short time-period, a few seconds).

b) The proposed RS-ATSC algorithm was validated using real-world traffic data obtained from two signalized intersections in the city of Surrey, British Columbia.

c) The proposed RS-ATSC algorithm is superior to the traditional actuated signal control (ASC) system in terms of the number of traffic conflicts, the average delay time, the number of stops, the maximum queue length, and the 95th percentile of queue length.

d) The proposed RS-ATSC algorithm was tested under various MPRs of CVs and was found to be effective and feasible under low MPR values.

1.4 Thesis Structure

This thesis is divided into eight chapters. This chapter includes an introduction to the thesis, statement of the research problems, the key contributions, and the thesis structure. Chapter two provides a detailed literature review of previous research related to the topics addressed in the
thesis. Chapter three describes the development of real-time safety models for signalized intersections using real-world traffic video data. Chapter four presents the development of the Full Bayesian real-time safety models that incorporate conflict severity and unobserved heterogeneity. Chapter five contains the transferability analysis of the developed real-time safety models to new jurisdictions. Chapter six presents a procedure to integrate the developed real-time safety models with traffic microsimulation models. Chapter seven provides details on the developed self-learning adaptive traffic signal control algorithm for real-time safety optimization. Finally, chapter eight contains a summary of the thesis, the key findings of this research, and the suggested future research areas. An outline of the research problems and contributions in each chapter is presented in Table 1.1.
Chapter 1: Background, research problems, and key contributions

Chapter 2: Literature review

Chapter 3: Development of real-time safety models for signalized intersections using real-world traffic video data

Chapter 4: Development of Full Bayesian real-time safety models that incorporate conflict severity and unobserved heterogeneity

Chapter 5: Transferability analysis of the developed real-time safety models to new jurisdictions

Chapter 6: Integrating the real-time safety models with traffic microsimulation models

Chapter 7: Self-learning adaptive traffic signal control algorithm for real-time safety optimization

Chapter 8: Summary, conclusions, and future research areas

Table 1.1 Thesis structure
Chapter 2: Literature Review

This chapter provides a background on the relevant previous research to date and to develop a foundation on which this thesis is based. Five main topics are covered in this chapter. First, existing approaches to evaluate the safety of signalized intersections are reviewed. Second, a background on the connected-vehicles (CVs) technology is provided. Third, the differences between automated vehicles and connected vehicles are defined. Fourth, previous studies that utilized traffic microsimulation models to simulate road facilities under a connected-vehicle environment are discussed. Lastly, existing adaptive traffic signal control (ATSC) algorithms are summarized. As a considerably high number of related previous studies were found, the literature review in this chapter focuses on a reduced list of selected key studies that have a high impact in their fields.

2.1 Safety Evaluation of Signalized Intersections

2.1.1 Collision-based SPFs at Signalized Intersections

Safety performance functions (SPFs)—also known as collision prediction models—are regression models that correlate quantitatively the expected number of collisions with traffic exposure and geometric characteristics of road facilities. SPFs of signalized intersections have been widely developed, investigated and calibrated in the literature. The Highway Safety Manual (HSM) [22] provides various SPFs that estimate the average crash frequency for signalized intersections on different road classes including rural two-lane roads, rural multi-lane roads, urban and suburban arterials. Several studies have also developed and calibrated collision-based SPFs for signalized intersections to suit local conditions of specific jurisdictions (e.g., [23] [24] [25] [26] [58] [59] [60] [61] [62]). The traffic exposure measure used in most of these studies was an aggregation of the traffic volume (e.g. AADT) and the predicted number of collisions was usually aggregated to several years.
2.1.2 Transferability of Collision-based SPFs

Many previous studies have examined transferring and calibrating collision-based SPFs from one jurisdiction to another. Several approaches were proposed in the literature to calibrate the transferred safety models locally at the destination jurisdiction. For example, the HSM [22] presents a calibration procedure to adjust the predictive SPFs which was developed with data from one jurisdiction for application in another jurisdiction. The procedure aims to account for differences between jurisdictions in factors such as climate, driver populations, etc. In this procedure, the baseline SPFs should be first modified by collision modification factors (CMFs) to account for differences in features from the baseline conditions, such as the lane width for two-lane roads or the existence of left-turn lane at signalized intersections. Afterwards, a calibration factor (C) should be applied to adjust the number of the predicted collisions at the new jurisdiction. As shown in Eq. (2.1), the calibration factor (C) is the ratio of the total observed crash frequencies for a selected set of sites at the new jurisdiction to the total predicted crash frequencies for the same sites, during the same time period [22].

\[ C = \frac{\sum Observed\ Crashes}{\sum Predicted\ Crashes} \quad \text{Eq. (2.1)} \]

The HSM calibration procedure has been applied in many previous studies in different jurisdictions for different types of road facilities. Table 2.1 provides a sample of these studies with their description.
Table 2.1 Sample of previous studies that adopted the HSM’s calibration procedure

Although it was applied widely in the literature, the HSM’s calibration procedure was criticized by some researchers for several reasons. First, the procedure does not provide a method for testing the model transferability. Moreover, there is no evidence to show that the calibration procedure accounts for the safety differences between various regions. Thus, the procedure may lead to inaccurate estimations and predictions when applied to some jurisdictions, especially outside the United States, due to the large variation in the general level of crash frequencies and the risk factors that vary between jurisdictions. Lastly, the HSM’s calibration procedure is an aggregate method that does not correct for the errors in the predicted crashes of individual locations [72] [73] [74] [71] [75].
To overcome the limitations of the HSM’s procedure, several approaches have been proposed in previous research for calibrating the transferred SPFs locally at the new jurisdiction. This includes the intercept and over-dispersion parameter calibration [72], the Bayesian Modelling Averaging [74], the calibration function for the Negative Binomial distribution of collisions [76], the Modified Empirical Bayes [77], the informative priors [78], and the local regression [75], among others. To assess the goodness-of-fit of the transferred models, various statistical measures have been applied. This includes cumulative residual (CURE) plots ( [73] [74] [79] [71]); the transfer index ( [80] [77] [81]); the Pearson chi-squared and Z-score ( [72] [71]); and the mean prediction bias, the mean absolute deviation, and the mean absolute percentage error ( [74] [79] [71] [77] [75]).

2.1.3 The Traffic Conflict Technique (TCT)

2.1.3.1 Traffic Conflicts Vs Traffic Collisions

Relying on collision data in safety analysis is associated with several limitations. First, collisions must occur and be recorded over an adequately long period (usually years) to conduct a statistically sound safety diagnosis [27] [28]. Second, the use of several years of collisions requires reliance on aggregate exposure measures such as the annual average daily traffic (AADT), which does not explicitly account for the fact that not all vehicles are interacting unsafely and does not represent the variation of traffic flow within shorter periods. Third, there are well-recognized availability and quality problems associated with collision data [27] [28] [82] [40]. Due to these limitations, there has been a growing interest in traffic safety analysis techniques that rely on other surrogate safety measures. Generally, an acceptable surrogate measure must be correlated with a meaningful outcome, and must fully capture the effect of the treatment. Surrogate measures of traffic safety must be more frequent than collisions, have a statistical relationship to collisions, and have the
characteristics of near-accidents in a hierarchal continuum from collisions to safe undisturbed passages [83] [84].

One commonly used surrogate safety measure is traffic conflicts or near-misses. The traffic conflict technique (TCT) involves recording and evaluating the frequency and severity of near misses at a location which enables the safety professionals to immediately observe unsafe driving maneuvers at road locations without waiting for collisions to occur [30]. The concept of traffic conflicts was first proposed by Perkins and Harris [85] as an alternative to collision data. Their objective was to identify traffic events that occur frequently and can be related to traffic collisions. In their study, Perkins and Harris observed and counted instances in which drivers took evasive actions to avoid collisions. These actions, which presuppose the presence of critical situations, are identified by some observable responses made by drivers, such as a sudden changing of lanes or hard braking evidenced by the appearance of the brake lights. This approach came to be called the traffic conflict technique [85] [28]. A traffic conflict is generally defined as “an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remained unchanged” [30].

The use of traffic conflicts for safety diagnosis can have several advantages. First, traffic conflicts are more frequent than road collisions and are of marginal social cost. Second, Traffic conflicts provide insight into the failure mechanism that leads to road collisions. Third, conflict data can be gathered within a shorter time-period compared to accident data, and the analysis will be less affected by time-dependent factors. Moreover, the ethical dilemma associated with the need of a long collision history will be solved. Fourth, the effectiveness of any safety program can also be
assessed in a shorter period of time [28]. As such, the TCT is considered as a proactive approach that addresses several shortcomings associated with collision data, including data frequency and data quality. The use of traffic conflicts for safety diagnosis, therefore, has recently been accepted by road safety researchers as a surrogate or a complementary approach to the collision data analysis approach. Previous research has also shown that reducing traffic conflicts can lead to a reduction in the frequency of road collisions [38] [39].

2.1.3.2 Safety Continuum and Traffic Conflict Hierarchy

The interaction between road users can be hypothesized as a series of time-dependent events that range from undisturbed passages to actual collisions. This is referred to as the safety continuum of traffic events [36] [86] [87]. The theory of severity hierarchy of traffic events was firstly proposed by Hydén [86]. A visual representation of the frequency and severity of these events was proposed as a pyramid, as shown in Figure 2.1 [86]. The tip of the pyramid represents actual collisions and the base represents undisturbed passage, while the cross-sectional area of the pyramid represents the frequency of that severity level of interactions. It is well recognized that collisions are observed to occur less frequently than undisturbed passage. Therefore, the pyramid shape is logical. Although the extremes of the pyramid can be firmly detected (collisions and undisturbed passage), intermediate events require clear definitions, thresholds, and effective measurement procedures.

![Figure 2.1 The safety pyramid (Source: [86])](image-url)
According to the safety pyramid proposed by Hydén [86], there would be a continuous increase in the number of events as the severity of the event decreases. This is obviously true when all events are considered. However, if only interactions characterised by the presence of a collision course are considered, then it is likely that the shape is different [88]. Instead of the pyramid shape, Svensson [89] proposed a diamond shape for safety hierarchy. In fact, this is a more logical shape as the number of interactions does not continuously increase when the severity of the interaction decreases. There should be a lowest limit of severity at which there is a probability of taking an evasive action. Below this limit, the probability of taking evasive action must be zero. Therefore, a bottom with a peaked shape (diamond shape) must be more realistic than a bottom with a straight line in the traditional pyramid which there are numerous interactions [89].

2.1.3.3 Traffic Conflict Indicators

Traffic conflict indicators are quantitative measures of the closeness of a conflicting pair of road users, in space and time, in anticipation to a point of collision [90]. A number of traffic conflict indicators based on time and space proximity were developed in the literature. The most common indicators are: Time to collision (TTC) [31], Modified time to collision (MTTC) [32], Post-encroachment time (PET) [33], Deceleration to safety time (DST) [34], Deceleration rate to avoid the crash (DRAC) [35] [36], Time exposed time-to-collision (TET) [37], and Time integrated time-to-collision (TIT) [37]. Traffic conflict indicators were well documented in previous studies [91] [90] [92]. The following sections provide a brief description of these indicators.

2.1.3.3.1 Time to Collision (TTC)

The initial definition of TTC was proposed by Hayward [31] as “the time required for two vehicles to collide if they continue at their present speeds and on the same path”. A later definition of TTC was presented by Amundsen and Hydén [30] as “an observable situation in which two or more
road users approach each other in space and time to such an extent that there is a risk of collision if their movements remained unchanged”. The TTC, or some versions based on the TTC concept, may be considered as the most widely used conflict indicator. The TTC concept is based on predicting future positions of pair of road users to identify the time till the hypothesized occurrence of collision course between them. Different implementations of the TTC concept vary in the method of extrapolating positions of pair of users, and the instant of time at which the extrapolating applied.

Some studies have proposed a probabilistic approach for TTC estimation [50] [93] [94]. This approach predicts a road-user's future position using a probabilistic function that is based on common motion patterns. Computer vision techniques were used to produce common motion patterns and to assign a road-user's trajectory probabilistically. A road user’s instantaneous velocity is used to extrapolate its position along the assigned motion paths [50] [93] [94] [92].

The use of TTC as a traffic conflict indicator requires identifying a critical TTC threshold that distinguishes between near-misses (i.e., conflict events) and undisturbed passages (i.e., non-conflict events). Several researchers have attempted to identify such a threshold through field studies (e.g., [95] [31] [96] [97]). The literature review shows that there is a lack of agreement on the critical TTC threshold value. Hirst and Graham [98] reported that a TTC of 4 seconds could be used to distinguish between dangerous and non-dangerous situations. In a driving simulator experiment, Hogema and Janssen [99] indicated that the critical TTC threshold is 3.5 and 2.6 seconds for non-supported and supported drivers, respectively [99] [37]. Meanwhile, van der Horst [87] concluded that the distinct detection threshold of TTC to discriminate between normal and
critical encounters is 1.5 second. This result was obtained from an experiment involving the application of a driver simulator to a closed course road [87] [97].

It should be noted that the application of TTC as a safety indicator is faced by two main challenges. First, several combinations of speed and distance can produce the same TTC measure, which may not be of similar severity. Second, continuous measurements of TTC require detailed trajectories of road-users to be presented in time and space, which is difficult to achieve. However, this challenge has recently been addressed through advanced computer vision techniques that enable automated extraction of road-user trajectories and traffic conflicts from video recordings ( [100] [101] [50] [102] [94] [90] [103] [104]). Generally, the automated conflicts analysis approach overcomes many shortcomings in the manual collection of conflict data and provides a more practical and efficient way to capture traffic conflicts.

2.1.3.3.2 TTC-based Traffic Conflict Indicators

Several traffic conflict indicators on the basis of the TTC concept have been proposed in the literature. Hydén [86] attempted to simplify the TTC and developed a new conflict indicator referred to as the time to accident (TTA). The TTA is defined as “the time that passes from the moment that one of the road users reacted and starts braking or swerving until the moment the involved road user had reached the point of collision if both road users had continued with unchanged speed and direction” [86]. In other words, instead of continuous measurements of TTC, only single value of TTC is recorded at the instant the evasive action took place [91]. The TTA calculation assumes vehicles continue at their current velocity. The Swedish TCT developed at Lund Institute of Technology derives a measure of severity by dividing the TTA by the closing
speed. The closing speed is the instantaneous velocity of the vehicle taking evasive action at the
time this action is commenced [89] [92].

The TTC indicator were also extended by Minderhoud and Bovy [37], leading to a couple of
additional safety indicators: (1) Time exposed time-to-collision (TET), and (2) Time integrated
time-to-collision (TIT) [37]. The extended indicators can give a more comprehensive picture of
the safety level on a particular section of road during a particular period of time. The developed
TET indicator expresses the exposition time to safety-critical approach situations, whereas the
developed TIT indicator additionally considers the encountered TTC values during these safety-
critical approaches. The TET is a summation of all moments (over a considered time period) that
a driver approaches a front vehicle with a TTC-value below the TTC critical threshold. This critical
threshold is considered to be the boundary between safe and safety-critical events. Thus, the lower
the TET value, the safer the situation. The TET does not consider the variation in safety levels of
different TTC values below the threshold value; therefore, the TIT indicator has been developed.
The TIT integrates the difference between the TTC value and the threshold value over all time
periods that the TTC is below this threshold value. Thus, the TET and TIT combination accounts
for both the exposure duration and the proximity of collision at all instants. The main advantage
of the TET and TIT safety measures over the conventional TTC measure is the inclusion of time-
dependent TTC values of all subjects that use a road section during a time period [37].

Another TTC-based safety indicator was proposed by Ozbay et al. [32] for rear-end conflicts. The
indicator is referred to as the modified time to collision (MTTC). The difference between the TTC
and the MTTC is that the latter considers rear-end conflicts that can occur due to acceleration or
deceleration discrepancies. In other words, the MTTC accounts for relative positions, relative speeds, and relative accelerations of the conflicting vehicles [32].

2.1.3.3 Post-encroachment Time (PET)

Another common safety indicator is the post-encroachment time (PET). The PET is defined as “the time difference between the moment an offending vehicle leaves the area of potential collision and the moment the other vehicle arrives the collision area” [33]. The PET is less ambiguous than the TTC as it requires no projection of road-user positions into the future and can be measured discretely through the observation of road-user trajectories [92] [90]. However, the main disadvantage is that the PET does not require speed and distance measurement, hence missing many cues of conflict severity [84] [90]. Another disadvantage is the difficulty in identifying the willingness of the drivers to accept the risk [28]. Moreover, the PET can be calculated even there is no possibility of a collision course. This is another problem that usually happens in rear-end and merging conflict situations if the following vehicle has a lower or equal speed to the lead vehicle [84].

2.1.3.4 Gap Time (GT)

The Gap Time (GT) is a conflict indicator that is given by the projected time arrival of the vehicle in the main traffic stream reaches the conflict area minus the time required for the yielding vehicle to clear the conflict area. The projected time arrival of the main road vehicle is estimated using distance and speed relatives to the moment which the yielding vehicle begins the maneuver. This can also be described as the expected PET should road users’ trajectories and velocities remain unchanged [92] [91].
2.1.3.3.5 Deceleration to Safety Time (DST)

The deceleration to safety time (DST) is another conflict indicator that is related to the PET. The DST is defined by Hupfer [34] as “the required deceleration for a vehicle to attain a non-negative gap-time in relation to another road user”. In other words, for a pair of road users with a calculable gap time, it is the deceleration that one vehicle must undertake to arrive immediately following the other road user [92]. While the DST can have several applications, it is usually applied for vehicle-pedestrian interactions where a vehicle must decelerate to avoid hitting a pedestrian [105].

2.1.3.3.6 Deceleration Rate to Avoid Crash (DRAC)

The deceleration rate to avoid crash (DRAC) is a common indicator for rear-end conflicts [91]. The DRAC is defined as “the rate at which a vehicle must decelerate to avoid the collision with another conflicting vehicle” [35] [36]. Thus, high DRAC values indicate high risk of collision. A previous study by McDowell et al. [106] suggested four DRAC thresholds that address various severity levels: 6 m/s² (the most severe), 4.5 m/s², 3 m/s², and 1.5 m/s². It should be noted that the ability of the DRAC to accurately reflect traffic conflicts and potential crash situation has been criticized by some researchers [91] [107]. The main argument is that the DRAC does not consider the vehicle braking capability (e.g., a given DRAC value under wet pavement conditions is more critical to safety than the same value under dry pavement conditions).

2.1.4 Conflict-based SPFs at Signalized Intersections

Previous studies have attempted to develop SPFs for signalized intersections based on field-observed traffic conflicts. For example, Sayed and Zein [27] developed conflict prediction models for urban and suburban signalized intersections. The models relate the average hourly conflicts to the average hourly volumes of the intersected roads. In a related study by El-Basyouny and Sayed [40], a lognormal model was developed to predict traffic conflicts at signalized intersections using
a dataset corresponding to 51 signalized intersections in BC, Canada. Several covariates were considered in the lognormal model, including the traffic volume, the intersection area type (i.e., urban or suburban), and some geometric-related variables (e.g., existence of right/left turn lane) [40].

Other studies have focused on a specific type of conflicts when developing SPFs for signalized intersections. For example, opposing left-turn conflicts were modeled by Zhang et al. [41] using data collected from 20 signalized intersections. The generalized linear models (GLM) approach was applied to develop a negative binomial conflict model. The model’s covariates are: through and left traffic volumes, the median type, the number of lanes, and the green time allocated for left-turn movements [41]. Sacchi and Sayed [108] have developed SPFs to predict two types of traffic conflicts at signalized intersections: left-turn conflicts and rear-end conflicts. Conflict data for 49 signalized intersection throughout BC, Canada were utilized in the analysis. Traffic conflicts were assumed to follow a Poisson–gamma distribution, and the traffic volume was used as a covariate [108]. Another study by Sacchi and Sayed [109] employed the Bayesian approach to develop several SPFs that predict the number of rear-end conflicts at different intersection approaches. Traffic conflict data for several urban and suburban intersections in BC were automatically extracted from videos using computer vision video analysis techniques [109]. Rear-end conflicts has also been considered in a before-and-after (BA) safety study by Reyad et al. [110]. The Empirical Bayes (EB) method was applied to estimate the treatment effectiveness of two traffic-signal-visibility-improvement projects in the city of Edmonton, Alberta. Several SPFs were developed using the GLM approach to predict rear-end conflict at the intersection’s approaches given the hourly traffic volume and the length of the conflict area [110].
As noticed, the exposure measure in most of the conflict-based SPFs studies is represented by the average hourly traffic volume, while the frequency of traffic conflicts is aggregated to hours (i.e. number of conflicts/hour). Due to this aggregation, important safety-related dynamic traffic variables (e.g., shock waves, platoon ratio, traffic signal timing changes) are disregarded; subsequently, the existing conflict-based SPFs cannot be used for evaluating safety of signalized intersections in real time.

2.1.5 Safety of Signalized Intersection Using Microsimulation Models

Using traffic simulation for safety analysis is a promising approach that has been recently proposed ([45] [46]) and increasingly applied ([111] [112] [107] [47] [113] [114] [115] [116] [117]). In this approach, vehicle trajectories extracted from traffic simulation models are usually analyzed using the Surrogate Safety Assessment Model (SSAM) [46]. Sponsored by the Federal Highway Administration (FHWA) of the United States, the SSAM tool has recently been developed by (Siemens Energy & Automation, Inc.) to estimate traffic conflicts from four commonly-used microscopic simulation models: VISSIM, AIMSUN, PARAMICS, and TEXAS. The SSAM can estimate several traffic conflict indicators as surrogate measures of safety, such as TTC, PET, deceleration rate, and speed differential. The estimated conflicts can also be classified into three maneuver types: rear-end, lane-change, and crossing [46].

Conducting safety analysis using traffic simulation models can have several advantages. First, using traffic conflicts [85] overcomes the well-recognized quality and quantity limitations of collision data [27]. Second, simulation models and SSAM can be used to estimate simulated conflicts easily without actually observing them in the field. Third, traffic simulation is the simplest way to investigate new designs and innovative applications before implementing them in
the real-world. For example, most of connected-vehicles (CVs) applications, proposed in recent research (e.g., [13] [14] [118] [11] [119]), were developed and tested using simulation models to evaluate their potential mobility and/or safety benefits without actual field implementation. Lastly, simulation models are extremely valuable in assessing the relative performance of one design versus another [46].

Despite the aforementioned advantages, various concerns about using traffic simulation models in safety studies have been raised. First, all simulation models were originally designed with the assumption that drivers behave in a safe manner [45] [44]. Thus, vehicles in simulation models follow specific rules (i.e., car-following models, gap acceptance rules, lane-changing behavior) that aim to produce a crash-free environment. Using these safe-moving vehicles to evaluate conflicts and near-misses may lead to inaccurate results [47]. Second, every simulation model has many input parameters. Changing the value of these parameters can have a significant impact on road user behavior in the simulation model and subsequently on the estimated number of traffic conflicts. Third, there are usually many assumptions and different ways to model traffic in simulation models (e.g., priority rules, conflicts areas, traffic distribution). The results of simulated conflicts can vary significantly depending on the approach used in modelling [46] [48] [47]. Moreover, unrealistic crashes and abnormal movements are often recorded in traffic simulations, most likely due to an insufficient minimum gap size, a failure to yield to a priority rule, an abrupt lane change of a vehicle in an intersection or during queuing, or an irregular queuing up at left/right turn bay tapers [44] [45] [46].
In recognition of the above-mentioned advantages and concerns, numerous studies have examined the reliability of the safety results obtained from traffic simulation models. Some researchers investigated the relationship between simulated conflicts and observed crashes ([46] [111] [120]), while others explored the relationship between simulated conflicts and field-observed conflicts ([47] [48] [113] [114] [115]). Other studies used vehicle trajectories extracted from traffic simulation models to propose new surrogate safety measures beyond those incorporated in SSAM, such as the crash potential index (CPI) [107] and the aggregated crash propensity metric (ACPM) [121] [122]. In addition, various procedures were proposed in the literature to calibrate simulation models for safety analysis. This includes multi-step calibration procedures ([107] [112]), arrival pattern calibration ([47] [48] [49] [115]), calibrating the simulation model parameters using Genetic Algorithm ([107] [47] [113] [114]), and calibrating the TTC threshold in SSAM ([113] [114]). The measure of performance in the calibration process took several forms, including the mean absolute percentage error obtained by comparing simulated and observed conflicts ([113] [114]), the residual sum of squares error obtained by comparing simulated and observed measures of CPI [107], the correlation between simulated and observed conflicts ([47] [48] [49] [115]), the root-mean squared percentage error obtained by comparing simulated and observed speeds and volumes [112]. In general, previous research has reached an agreement that there is a correlation between traffic conflicts extracted from simulation models and field-observed conflicts/crashes. Calibrating simulation models was also shown to be necessary for enhancing this correlation. Moreover, it was shown that using traffic simulation models in safety analysis without a proper calibration may produce misleading results.
However, despite the existing research efforts on calibrating simulation models for safety analysis, several major issues regarding the application of simulated traffic conflicts remain unsolved. The first issue is the complexity of the calibration process of the simulation model. While it is necessary for obtaining reliable conflict results, the calibration process is time consuming and usually requires real conflict/crash data to be collected [48]. Secondly, the results of simulated conflicts are highly sensitive to many parameters in the simulation model. The analysis mainly ends up with a wide range of the estimated number of conflicts, leading to poor conflict prediction and less reliability. The third issue is the remarked discrepancies between simulated and field-observed conflicts. Although high correlation values between simulated and field-observed conflicts was obtained in previous studies, systematic overestimation or underestimation of the real number of conflicts were also found. Furthermore, major differences between simulated and field-observed conflicts in spatial distribution were detected ([47] [48] [49] [115]). These discrepancies suggest that the high correlation between simulated and field-observed conflicts/crashes might come from the exposure dependency (i.e., both simulated and field-observed conflicts/crashes are correlated with traffic volume), not from the ability of simulation models to capture the real driving behavior and the actual conflict mechanism. All of these issues highlight the need for more research on using simulation models for safety analysis.

2.1.6 **Dilemma Zone and Red-light-runner Violations**

Safety analysis of signalized intersections considering dilemma zone and red-light-runners has also been introduced in the literature. A dilemma zone is defined as the area upstream of signalized intersections in which drivers have to decide whether to continue through the intersection or to stop at the beginning of the yellow time. Different decisions in dilemma zone for a couple of consecutive vehicles may lead to a risk of rear-end collision. Papaioannou [42] developed a binary
choice model relating the probability of stopping at the stop line or crossing it to approach speed, distance from intersection, gender, age group, and existence of a dilemma zone. The results showed that a large percentage of drivers facing the yellow signal are caught in a dilemma zone and exercise an aggressive behavior [42]. Elmitiny et al. [123] used a video-based system to observe driver’s behavior associated with the signal change at high-speed signalized intersections. A model was developed to predict stop/go decisions and red-light-runner violations based on many factors such as the vehicle speed at yellow-onset and the vehicle distance from the intersection [123]. Machiani and Abbas [43] developed a new surrogate safety measure that captures the degree and frequency of rear-end conflicts in the dilemma zone at signalized intersections [43]. Jahangiri et al. [124] developed models to predict red-light-runner violations before they occur using observational and simulator data. Ren et al. [125] identified factors that can significantly affect red-light-runner behavior using high-resolution traffic data collected by loop detectors from three signalized intersections [125]. Wu et al. [126] proposed a new warning system that integrates the pavement marking and flashing yellow system to reduce the dilemma zone and enhance the traffic safety at signalized intersections. The system can provide drivers with better suggestions about stop/go decisions based on their arriving time and speed [126].

2.1.7 Real-time Crash Prediction

To enable real-time traffic safety evaluation, various real-time crash prediction models have been introduced in the literature. Although a large number of previous studies have focused on freeways in terms of real-time crash risk analysis (e.g., [127] [128] [129] [130] [131] [132] [133]), a few studies have considered signalized intersections and urban arterials (e.g., [134] [135] [136] [137]). Theofilatos [134] investigated accident likelihood and severity using real-time traffic and weather data collected from two urban arterials in Athens, Greece. Traffic data were aggregated to one-
hour interval, which might not capture the variations in traffic parameters within shorter time periods. Yuan et al. [136] [137] investigated the relationship between crash occurrence on urban arterials and real-time traffic, signal phasing, and weather characteristics using Bluetooth data, weather data, and adaptive signal control datasets. Time interval of 5 minutes was considered [136] [137]. Although this time period is considerably shorter than the analysis period in the traditional safety performance functions, evaluating safety for a 5-minute time period does not capture the safety effects of real-time variations in traffic conditions and signal timing (such as traffic variation at the signal cycle level). Developing real-time safety models that consider shorter time-periods such as the signal cycle length is recommended to account for dynamic and safety-related traffic parameters (e.g., shock wave characteristics, platoon ratio). Such models can be very useful for futuristic real-time safety optimization of signalized intersections, especially with the increasing emergence of the CVs technology.

2.2 Connected Vehicles (CVs) Technology

The concept of CVs refers to the capability of various elements of the transportation system (vehicles, bicycles, pedestrians, road infrastructure, traffic control, management centers, etc.) to continuously intercommunicate in real time [7]. Connected vehicles use wireless technology to connect with each other [i.e., vehicle to vehicle communication (V2V)] and/or with transportation infrastructures [i.e., vehicle to infrastructure (V2I)]. The two communication types V2V and V2I are generally denoted as V2X, which means a communication between a connected vehicle and any other device (e.g., vehicle, infrastructure, smartphone, etc.). The V2V connectivity allows vehicles to share their position, speed, brake status, and other information in real time with other similar connected vehicles [8]. Meanwhile, the V2I connectivity allows real-time exchange of
information between the connected vehicle and the transportation infrastructures equipped by the CV technology, such as traffic signals, roadway signage, and traffic management centers.

Both V2V and V2I communications occur over dedicated short-range communication (DSRC) systems. The DSRC is a wireless technology that allows rapid communications (up to 10 times per second) between connected vehicles within a distance ranges from 150 to 300 meters [7]. The DSRC network primarily communicates using a language dictionary standardized by the Society of Automotive Engineers (SAE) International in SAE J2735. The most common data element is called a basic safety message (BSM). The BSM contains a vehicle’s location, speed, direction, brake status, and other information [9][10]. Cellular phone technology is also expected to facilitate the use of many connected vehicle concepts [7].

The CVs technology has recently become an area of increasing interest among researchers and practitioners. This technology is moving rapidly from the experimental phase into real-world applications and is expected to be the next generation of intelligent transportation systems [7]. In the era of CVs, a considerable amount of high-resolution data on vehicle positions and trajectories can be generated in real time. Analyzing such big traffic data in real time has become feasible with the availability of innovative machine learning and artificial intelligence techniques. This enables developing strategies for real-time traffic optimization at signalized intersections. Via real-time connectivity and data transmissions, drivers can be supported with advisories and warnings to avoid collisions or unnecessary delays. In addition, traffic control devices, such as traffic signals and variable message signs (VMS), can be adapted in real time to relieve congestion and improve safety. Existing
research has demonstrated that CVs can potentially have considerable mobility, safety, and environmental sustainability benefits to road networks (e.g., [10] [11] [12]).

In terms of improving road safety, CVs can play an important role in decreasing traffic collisions. Safety applications of CVs can provide drivers with 360-degree awareness of hazards and situations they cannot see. For example, V2V communications can provide drivers with awareness of imminent crash situations such as a sudden stop by a vehicle ahead, an icy road, a dangerous curve, or a car exists in the driver’s blind spot. In addition, V2I communications can provide drivers with awareness in various situations such as when the traffic light is about to change or when the driver is entering a school or a construction zone [138] [7]. V2I communications can also be used to dynamically adapt various road-side infrastructure to avoid crashes and minimize traffic conflicts. For example, the design of traffic signals and the contents of the VMS can be dynamically changed to accommodate real-time traffic conditions, hence optimizing traffic efficiency and improving safety.

Regarding mobility, CVs could help in reducing both recurrent and non-recurrent congestions. Throughout real-time communications, CVs mobility applications can provide drivers with real-time information necessary to navigate roads more efficiently, leading to fewer delays. In addition, CVs could help transportation system operators improve the functioning of the overall system [9]. Real-time communications can also be used to perform a real-time mobility optimization for various road-side infrastructures design, such as VMS and traffic signals, to minimize traffic delays. Moreover, providing travelers with real-time information could make public transportation more appealing. For example, travelers will have a realistic idea of when transit vehicles will
arrive, and they will be able to improve bus and train connections. Overall, the data-rich environment of CVs is expected to be the core motivation for a large number of new mobility applications that will help to keep traffic flowing, reduce congestion, and make it easier for people to plan their travel [9] [7] [138].

Connected vehicles could also have potential environmental sustainability benefits to transportation networks. Real-time CVs data can be used by drivers and transportation managers to make transportation networks more ecofriendly. For example, CVs-based applications could help in reducing congestion, improving lane management, eliminating unnecessary stop, and subsequently improving fuel efficiency and reducing emissions. In addition, using real-time data, travelers may also be encouraged to make green transportation choices, such as avoiding congestion by taking alternate routes or public transit, or rescheduling their trips [9] [7] [138].

2.3 Difference between Automated Vehicles (AVs) and Connected Vehicles (CVs)

The two terms AVs and CVs are not synonymous, although they can share some of the same technology. Connected vehicles use wireless technology to connect with other vehicles, transportation infrastructure, and mobile devices to give motorists the information they need to drive more safely [139]. Meanwhile, automated vehicles, also known as self-driving vehicles or autonomous vehicles, rely on sensors (e.g., camera, radar) and computer analytics to sense their environments and navigate without human input [139]. Figure 2.2 [9] illustrates the difference between connected vehicles and automated vehicles. There are many ways to combine connectivity and automation. In general, a vehicle can be in one of the following cases: (1) conventional (non-automated and non-connected); (2) connected and non-automated; (3) automated and non-connected; (4) connected and automated (CAV). There are also several levels
of automation. According to the Society of Automotive Engineers (SAE) international’s standard J3016 [140], there are 6 levels of automations starting from level 0, which represents no automation level, to level 5, which represents the full automation level. **Figure 2.3** [140] provides more details on the different automation levels.

![Figure 2.2 Automated and connected vehicles (Source: [9])](image_url)
Figure 2.3 Automation levels according to SAE J3016 (Source: [140])

It should also be noted that both CVs and AVs are often combined with intelligent transportation system (ITS). According to ITS Canada [141], ITS can be defined as “the application of advanced and emerging technologies (computers, sensors, control, communications, and electronic devices) in transportation to save lives, time, money, energy and the environment.”. ITS represents the much wider concept that includes CVs and AVs in addition to a variety of advanced applications that are beyond the vehicle system such as remote traffic monitoring, adaptive signal control, etc.

Figure 2.4 [10] identifies the three categories: CVs, AVs, and ITS.
2.4 Connected Vehicles in Microsimulation Models

Numerous studies in the literature have investigated the mobility, safety, and environmental sustainability impacts of the CVs technology. Since this technology is still under development, most of previous research have utilized microsimulation models to analyze the performance of various road facilities under the CVs environment. As a considerably high and increasing number of previous studies were found, this section summarizes a reduced list of selected key studies that have high impact in the field of testing CVs in microsimulation models.

Lee and Park [142] proposed a Cooperative Vehicle Intersection Control (CVIC) algorithm that enables cooperation between vehicles and infrastructure for effective intersection operations without traffic signal controllers. The developed algorithm was tested on a hypothetical four-way single-lane approach intersection modeled using the microsimulation model VISSIM. The results indicated that the CVIC system significantly improved the intersection performance in terms of the delay time, the air quality, and the energy saving. However, this study focused only on the
mobility and the environmental performance. Safety performance was not considered, except for one constraint in the algorithm that aims at avoiding collisions between vehicles in the absence of the traffic signal. Lee et al. [143] expanded the previous study and implemented the CVIC algorithm to a corridor that consists of multiple intersections. The safety and environmental impact of the implementation of the CVIC algorithm were also investigated. The safety was evaluated using the SSAM tool [44]. Nevertheless, the two previous studies assumed that all vehicles are fully automated and connected (CAVs). Imperfect market penetration rates (MPRs) of CAVs were not considered.

Lee et al. [13] proposed a cumulative travel-time responsive (CTR) algorithm that optimizes traffic signals in real time to minimize the total delay at signalized intersections in a connected-vehicle environment. The simulation model VISSIM was utilized to develop simulate CVs and test the CTR algorithm. The update interval used in the algorithm was assumed to be 5 seconds. Multiple MPRs of CVs were considered. In addition, the environmental impact of the proposed algorithm was evaluated. However, the safety of signalized intersections was neither evaluated nor optimized.

Goodall et al. [144] developed a traffic control algorithm to adapt traffic signals in real time using CVs data. The developed algorithm was tested using VISSIM with a 15-second update interval. Multiple objective functions were considered in the optimization process, including delay time, number of stops, and decelerations. Various CVs MPRs were also investigated. However, the safety performance of the proposed algorithm was disregarded.
Paikari et al. [12] used the traffic microsimulation model PARAMICS to evaluate the safety and mobility impacts of CVs for freeways. V2V and V2I systems were implemented in the simulation model to represent rerouting guidance and advisory speed using VMS. Five scenarios were tested to reflect various MPRs of CVs. The mobility measure was the point-to-point travel time along the freeway section, while the safety measure was the crash probability estimated from a crash likelihood model that was earlier presented by Abdel-Aty et al. [145].

Li et al. (2014) developed a signal control optimization algorithm to minimize the delay time, assuming a signalized intersection with two single-lane approaches. The algorithm optimizes vehicle trajectories based on the assumption that all vehicles are automated and connected to the signal controller. The simulation model CORSIM was utilized to test the algorithm’s performance. The results indicated that the proposed algorithm reduced the average travel time delay by 16.2–36.9%, compared to the traditional actuated signal control. The safety performance of the algorithm was not investigated.

Guler et al. [14] developed an ATSC algorithm to minimize the total delay time using information obtained from CVs. The developed algorithm considers vehicles within a certain radius of the intersection, enumerates the possible discharge sequences for these vehicles, and picks the best strategy. The developed algorithm was tested at multiple MPRs of CVs using a simulation model. A hypothetical intersection of two one-way streets was modeled. The objective function was to minimize the total delay time. The results indicated that the algorithm can reduce the total delay time up to 60%. In a related study, Yang et al. [16] extended the aforementioned algorithm by including a certain percentage of AVs. Considering a percentage of AVs enables bidirectional V2I
communications in the signal control scheme and allows the central controller to optimize AVs trajectories, hence a further improvement in the intersection performance. The Intelligent Driver Model (IDM) [146] was used as the basic car-following model; and a Java script was used to model the simulation platform. The results indicated improvement in both the delay time and the number of stops. However, in both studies [14] [16], safety was not considered.

Feng et al. [15] proposed a real-time adaptive signal phase allocation algorithm using CVs data. The developed algorithm optimizes the phase sequence and duration, considering two objective functions: minimization of total vehicle delay and minimization of queue length. The algorithm was developed and tested using the simulation model VISSIM. Multiple MPRs of CVs were investigated. The results indicated that the developed algorithm outperforms the traditional actuated signal controller and reduces the total delay by 16.33%. Most importantly, the results showed that different objective functions can result in different signal timing design. The minimization of total vehicle delay usually generates lower total vehicle delay, while the minimization of the queue length serves all phases in a more balanced way [15]. The safety performance was neither optimized nor evaluated.

Kamal et al. [147] presented a coordination scheme for an intersection without traffic signals. All vehicles were assumed to be CAVs using two-way communication network. Approaching vehicles from all sections were globally coordinated to achieve smooth traffic flows. Firstly, vehicles were assumed to follow the IDM [146] as the basic car-following model. Next, the vehicle trajectories were optimized to avoid any cross-collision risks around the intersection. The proposed scheme prevents any pair of conflicting vehicles from approaching their cross-collision point at the same
time [147]. The simulator model AIMSUN was used to test the coordination scheme. Unlike the earlier studies by Lee and Park [142] and Li et al. [148], the proposed scheme was evaluated using simulation in a hypothetical intersection with multi-lanes approaches with left and right-turn movements. Compared to the traditional signalized intersection, the proposed scheme significantly improved the intersection performance in terms of delay time, capacity, and fuel consumption.

So et al. [118] adopted an integrated simulation approach to assess the safety impact of CVs-based applications by considering potential positioning errors and communication delays which are likely to occur in reality. Safety applications (i.e., driver warnings) based on Global Position System (GPS) devices and V2V/V2I communications were investigated. The simulation model VISSIM was used as the basic traffic simulator. Traffic safety was evaluated based on the number of conflicts obtained from the SSAM tool [46]. The results showed that V2V/V2I communication delays can reduce the safety effectiveness of driver warnings by 3-13%. Imperfect MPRs of CVs were not considered in this study.

Stevanovic et al. [149] proposed a method to optimize traffic signal considering three objective functions: mobility, safety, and environment. The multi-objective optimization algorithm was based on 3-dimensional Pareto fronts (i.e., the set of Pareto optimal solutions that are not dominated by any other feasible solutions) of signal timing. The Genetic Algorithm (GA) technique was applied to get the Pareto fronts by evaluating several signal timing plans. Various types of signal controller were considered, including fixed and actuated signals. Some of the signal timing scenarios were combined with a connected-vehicle application referred to as the green light optimized speed advisory (GLOSA) [150]. The GLOSA guides drivers, through infrastructure-to-
vehicle communication, to adopt a recommended speed for a more uniform commute with less stopping time through traffic signals. To test the multi-objective optimization algorithm, five signalized intersections were used as a test bed. The simulation model VISSIM was used to simulate the selected intersections. The SSAM was used to evaluate safety impacts, while the Comprehensive Modal Emission Model (CMEM) [151] were used to evaluate the environmental impacts. The results showed that the optimal balance for mobility, safety, and environmental impacts does not seem to produce very different signal timings. However, future studies were recommended to test the hypothesis that such differences may get pronounced when tested under stochastic traffic flows [149]. It should also be noted that this study did not adopt a real-time optimization process; rather, predeveloped signal timing plans were simulated and tested (i.e., offline optimization). Thus, the optimization process aimed only to select the optimum signal plan, not to adapt traffic signals in real time.

Olia et al. [11] assessed the potential safety, mobility, and environmental sustainability benefits of CVs. A real-world network located in the city of Toronto, Ontario, Canada was simulated using the PARAMICS microsimulation model. A combination of CVs and non-CVs was considered. Real-time routing guidance and advisory warning messages for CVs were simulated. Other sources of information were also considered for non-CVs, such as GPS and VMS. The mobility measure was the total travel time estimated from PARAMICS. The safety of the traffic network was assessed using the number of traffic conflicts obtained from SSAM [46]. The environmental impact was evaluated using CMEM [151]. Multiple MPRs of CVs were investigated. The results showed that the CVs MPR and the level of information among non-CV vehicles can play an
essential role in improving congestion, enhancing safety, and reducing emissions of transportation networks [11].

Li et al. [152] presented a CVs-based application referred to as high-speed differential warning (HSDW). The main goal of this application is to improve road safety through wireless communications. The application identifies potential hazards resulting from high-speed differentials and then provides alerts to drivers to help them take appropriate actions. A traffic network was developed using the PARAMICS simulation model. The average speed was used as a mobility measure. The Motor Vehicle Emission Simulator (MOVES) [153] was used to estimate the energy consumption and evaluate emissions. The safety of the traffic network was assessed using the number of rear-end traffic conflicts obtained from SSAM [46]. Various MPRs of CVs were investigated. The analysis showed that the proposed application can improve traffic safety without compromising mobility and environmental sustainability [152].

Al Islam and Hajbabaie [17] presented a real-time distributed-coordinated technique for signal timing optimization on urban street networks. The main objective of the optimization technique is to find the signal timing parameters that maximize the traffic throughput and control the queue length by preventing queue spillbacks. The traffic simulation model VISSIM was utilized to test the proposed technique on two case studies: (1) network with two intersections; and (2) network with nine intersections. The basic assumption was that all vehicles and intersections are connected and intersections can share information with each other. The results showed that the proposed algorithm controls queue length and increases intersection throughput by 1-5% compared to the
actuated coordinated signal control system. The algorithm was also shown to reduce the travel time by 17-48%. The safety performance of the algorithm was neither optimized nor evaluated.

Jiang et al. [20] proposed an eco-driving system for an isolated signalized intersection under partially connected and automated vehicles environment. A certain percentage of vehicles were assumed to be CAVs. The proposed system optimizes speed profiles of CAVs to improve mobility and fuel efficiency. The simulation model VISSIM was utilized to test the proposed system under multiple MPRs. The results indicated that the system can improve the traffic throughput up to 10.80%, reduce the fuel consumption by 2.02-58.01%, and smooth out the shock wave caused by signal controls. The system was also shown to be robust over the impedance from conventional vehicles and randomness of traffic [20]. However, the safety performance was not considered in this study.

Xu et al. [21] proposed an optimization algorithm based on the V2I cooperation between the traffic signal and approaching automated vehicles (CTV). The proposed algorithm optimizes traffic signal and vehicles’ trajectories concurrently to minimize the travel time and the fuel consumption. All vehicles were assumed to be CAVs. The algorithm was tested using the simulation model VISSIM. The results indicated that, compared with the actuated signal control, the proposed algorithm can improve travel time and fuel consumption by 19.7% and 23.7% respectively. The safety of signalized intersections was not considered except for some constraints in the optimization process that aim to provide a minimum safe distance and avoid collisions.
Khazraeian et al. [119] investigated the accuracy and the safety benefits of the queue warning systems (QWS) in a connected-vehicle environment. The main concept of QWS is to increase traffic safety by informing drivers about queued traffic ahead so they can time-properly react to the queue. Freeway sections with CVs and QWS were simulated in VISSIM. Multiple MPRs were investigated. The safety benefits were evaluated using the number of traffic conflicts obtained from SSAM [46]. The results showed that low MPRs, 3% to 6%, are enough for an accurate estimation of the queue length. The results also indicated that CVs data allowed faster detection of the bottleneck and queue formation. The safety impacts of QWS were shown to be dependent on the driver compliance to the queue warning messages [119].

Liang et al. 2020 [154] developed an ATSC algorithm for real-time optimization of traffic signal control at isolated intersections using CVs data. The algorithm has two competing objectives: (1) efficiency, represented by the average vehicle delay; and (2) equity, represented by the maximum delay any individual vehicle may experience. The algorithm was tested using the simulation model AIMSUN with various MPRs of CVs. The results showed that the proposed algorithm can significantly reduce long delays and inequitable treatment of vehicles at signalized intersections. The proposed algorithm was also shown to be effective under MPR values higher than 40% [154].

Rafter et al. 2020 [155] proposed a traffic signal control algorithm, referred to as Multi-mode Adaptive Traffic Signals (MATS). The algorithm combines position information from CVs with data obtained from existing inductive loops and signal timing plans in the network to perform decentralised traffic signal control at urban intersections. The algorithm was tested using the simulation platform SUMO [156] under various MPRs of CVs. The results indicated that the
MATS algorithm offers up to 28% reduction in the average delay compared to MOVA (MOVA is a traffic control strategy in UK that is specifically designed to maximise the operational efficiency of a junction/crossing). The MATS algorithm was also shown to be robust under low MPRs of CVs and under non-ideal communication channel conditions [155].

Tables 2.2-2.5 present a summary of the above-mentioned studies that have focused on using microsimulation models to develop and/or test CVs-based applications.
<table>
<thead>
<tr>
<th>Study</th>
<th>CVs</th>
<th>AVs</th>
<th>MPR</th>
<th>Road Facility</th>
<th>Simulation model</th>
<th>Mobility Measure</th>
<th>Safety Measure</th>
<th>Real-time Optimization</th>
<th>Optimizing for Mobility</th>
<th>Optimizing for Safety</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lee and Park (2012) [142]</td>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>Signalized Intersections</td>
<td>VISSIM</td>
<td>Delay</td>
<td>✗</td>
<td>✓</td>
<td>✗</td>
<td>✗</td>
<td>- New algorithm (CVIC) to operate intersections without signal controller - All vehicles are CAVs</td>
</tr>
<tr>
<td>Lee et al. (2013) [143]</td>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>Signalized Intersections</td>
<td>VISSIM</td>
<td>Delay</td>
<td>✗</td>
<td>SSAM</td>
<td>✗</td>
<td>✗</td>
<td>- Extension of the CVIC algorithm to include a corridor - All vehicles are CAVs</td>
</tr>
<tr>
<td>Lee et al. (2013) [13]</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
<td>Signalized Intersections</td>
<td>VISSIM</td>
<td>Travel time</td>
<td>✗</td>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>- CTR algorithm for real-time optimization of traffic signals to minimize the total delay</td>
</tr>
<tr>
<td>Goodall et al. (2013) [144]</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
<td>Signalized Intersections</td>
<td>VISSIM</td>
<td>Delay/Number of stops</td>
<td>✗</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>- Real time ATSC algorithm - Multiple objective functions (delay, number of stops, decelerations)</td>
</tr>
<tr>
<td>Paikari et al. (2014) [12]</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
<td>Freeways</td>
<td>PARAMICS</td>
<td>Point-to-point travel time</td>
<td>✗</td>
<td>Crash Probability Model</td>
<td>✗</td>
<td>✗</td>
<td>- V2V and V2I systems were implemented in simulation to represent rerouting guidance and advisory speed using VMS</td>
</tr>
<tr>
<td>Li et al. (2014) [148]</td>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>Signalized Intersections</td>
<td>CORSIM</td>
<td>Delay</td>
<td>✗</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>- A signal control optimization algorithm to minimize delay time - All vehicles are CAVs - Average delay reduced by 16.2–36.9%</td>
</tr>
<tr>
<td>Guler et al. (2014) [14]</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
<td>Signalized Intersections</td>
<td>No specific software mentioned</td>
<td>Delay</td>
<td>✗</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>- A traffic control algorithm to adapt traffic signals to minimize the total delay - A hypothetical intersection of two one-way streets was modeled - The algorithm reduced the total delay time up to 60%</td>
</tr>
</tbody>
</table>

Table 2.2 Summary of previous research on CVs using microsimulation models
<table>
<thead>
<tr>
<th>Study</th>
<th>CVs</th>
<th>AVs</th>
<th>MPR</th>
<th>Road Facility</th>
<th>Simulation model</th>
<th>Mobility Measure</th>
<th>Safety Measure</th>
<th>Real-time Optimization</th>
<th>Optimizing for Mobility</th>
<th>Optimizing for Safety</th>
<th>Remarks</th>
</tr>
</thead>
</table>
| Yang et al. (2016) [16]     | ✓   | ✓   | ✓   | Signalized Intersections | JAVA script     | Delay time / Number of stops      | ✗             | ✓                      | ✓                       | ✗                    | - Real-time ATSC algorithm to minimize the total delay  
- A hypothetical intersection of two one-way streets  
- AVs trajectory optimization  
- IDM car-following model  
- Improvement in both the delay time and the number of stops |
- Two objective functions: total vehicle delay, and queue length  
- 16.33% reduction in delay  
- The results showed that different objective functions can result in different signal timing design |
| Kamal et al. (2015) [147]   | ✓   | ✓   | ✗   | Signalized Intersections | AIMSUN          | Delay time / Capacity             | ✗             | ✓                      | ✗                       | ✗                    | - A coordination scheme for an intersection without traffic lights  
- All vehicles are CAVs  
- IDM car-following model  
- Vehicle trajectory optimization to avoid any cross-collision risks  
- A hypothetical intersection with left and right-turn movements  
- Significant improvement in delay time, capacity, and fuel consumption |
| So et al. (2015) [118]      | ✓   | ✓   | ✗   | Signalized Intersections | VISSIM          | ✗                                 | SSAM           | ✗                      | ✗                       | ✗                    | - Assessment of the safety impact of CVs-based applications considering potential positioning errors and communication delays |

Table 2.3 Summary of previous research on CVs using microsimulation models (continued)
<table>
<thead>
<tr>
<th>Study</th>
<th>CVs</th>
<th>AVs</th>
<th>MPR</th>
<th>Road Facility</th>
<th>Simulation model</th>
<th>Mobility Measure</th>
<th>Safety Measure</th>
<th>Real-time Optimization</th>
<th>Optimizing for Mobility</th>
<th>Optimizing for Safety</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stevanovic et al. (2015) [149]</td>
<td>✓</td>
<td>✗</td>
<td>✗</td>
<td>Signalized Intersections</td>
<td>VISSIM</td>
<td>Travel time</td>
<td>SSAM</td>
<td>✗</td>
<td>✗</td>
<td>✓</td>
<td>- Optimizing traffic signal considering three objective functions: mobility, safety, and environment - Offline optimization</td>
</tr>
<tr>
<td>Olia et al. (2016) [11]</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
<td>Road Network</td>
<td>PARAMICS</td>
<td>Travel time</td>
<td>SSAM</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
<td>- Assessment of the potential safety, mobility and environmental benefits of the CVs deployment - Routing guidance and advisory warning messages for CVs - GPS and VMS for non-CVs</td>
</tr>
<tr>
<td>Li et al. (2017) [152]</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
<td>Road Network</td>
<td>PARAMICS</td>
<td>Average speed</td>
<td>SSAM</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
<td>- A CV application (HSDW) to improve road safety - Identifying potential hazards resulting from high-speed differentials - Improving safety without compromising mobility</td>
</tr>
<tr>
<td>Al Islam &amp; Hajbabaie (2017) [17]</td>
<td>✓</td>
<td>✗</td>
<td>✗</td>
<td>Network of Signalized Intersections</td>
<td>VISSIM</td>
<td>Traffic throughput/ Queue/ Travel time</td>
<td>✗</td>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>- A real-time distributed-coordinated technique for signal timing optimization - All vehicles and intersections are assumed to be connected - 1% to 5% increase in traffic throughput - 17% to 48% reduction in travel time</td>
</tr>
</tbody>
</table>

Table 2.4 Summary of previous research on CVs using microsimulation models (continued)
### Table 2.5 Summary of previous research on CVs using microsimulation models (continued)

<table>
<thead>
<tr>
<th>Study</th>
<th>CVs</th>
<th>AVs</th>
<th>MPR</th>
<th>Road Facility</th>
<th>Simulation model</th>
<th>Mobility Measure</th>
<th>Safety Measure</th>
<th>Real-time Optimization</th>
<th>Optimizing for Mobility</th>
<th>Optimizing for Safety</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>- Eco-driving system - A certain % of vehicles are CAVs - Optimizing CAVs speed profiles for mobility and fuel efficiency - Throughput benefits: 10.80% - Fuel consumption benefits: 58%</td>
</tr>
<tr>
<td>Xu et al. (2017) [21]</td>
<td>✔️</td>
<td>✔️</td>
<td>✗</td>
<td>Signalized Intersections</td>
<td>VISSIM</td>
<td>Travel time</td>
<td>✗</td>
<td>☑️</td>
<td>☑️</td>
<td>☑️</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>- CTV algorithm to optimize signal and vehicle trajectories - All vehicles are CAVs - Travel time benefits: 19.7% - Fuel consumption benefits: 23%</td>
</tr>
<tr>
<td>Khazraeian et al. (2017) [119]</td>
<td>✔️</td>
<td>✗</td>
<td>✔️</td>
<td>Freeways</td>
<td>VISSIM</td>
<td></td>
<td>✗</td>
<td>☑️</td>
<td>☑️</td>
<td>☑️</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>- Investigation of the accuracy and the safety benefits of the QWS in the CVs environment</td>
</tr>
<tr>
<td>Liang et al. (2020) [154]</td>
<td>✔️</td>
<td>✗</td>
<td>✔️</td>
<td>Signalized Intersections</td>
<td>AIMSUN</td>
<td>Average delay time</td>
<td>✗</td>
<td>☑️</td>
<td>☑️</td>
<td>☑️</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>- ATSC algorithm to optimize traffic efficiency and equity - Effective under MPRs ≥ 40%</td>
</tr>
<tr>
<td>Rafter et al. (2020) [155]</td>
<td>✔️</td>
<td>✗</td>
<td>✔️</td>
<td>Signalized Intersections</td>
<td>SUMO</td>
<td>Average delay time</td>
<td>✗</td>
<td>☑️</td>
<td>☑️</td>
<td>☑️</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>- ATSC algorithm to optimize traffic delay using CVs and loop detectors data - Delay time benefits: 28%</td>
</tr>
</tbody>
</table>
2.5 Adaptive Traffic Signal Control (ATSC)

2.5.1 Implemented ATSC Algorithms

Over the past few decades, several ATSC algorithms have been implemented around the world. The earliest two algorithms were the Sydney Coordinated Adaptive Traffic System (SCATS) [157], and the Split Cycle Offset Optimization Technique (SCOOT) [158]. After that, Federal Highway Administration (FHWA) adaptive control systems were developed and used, including the Optimization Policies for Adaptive Control (OPAC) [159], the Real Time Hierarchical Optimized Distributed Effective System (RHODES) [160], and, more recently, the ACS Lite [161]. These algorithms differ in operation, but they share a common objective of accommodating current traffic demands to maximize throughput capacity and minimizing traffic delays [162]. However, these ATSC systems generally suffer from several operational limitations, such as handling several intersections at the same time, using a centralized control system, and relying on loop detectors for detection and estimation [55] [57]. More importantly, these systems do not consider optimizing traffic safety as an objective.

2.5.2 ATSC Algorithms Using CVs Data

With the increasing emergence of the CVs technology, numerous traffic signal control algorithms have recently been proposed to optimize traffic efficiency using CVs real-time data. Some studies, for example, proposed various algorithms to optimize and coordinate traffic movement in road intersections without using any traffic lights, assuming that all vehicles are connected and autonomous (e.g., [142] [143] [147] [163]). More realistically, other studies assumed various market penetration rates of CVs to develop and test ATSC algorithms. The developed algorithms generally aim at minimizing the total delay (e.g., [13] [14] [16] [154] [155]). Several studies have also considered multiple objectives, such as minimizing the total delay and the number of stops.
[144], or minimizing the total delay and the queue length [15]. Most of the existing algorithms optimize the traffic signal timing based on real-time vehicle information, assuming one-way vehicle-to-infrastructure (V2I) communications. Some algorithms, however, optimize both the traffic signal timing and vehicle trajectories, assuming a specific percentage of autonomous vehicles and bidirectional V2I communications (e.g., [16] [17] [20] [21] [164]). While the majority of previous studies has mainly focused on adapting traffic signals to improve mobility, a limited number of studies have considered optimizing traffic signals to reduce traffic emissions and fuel consumption (e.g., [21] [20] [164]). On the other hand, optimizing traffic safety has generally been disregarded. More details and a systematic review of research on using CVs real-time data for urban traffic signal control can be found in a recent study by Guo et al. [165].

2.5.3 Self-learning ATSC Algorithms

Self-learning ATSC algorithms are emerging methods that rely on learning the control policy from the direct interaction with the traffic environment without needing a predefined model for the environment nor human intervention. A significant amount of research has been conducted on developing self-learning ATSC algorithms with the goal of improving traffic efficiency and optimizing mobility using real-time traffic data. The Reinforcement Learning (RL) technique seems to be the most attractive approach in the literature to develop self-learning ATSC algorithms. Several RL methods have been applied, including model-based Q-learning [166], Q-learning (e.g., [56] [167] [168] [169] [170] [171] [57]), State-Action-Reward-State-Action (SARSA) (e.g., [172] [57] [173]), Multiagent Reinforcement Learning (e.g., [166] [174]), and, more recently, Deep Q-Network (DQN) (e.g., [175] [19]). Various objectives have been considered to optimize mobility, including minimizing queue length, minimizing travel time, minimizing total delay, and maximizing vehicle throughput.
Although these RL-based ATSC algorithms have shown a significant improvement in traffic mobility, they have not considered evaluating or optimizing traffic safety. The safety evaluation in these studies is limited to avoiding crashes between simulated vehicles, providing standard signal times (e.g., yellow time, all-red time, minimum green time), and prohibiting conflicting signal phases from being operated simultaneously.
Chapter 3: Real-time Safety Models for Signalized Intersections

3.1 Background

The safety of signalized intersections has often been evaluated at an aggregate level relating historical collision records to annual traffic volume and the geometric characteristics of the intersection. The collision-based safety evaluation is very useful in several applications such as identifying and ranking hazardous locations, and conducting before-and-after safety studies. However, collisions at signalized intersections can occur for several reasons including drivers’ behavior in dilemma zones, approach queues, and shock waves [42] [43]. For intersection safety solutions that target these collisions, it is essential to understand how changes in traffic parameters and signal control affect safety in real time or at the signal cycle level. Unfortunately, modeling the safety of signalized intersections using collisions at the cycle level can be difficult for several reasons:

a) The use of the historical collision data in safety analysis requires collisions to occur and be recorded over an adequately long period (e.g. years) in order to conduct a statistically sound safety diagnosis [27] [28].

b) The use of several years of collisions requires reliance on aggregate exposure measures such as the annual average daily traffic (AADT), which does not explicitly account for the fact that not all vehicles are interacting unsafely [40] and does not represent the variation of traffic flow between cycles.

c) Collecting data on important traffic parameters such as delay, queue length, and traffic volume at each cycle is difficult and requires special sensing needs.
d) Important dynamic cycle-related variables that can affect the intersection safety such as the arrival type and the shock wave characteristics are difficult to collect and need special advanced algorithms.

This chapter presents the development of new safety performance functions (SPFs) for signalized intersections at the signal cycle level. The developed SPFs can be considered as real-time safety models, since they relate the number rear-end conflicts occurring in each signal cycle to dynamic traffic variables such as traffic volume, maximum queue length, shock wave characteristics (e.g. shock wave speed and shock wave area), and platoon ratio. The developed models can provide insight into how real-time changes in the signal cycle design affect the safety of signalized intersections. The overall goal is to use the developed models for the real-time safety optimization at signalized intersections by changing the signal design. The SPFs development approach presented in this chapter provides several advantages as follows:

a) The use of real-world traffic data, obtained by video recordings at six different intersections, which reflects the actual driving behavior (i.e., the results are not based on microsimulation models).

b) Proposing a video analysis procedure to collect data at the signal cycle level.

c) The use of traffic conflicts as a measure of safety. Conflicts were extracted automatically and quantified using a conflict indicator (e.g., TTC). The actual conflict location was also determined.

d) The proposed approach allows for the extraction of various dynamic traffic parameters including: the traffic volume, the maximum queue length, the shock wave characteristics, and the platoon ratio.
e) The traffic conflict data and the various traffic parameters were measured directly from the video data and evaluated at a cycle level. As such, no hourly aggregation is needed.

The following sections in this chapter provide a detailed description of the study locations and video data collection; the methodology applied to analyze video data and to develop real-time SPFs; the results of the developed SPFs; and the potential applications.

3.2 Study Locations and Data Collection

Data from six signalized intersections in two cities were used in this study. Figure 3.1 shows the study locations 1 and 2 in the city of Edmonton, Alberta. Figure 3.2 shows the study locations 3, 4, 5, and 6 in the city of Surrey, British Columbia. For all the six sites, video cameras were installed to record video data. The video cameras were fixed on an existing post located either downstream the stop line or upstream the functional area of the signalized intersection. The camera scenes mainly focused on the intersection approaches where most of rear-end conflicts occur. To enable accurate analysis for rear-end conflicts and shock waves, two issues were considered during the camera installation process. First, the camera scenes must cover a sufficient length of the intersection’s approaches upstream the stop line. Second, the stop line and the traffic signal indicators must be clearly captured in the video recordings.
Figure 3.1 Study locations in the city of Edmonton, Alberta
Figure 3.2 Study locations in the city of Surrey, British Columbia

Table 3.1 provides more details on the selected intersections that include: the location; the selected approaches; the number of lanes per approach; signal timing; the date of data collection; the Google-image; and the video scene.
### Table 3.1 Description of the study locations

<table>
<thead>
<tr>
<th>Location #</th>
<th>City (Province)</th>
<th>Intersected roads</th>
<th>Video-data was recorded in</th>
<th>Selected intersection approaches</th>
<th>Number of Lanes per approach</th>
<th>Traffic signal timing (seconds)</th>
<th>Google image</th>
<th>Video scene</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Edmonton (AB)</td>
<td>Stony Plain Rd &amp; 170 St</td>
<td>May 27th, 2015, June 2nd, 2015</td>
<td>170 St (Northbound)</td>
<td>1 (Right) 1 (Left) 4 (Through)</td>
<td>51 4 65</td>
<td><img src="image1" alt="Google image" /> <img src="video1" alt="Video scene" /></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Edmonton (AB)</td>
<td>Gateway Blvd &amp; 34 Ave</td>
<td>May 26th, 2015</td>
<td>Gateway Blvd (Northbound)</td>
<td>1 (Right) 1 (Left) 4 (Through)</td>
<td>53 to 73 4 43 to 53</td>
<td><img src="image2" alt="Google image" /> <img src="video2" alt="Video scene" /></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Surrey (BC)</td>
<td>72 Ave &amp; 128 St</td>
<td>March 28th, 2012, March 29th, 2012</td>
<td>72 Ave (Eastbound &amp; Westbound)</td>
<td>1 (Left) 2 (Through)</td>
<td>31 to 57 4 * 29 to 64</td>
<td><img src="image3" alt="Google image" /> <img src="video3" alt="Video scene" /></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Surrey (BC)</td>
<td>72 Ave &amp; 132 St</td>
<td>April 3rd, 2012</td>
<td>72 Ave (Westbound)</td>
<td>1 (Left) 2 (Through)</td>
<td>17 to 49 4 * 37 to 69</td>
<td><img src="image4" alt="Google image" /> <img src="video4" alt="Video scene" /></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Surrey (BC)</td>
<td>64 Ave &amp; King George Blvd</td>
<td>June 10th, 2015, June 11th, 2015</td>
<td>King George Blvd (Southbound)</td>
<td>1 (Right) 1 (Left) 2 (Through)</td>
<td>43 to 76 4 * 34 to 66</td>
<td><img src="image5" alt="Google image" /> <img src="video5" alt="Video scene" /></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Surrey (BC)</td>
<td>Fraser Highway &amp; 168 A St</td>
<td>June 10th, 2015, June 11th, 2015</td>
<td>Fraser Highway (Southbound)</td>
<td>1 (Bike lane) 1 (Left) 2 (Through)</td>
<td>27 to 60 4 * 50 to 81</td>
<td><img src="image6" alt="Google image" /> <img src="video6" alt="Video scene" /></td>
<td></td>
</tr>
</tbody>
</table>

* Protected-permissive left turns
3.3 Methodology

This section describes the methodological framework utilized in this research to analyze video-data at the signal cycle level and to develop various conflict-based SPF$s incorporating different traffic characteristics and shock wave effect.

3.3.1 Shock Waves at Signalized Intersections

The shock wave analysis is commonly undertaken at signalized intersections due to the concern of the length of queues formed upstream the intersection approaches. Shock waves at signalized intersections can be analyzed if the flow-density relationship is known for the approach and the flow state of the approaching traffic is specified [176]. Figure 3.3 shows a hypothetical space-time diagram for one lane approach at a signalized intersection. The vehicle trajectories are shown in dash lines, and the signal timing (i.e. green, yellow, and red) is overlaid on the stop line location. Typically, four traffic flow states (shown in cyan circles) and five shock waves are depicted in such a space-time diagram.
From safety perspective, most of vehicle interactions occur around the triangle that surrounds the area in which the traffic flow state is (II). In addition, the shock wave $S_{12}$, which separates the two consecutive traffic flow states I and II, represents the maximum change or a sudden decrease in the traffic speeds. Theoretically, such a sudden decrease in the traffic speeds can result in a high risk in terms of rear-end conflict occurrence. Therefore, of the shock wave characteristics shown in Figure 3.3, two characteristics were considered in the analysis: (1) the shock wave area where the traffic flow state is II (the triangle area); and (2) the speed of the backward-moving shock wave $S_{12}$. 

Figure 3.3 Theory of shock wave at signalized intersections

* This figure was adapted from the original figure provided by May, Adolf D. [176]
It is noteworthy that the relationship between shock waves and rear-end crashes has been proven in previous studies (e.g., [177] [178] [43]). Chatterjee and Davis [177] investigated a condition for a shock wave to produce a rear-end crash using 41 shock waves including 5 resulted in rear-end crashes. Zheng et al. [178] reported that traffic oscillation (stop-and-go driving) is a significant factor that can affect the occurrence of rear-end crashes on freeways. Machiani and Abbas [43] developed a surrogate safety histogram for signalized intersections based on the relationship between rear-end conflicts and shock waves.

3.3.2 Video-data Processing

The processing of video-data was essential for estimating the number of traffic conflicts, as well as measuring values of different traffic parameters at each signal cycle using the recorded video data. The following subsections describe the main steps of the video analysis procedure.

3.3.2.1 Signal Timing Detection

The first step of the video analysis procedure was to identify traffic signal cycles for each intersection. A MATLAB code was developed to extract the actual signal timing program for each video-hour. At each video frame, the code identifies the traffic signal indicator (e.g. green, red, or yellow) by detecting the RGB (red-green-blue) values of the signal head. Finally, the results were aggregated for all frames and the overall signal program was identified.

3.3.2.2 Vehicle Trajectories and Space-time Diagram

The second step of the video analysis procedure was to extract vehicle trajectories and to plot the space-time diagram for each signal cycle. A computer code was developed to automate the process. First, the overall signal cycle program identified previously was used to determine the start frame and the end frame of each signal cycle. Second, within each cycle’s frames, the RGB values of number of points (e.g. 50 or 100 points) located along the centerline of the studied lane were
detected at each frame. The studied lane was selected to be a lane that has a through movement. Exclusive left-turn and right-turn lanes were not included. Third, a five-dimensional (5D) matrix was created. Each individual element of this matrix has the following values: (1) the point number along the centerline, (2) the frame number, and (3-5) the RGB values of this point at that frame. Subsequently, the 5D matrix was plotted as a two-dimensional image where the horizontal axis represents the point number and the vertical axis represents the frame number. This image represents the space-time diagram for the whole traffic cycle.

Fourth, for each column of pixels (at each x-value) in the space-time image, the pixels that represent a sudden change in the RGB values were detected and identified. These pixels represent arrival or departure of vehicles that passing through this point. Fifth, the identified pixels in the space-time image were grouped along consecutive columns in order to create vehicle trajectories. Pre-specified rules were followed during creating the trajectories. These rules consider the factual movement in terms of the maximum speed, the maximum acceleration, the minimum headway, and the maximum deceleration. Afterwards, the created trajectories were visual inspected to ensure that the created trajectories accurately represent the moving vehicles.

A further adjustment is needed in order to obtain the real-world positions of the vehicle trajectories. This adjustment was performed using a camera calibration process to identify a mapping between the three-dimensional real world and the two-dimensional image space [179]. Following the procedure presented Ismail et al. [179], a linear transformation was defined to convert 3D coordinates into 2D coordinates. The linear transformation was defined by a matrix, called the “homography matrix”. The camera calibration is the process of determining the “homography
The camera calibration process was performed at each intersection based on feature correspondences between the video image and the orthographic image of that intersection. Google Satellite image was used in this study as an orthographic image. Four types of annotations were used for camera calibration optimization: (1) corresponding points; (2) distances; (3) angels; and (4) global up directions. The calibration error was represented by the discrepancy between estimated and annotated segment lengths normalized by the length of each segment. The calibration error was very small and should have no impact on the accuracy of the estimated trajectories. More details about the camera calibration process can be found in a previous study by Ismail et al. [179].

Afterwards, the positions of the tracked trajectories were converted to the real-world coordinate system using the “homography matrix”. As a final check, the trajectories were then overlaid on the original video and visually observed to ensure their accuracy. Also, during this visual observation of the video, vehicle lengths were observed and assigned to each trajectory in order to be considered in conflict analysis. Finally, the space-time diagram for the whole signal cycle was plotted using the final vehicle trajectories and the signal timing program. Figure 3.4 illustrates, through examples, the performed procedure of extracting vehicle trajectories and obtaining the space-time diagram of signal cycles.
Figure 3.4 Platform of extract vehicle trajectories and plot space-time diagram using video data
3.3.2.3 Shock Wave Analysis

After plotting the space-time diagram for each cycle, shock wave characteristics can be analyzed. As mentioned earlier, two shock wave characteristics were considered in the analysis: (1) the shock wave area where the traffic flow state is (II) (the triangle area shown in Figure 3.3); and (2) the speed of the backward-moving shock wave $S_{12}$. In reality, the shock wave area is not exactly a triangle as appeared in the shock wave theory; rather, it might be a polygon. As well, the backward-moving shock wave speed is not a constant speed represented by one line from the first to the last vehicle in the queue; rather, the shock wave speed varies between each couple of consecutive vehicles. A computer code was developed to compute the shock wave area and the speed using vehicle trajectories and signal timing plan. The program computes the shock wave speed between each couple of consecutive vehicles then average shock wave speed was calculated for the whole cycle. In addition, the maximum queue length of each cycle was measured and recorded.

3.3.2.4 Traffic Conflicts

Traffic conflicts can be analyzed using vehicle trajectories. The conflict analysis involves the calculation of conflict indicators such as the Time-to-Collision (TTC) or Post-Encroachment-Time (PET). This research focuses only on rear-end conflicts; therefore, the TTC was selected since it is generally recognized as the most frequently used indicator to identify rear-end conflicts. The TTC is defined as “the time required for two vehicles to collide if they continue at their present speeds and on the same path” [31]. For each two constitutive vehicle trajectories moving in the same lane, the TTC can be continuously estimated over time using the following equation.

$$TTC_t = \frac{X_{j,t} - X_{j+1,t} - L_j}{V_{j+1,t} - V_{j,t}} ; \forall (V_{j+1,t} - V_{j,t}) > 0$$

Eq. (3.1)
Where:

\( t \): The time interval;

\( j \): The leading vehicle;

\( j + 1 \): The following vehicle;

\( X \): The position of the vehicle;

\( V \): The speed of the vehicle;

\( L \): The length of the vehicle.

The minimum TTC can be extracted to represent the conflict severity. A critical value of a conflict indicator must be drawn from each interaction. Typically, the most severe value is used to represent the overall severity of a traffic event. Using the minimum TTC of each conflict, the number of rear-end conflicts was determined for each signal cycle at different TTC thresholds. Thresholds of TTC ranged from 0.5 second to 3 seconds in 0.5 second increments. As well, rear-end conflict positions with reference to the stop line were determined using the coordinates of the critical event position (minimum TTC).

### 3.3.2.5 Platoon Ratio

The quality of progression is a critical characteristic that must be quantified for the analysis of signalized intersections. The arrival type is a parameter that describes this characteristic for each lane group. According to the Highway Capacity Manual (HCM) [180], six arrival types are typically defined to approximate the quality of progression. Although there are no definitive parameters to quantify arrival type, the platoon ratio is useful. The platoon ratio is defined as the proportion of all vehicles arriving during green multiplied by the ratio of the signal cycle length to the effective green time of the subject movement [180]. The platoon ratio and the arrival type can have a significant effect on the frequency of the rear-end conflicts at signalized intersections [47]
Therefore, the platoon ratio was considered in this study for the safety assessment of signalized intersections at the cycle level. For each cycle, the platoon ratio was measured using the space-time diagram. The effective green time was considered to be the green time plus half of the yellow time. To determine the percentage of vehicles arriving during green time, vehicle trajectories were analyzed. If a vehicle did not stop, it was considered to be arrived on green. If a vehicle stopped, the first point of time of its stopping was compared to the signal timing to determine whether this vehicle arrived on red or green.

3.3.2.6 Summary of Video Data Outputs

In summary, the outputs of the video-data analysis for each cycle are: (1) shock wave area (A); (2) traffic volume (vehicles/lane/cycle) (V); (3) backward-moving shock wave speed (S12); (4) platoon ratio (P); (5) maximum queue length (Q); (6) number of rear-end conflicts that have TTC equals or less than different TTC thresholds (i.e. TTC ≤ 0.5, 1, 1.5, 2, 2.5, or 3 seconds). Figure 3.5 illustrates the outputs (measurements) of the video data analysis process. It should be noted that all the aforementioned traffic characteristics were measured only for cycles that are under-saturated. Over-saturated cycles, where a vehicle can stay in the same approach for more than one cycle, were neglected in this research. Future research is recommended to consider over-saturated flow when evaluating safety at the cycle level.
3.3.3 Conflict-based SPFs at the Cycle Level

After obtaining the aforementioned measurements (V, A, Q, S₁₂, P, and the number of rear-end conflicts) for each traffic cycle using the proposed video analysis process, the next step was to develop conflict-based SPFs to investigate the impact of different traffic characteristics within a signal cycle on the number of rear-end conflicts that occurred at the same cycle. The SPFs are developed using the GLM approach.

The GLM approach has been widely used in literature for the development of collision and conflict prediction models (e.g., [181] [40] [182]). Previous studies have shown that the number of potential traffic conflicts related to the number of vehicles arriving within a small time-interval at a road site occurs by a Poisson process [183]. Assuming that traffic conflict data are non-negative, discrete, and rare events compared to the circulating traffic volume, mixed-Poisson distribution family might be used in this regard as with crash data [109]. The GLM approach used to model
traffic conflict occurrence assumes an error structure that is Poisson or Negative Binomial (Poisson-Gamma). Generally, the model must yield logical results. That is, it must not lead to a negative number of conflicts, as well as it must predict zero values of conflict frequency for zero values of exposure variable (i.e. traffic volume). A commonly used model form consists of an exposure measure(s) raised to some power and multiplied by an exponential function incorporating the remaining explanatory variables. Such a model form can be linearized by the logarithm link function [184]. The conflict prediction models used in this research can be expressed mathematically as follows:

\[
E(Y) = V^{a_1} \exp \left[ a_0 + \sum_j b_j x_j \right]
\]

Eq. (3.2)

Where:

\( E(Y) \): The predicted number of rear-end conflicts per cycle;

\( V \): The traffic volume per lane per cycle (exposure);

\( x_j \): Any other explanatory variables (such as A, Q, S12, or P);

\( a_0, a_1, b_j \): The model parameters.

In order to decide whether the error structure follows Poisson or Negative Binomial distribution, the methodology presented by Sawalha and Sayed [184] was applied. First, Poisson distribution was assumed and the model parameters were estimated. Then the dispersion parameter (\( \sigma_d \)) was calculated using the following equation:

\[
\sigma_d = \frac{Pearson \chi^2}{n - p}
\]

Eq. (3.3)

Where:

\( n \): The number of observations;
The number of model parameters.

*Pearson* $\chi^2$ is defined as follows:

$$
\text{Pearson } \chi^2 = \sum_{i=1}^{n} \left[ \frac{y_i - E(Y_i)}{Var(Y_i)} \right]^2
$$

Eq. (3.4)

Where:

$y_i$: The observed number of rear-end conflicts at cycle $(i)$;

$E(Y_i)$: The predicted frequency of rear-end conflicts at cycle $(i)$ as obtained from the conflict prediction model;

$Var(Y_i)$: The variance of conflict frequency for the cycle $(i)$.

The dispersion parameter ($\sigma_d$) is a useful statistic measure for assessing the amount of variation in the observed data. If the estimated value of ($\sigma_d$) is significantly greater than 1.0, this means that the data have a greater dispersion than what can be explained by the Poisson distribution, and then the Negative Binomial distribution provides a better fit to the data [181] [184].

Various models were developed in this research using different combinations of the explanatory variables (V, A, Q, S12, and P). The reason behind developing various models is to investigate the impact of adding different explanatory variables, as well as to make the proposed approach applicable in different situations where the availability of measuring or estimating some explanatory variables is limited. The procedure recommended by Sawalha and Sayed [181] [184] to add explanatory variables into the GLM model was utilized. The procedure is a forward procedure that seeks parsimonious models. In this procedure, the variables are added to a model one by one, and the decision on whether a variable is to be retained in the model is based on: (1) the significance of the estimated coefficient of this variable (t-ratio), and (2) the significance of
the drop in the scaled deviance of the model caused by adding this variable. Also, variables that represent exposure (e.g. traffic volume) must be included first [181] [184].

The goodness-of-fit of the developed GLM models was assessed using two main statistical measurements: the scaled deviance (SD), and the Pearson chi-squared ($\chi^2$). Generally, for a well-fitted model with a relatively large number of observations, the expected values of ($\chi^2$) and SD will be approximately equal to the number of degrees of freedom (df) [181]. In addition to (SD) and ($\chi^2$), different developed models were compared using Akaike’s Information Criterion (AIC) [185], which can be estimated as per Eq. (3.5).

$$AIC = 2p - 2(\text{LogLik}_{\text{full}})$$

\text{Eq. (3.5)}

Where:

$p$: The number of model parameters;

$\text{LogLik}_{\text{full}}$: Log-likelihood for the full model.

The free software environment for statistical computing “R” was used to develop the GLM models and to estimate different statistical measurements.

3.4 Results and Discussion

3.4.1 Summary of Data Statistics

The data used for the analysis was obtained at the six study locations at the signal cycle level using the video analysis procedure described earlier. Table 3.2 provides summary statistics of the measured data. It is noteworthy that the correlation values between V and the number of rear-end conflict increase steadily with the TTC thresholds. For example, the correlation increases from 0.27 at TTC threshold of 0.5 seconds to 0.55 at TTC threshold of 3.0 seconds. That is, the higher the TTC threshold, the higher the dependency of the rear-end conflicts on the exposure. This is
confirming with the findings provided in previous studies ([47] [48] [49]). The covariates A, Q, S12, and P have good correlations with the number of rear-end conflicts, meaning that they can provide a better conflict prediction if they are incorporated in the conflict-based SPF.

In addition, considering that the data are collected sequentially in time, the assumption that the error in the developed models is independent might not be appropriate. Therefore, the serial correlation between the observed conflicts in consecutive signal cycles at each location was estimated using the Durbin-Waston (DW) statistic. The results showed that the serial correlation had low insignificant values and should have little impact on the results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>V</td>
<td>Volume per lane per cycle</td>
<td>---</td>
<td>11.58</td>
<td>3.56</td>
<td>2</td>
<td>22</td>
</tr>
<tr>
<td>A</td>
<td>Shock wave area</td>
<td>km. seconds</td>
<td>1.05</td>
<td>0.96</td>
<td>0</td>
<td>3.93</td>
</tr>
<tr>
<td>Q</td>
<td>Maximum queue length</td>
<td>meter</td>
<td>40.42</td>
<td>24.54</td>
<td>0</td>
<td>97.46</td>
</tr>
<tr>
<td>S12</td>
<td>Backward-moving shock wave speed</td>
<td>meter/second</td>
<td>-2.07</td>
<td>2.65</td>
<td>-27.2</td>
<td>0</td>
</tr>
<tr>
<td>P</td>
<td>Platoon ratio</td>
<td>---</td>
<td>1.26</td>
<td>0.40</td>
<td>0</td>
<td>2.27</td>
</tr>
<tr>
<td>TTC0.5</td>
<td>Number of rear-end conflicts (TTC≤ 0.5sec)</td>
<td>---</td>
<td>0.49</td>
<td>0.85</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>TTC1.0</td>
<td>Number of rear-end conflicts (TTC≤ 1.0sec)</td>
<td>---</td>
<td>0.97</td>
<td>1.40</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>TTC1.5</td>
<td>Number of rear-end conflicts (TTC≤ 1.5sec)</td>
<td>---</td>
<td>1.88</td>
<td>1.88</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>TTC2.0</td>
<td>Number of rear-end conflicts (TTC≤ 2.0sec)</td>
<td>---</td>
<td>2.97</td>
<td>2.30</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>TTC2.5</td>
<td>Number of rear-end conflicts (TTC≤ 2.5sec)</td>
<td>---</td>
<td>3.82</td>
<td>2.57</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>TTC3.0</td>
<td>Number of rear-end conflicts (TTC≤ 3.0sec)</td>
<td>---</td>
<td>4.25</td>
<td>2.73</td>
<td>0</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 3.2 Summary of data statistics

3.4.2 Conflict-based SPF at the Cycle Level (Real-time Safety Models)

Various models were developed in this research using different combinations of the covariates (V, A, Q, S12, and P). For all models, the response (Y) denotes the number of rear-end conflicts per cycle that have TTC values equal or less than 1.50 seconds. The TTC threshold of 1.50 seconds is commonly used by researchers to define rear-end conflicts [96] [97].

The results of the developed models are provided in Table 3.3. The first model represents the exposure only. In addition to the first model, the table shows four models that consider the
exposure and one additional variable. Furthermore, the last model in the table considers the
exposure and a combination of three additional explanatory variables. The significance of the
explanatory variables, the goodness-of-fit statistics, and the error structure for all models are
provided in the table.

<table>
<thead>
<tr>
<th>Model#</th>
<th>Variables</th>
<th>Error Structure</th>
<th>K</th>
<th>SD</th>
<th>df</th>
<th>\chi^2</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Exposure only):</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1:</td>
<td>$V^{1.563} \exp(-3.231)$</td>
<td>NB</td>
<td>3.05</td>
<td>249</td>
<td>220</td>
<td>356</td>
<td>775</td>
</tr>
<tr>
<td>(Exposure + One Variable):</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 2:</td>
<td>$V^{0.706} \exp(-1.797 + 0.501 A)$</td>
<td>NB</td>
<td>14.9</td>
<td>244</td>
<td>219</td>
<td>241</td>
<td>702</td>
</tr>
<tr>
<td>Model 3:</td>
<td>$V^{0.65} \exp(-2.046 + 0.0122 Q)$</td>
<td>NB</td>
<td>8.73</td>
<td>243</td>
<td>219</td>
<td>253</td>
<td>716</td>
</tr>
<tr>
<td>Model 4:</td>
<td>$V^{1.63} \exp(-3.316 + 0.05 S_{12})$</td>
<td>NB</td>
<td>3.10</td>
<td>248</td>
<td>219</td>
<td>347</td>
<td>775</td>
</tr>
<tr>
<td>Model 5:</td>
<td>$V^{1.571} \exp(-1.768 - 1.266 P)$</td>
<td>Poisson</td>
<td>---</td>
<td>276</td>
<td>219</td>
<td>281</td>
<td>706</td>
</tr>
<tr>
<td>Combined Model:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 6:</td>
<td>$V^{1.239} \exp(-1.624 + 0.294 A - 0.828 P + 0.119 S_{12})$</td>
<td>Poisson</td>
<td>---</td>
<td>240</td>
<td>217</td>
<td>215</td>
<td>674</td>
</tr>
</tbody>
</table>

K: Dispersion parameter for Negative binomial family
All variables are significantly different from zero at 95% confidence level
*Significantly different from zero at 90% confidence level

Table 3.3 Conflict-based SPFs at the cycle level

Generally, the developed models show good fit and almost all the explanatory variables are
statistically significant at a 95% confidence level. Based on the estimated value of the dispersion
parameter ($\sigma_d$), the error structure was assumed to follow Negative Binomial distribution for four
models, and Poisson distribution for two models. All covariates’ coefficients have logical signs.

In other words, higher conflict occurrence is expected during the signal cycles that have long
queues and bigger shock waves. On the other hand, the higher the platoon ratio, the more vehicle
arrivals during the green time, and subsequently, a better arrival type and lower chances that
conflicts occur during the cycle.
For the exposure-only model (model 1), the coefficient of V is statistically significant at a 95% confidence level. This model shows a good fit in terms of the (SD) value which is close to the degree of freedom (df). However, the model has a large value of the Pearson chi-squared ($\chi^2$) compared to the (df). The model also has the largest value of AIC compared to the other models. Thus, despite the significance of the exposure variable V, more explanatory variables are still needed to provide a better prediction of the conflict occurrence beyond what can be expected from the exposure only.

For the models that consider the exposure and one additional variable (models 2, 3, 4, and 5), all models are noted to have a better statistical fit compared to model 1. Also, the additional explanatory variable is significant at 95% confidence level. One exception of that is model 4 (volume and shock wave speed) whose additional variable (S12) is statistically significant at 90% confidence level. Model 2 (volume and shock wave area) represents the best model in this group in terms of AIC, ($\chi^2$), and (SD) values. Model 3 (volume and maximum queue length) shows a good fit in terms of the ($\chi^2$) and (SD) values. This model has an AIC value significantly lower than model 1 and slightly higher than model 2. Model 4 has a value of AIC similar to model 1; however, the value of ($\chi^2$) is better than model 1. Model 5 has a value of AIC very close to model 2 and significantly better than model 1. Thus, the shock wave area, the maximum queue length, the shock wave speed, and the platoon ratio are shown to be important characteristics that affect the number of rear-end conflicts at the signal cycle. Incorporating one of these characteristics (A, Q, S12, or P), along with the traffic volume, in the conflict-based SPF$s$ of signalized intersections is recommended to improve the model fit.
Finally, the last model in the table (model 6) combines the exposure measure (V) with three additional explanatory variables (A, P, S12). The maximum queue length (Q) was excluded from this model due to the strong correlation between A and Q, or in other words, the multicollinearity effect. Model 6 shows the best fit compared to all previous models. The model presents the minimum values of SD, (\(\chi^2\)), and AIC. As well, all variables’ coefficients are statistically significant in this model at 95% confidence level. However, the main disadvantage of this model is the inclusion of many explanatory variables which may be difficult to obtain in some cases.

3.4.3 Space-time Distribution of Traffic Conflicts

In addition to the developed real-time safety models, a space-time conflict heat map diagram was developed from all observed signal cycles to investigate the distribution of traffic conflicts. To plot the conflict space-time distribution, two measurements were considered for each conflict. The first measurement is the time of the conflict with regard to the signal timing and represented as a percentage. The second measurement is the position of the conflict location ascribed to the stop line location and represented as a distance. Figures 3.6 and 3.7 show heat maps that represent the space-time distribution of the rear-end conflicts at TTC thresholds of 1.5 seconds, and 3 seconds, respectively.
Figure 3.6 Space-time heat map for rear-end conflicts (TTC < 1.5 seconds) for all studied locations

Figure 3.7 Space-time heat map for rear-end conflicts (TTC < 3 seconds) for all studied locations
As shown in Figures 3.6 and 3.7, during the red light, all conflicts occur upstream the stop line. At the beginning of the red light, when the queue length is very short, most of conflicts occur just behind the stop line. After that, the queue length increased gradually, and the most intensive location of conflicts moves backward away from the stop line. By the start of the green light, the cumulative queue starts to discharge and the hot spot of conflicts disappeared gradually with the progression of the green time. It could also be noted that conflicts are distributed with time upstream and downstream the stop line during the green and yellow times. This is reasonable because, during these times, both of the conflicting vehicles are moving with a speed larger than zero which causes some conflicts to have a potential location downstream the stop line.

The heat maps in Figures 3.6 and 3.7 illustrate graphically the association between rear-end conflicts and the shock wave area. It can be noted that the intensive conflict area in the heat map (red, yellow, and green spots) forms, approximately, a polygon that is similar to the hypothetical triangle of the shock wave area where the traffic flow state is II (shown in Figures 3.3).

It is noteworthy that the heat maps show two areas with red spots (most intensive conflict areas). The first one occurs at the beginning of the red light, which most probably represents the dilemma zone where the traffic signal indication changes from green to yellow to red. The second one occurs during the start of the green time where the stopped flow starts to discharge gradually at low speed while other vehicles are arriving at higher speeds to the end of the queue. The heat maps show a relationship between the rear-end conflicts and the queue length. For example, the most intensive conflict area in the heat map is located upstream the stop line within a distance that approximately
represents the 50\textsuperscript{th} percentile of the maximum queue length. As well, most of the conflicts occur within a distance that approximately represents the 85\textsuperscript{th} percentile of the maximum queue length.

3.5 Potential Applications

The potential implementations of the developed real-time models can be summarized as follows:

3.5.1 Safety Evaluation Using Field-observed Data

The dynamic traffic parameters (\(V, A, Q, S_{12},\) and \(P\)) at each signal cycle can be observed in the field manually or by a video analysis process. They can then be inputted in the developed models to estimate the predicted number of rear-end conflicts, which is necessary for safety evaluation.

3.5.2 Calibration of Microsimulation Models for Safety Evaluation

Generally, the use of microsimulation models in safety analysis has been criticized for two main reasons. First, vehicles in the simulation models follow specific rules that aim at avoiding collisions. Therefore, it is very difficult to represent unsafe vehicle interactions and near misses. Second, there are many parameters and several ways to model traffic in microsimulation models. Therefore, the results can vary significantly depending on the input values of the model parameters and the approach used in modeling [47] [48] [49]. Furthermore, a rigorous calibration process is essential to avoid inaccurate results. Researchers have advocated the use of field measured conflicts in the calibration process but this data can be difficult to obtain [47] [48] [49]. The real-time safety models presented in this chapter can be used to facilitate the calibration process of microsimulation models. The target of calibration process can be matching the actual and simulated traffic parameters incorporated in the developed SPFs (\(V, A, Q, S_{12},\) and \(P\)) instead of matching the actual and simulated traffic conflicts.
3.5.3 **Real-time Safety Optimization of Signalized Intersections**

Real-time safety monitoring and evaluation is gaining interest among researchers as a proactive strategy to improve safety (e.g., [132] [186] [129], among others). Real-time traffic data will be available in connected-vehicle environments through V2V and V2I communications [8]. These data can be used to obtain various traffic parameters and performing a real-time adaption of signal design by minimizing the total delays and the queue length [15]. The models, presented in this chapter, can be used to predict the number of rear-end conflicts using the obtained traffic parameters in real time. This would provide insight into how real-time changes in the signal cycle design affect the safety of signalized intersections. Thus, the real-time adaption of the signal design can consider both mobility and safety. This can be obtained by solving a multi-objective optimization process that seeks minimizing both the total delays and the total number of traffic conflicts for all the intersection approaches.

### 3.6 Summary and Conclusion

The main objective of the work presented in this chapter is to develop conflict-based safety performance functions (SPFs) for signalized intersections at the signal cycle level. The developed SPFs can be considered as real-time safety models, since they relate the number of rear-end conflicts occurring in each signal cycle to dynamic traffic variables. Traffic video-data were recorded for six signalized intersections located in two cities in Canada. A video analysis procedure was proposed to collect rear-end conflicts and various traffic variables at each signal cycle from the recorded videos. The TTC was used as a traffic conflict indicator. The traffic variables include: traffic volume, maximum queue length, shock wave speed and area, and platoon ratio. The SPFs were developed using the GLM approach, where the traffic volume per cycle represents the exposure measure. The error structure in the developed models was assumed to be
Poisson or Negative Binomial (Poisson-Gamma). The goodness-of-fit of the developed GLM models was assessed using: scaled deviance (SD), Pearson chi-squared ($\chi^2$), and AIC.

The results showed that all the developed models have good fit and almost all the explanatory variables are statistically significant. All the covariates’ coefficients have logical signs. In other words, the number of traffic conflicts is expected to increase during signal cycles that have long queues, bigger shock waves, and lower platoon ratios. The shock wave area, the maximum queue length, the shock wave speed, and the platoon ratio are shown to be important characteristics that affect the number of rear-end conflicts at the signal cycle. Incorporating one of these characteristics or a combination of them, along with the traffic volume, in the conflict-based SPF of signalized intersections is recommended to improve the model fit and provide a better prediction of the conflict occurrence beyond what can be expected from the traffic volume only.

Furthermore, space-time conflict heat maps were developed from all observed signal cycles to investigate the distribution of traffic conflicts. The heat maps illustrated graphically the association between rear-end conflicts and both the shock wave area and the queue length. The heat maps also showed that most of rear-end conflicts occur at: (1) the beginning of the red light which represents the dilemma zone where the traffic signal changes from green to yellow to red; and (2) the start of the green time where the stopped-flow starts to discharge gradually at low speed while other vehicles are arriving at higher speeds to the end of the queue.
The real-time safety models presented in this chapter can have several potential applications, including facilitating safety evaluation of signalized intersections using field-observed data, simplifying the calibration process of the microsimulation models for safety evaluation, and real-time optimization of signalized intersection safety by changing the signal design.
Chapter 4: Full Bayesian Conflict-based Models for Real-time Safety

Evaluation of Signalized Intersections

4.1 Background

In the previous chapter, real-time safety models (i.e., SPFs at the signal cycle level) for signalized intersections were developed. The developed models relate rear-end conflicts occurring in each signal cycle to dynamic variables such as traffic volume, maximum queue length, shock wave characteristics, and platoon ratio. The Time to collision TTC was the only traffic conflict indicator. The TTC threshold that distinguishes between conflict and non-conflict events was assumed to be 1.50 seconds. The conflict severity was not investigated. Besides that, the safety models were developed using the GLM approach without accounting for the unobserved heterogeneity and variation of traffic conditions across different sites. Therefore, it would be useful to develop additional real-time safety models that consider other conflict indicators, different severity levels, and effects of the unobserved heterogeneity and site variation.

This chapter presents the development of additional real-time safety models for signalized intersections. The models incorporate various traffic conflict indicators, including the Time to collision (TTC) [31], the Modified time to collision (MTTC) [32], and the Deceleration rate to avoid the crash (DRAC) [35] [36]. To account for different severity levels, the models were developed by identifying conflicts at multiple thresholds of TTC, MTTC, and DRAC. In addition, conflict severity and temporal distributions were investigated. The Severity Index (SI) based on TTC [50], the extended time to collision measures (Time exposed time-to-collision (TET) and Time integrated time-to-collision (TIT) [37]) were investigated. To develop these models, both the
traffic video-data and the video analysis procedure described in chapter 3 were utilized in the analysis. The Full Bayesian (FB) approach was also applied to address the unobserved heterogeneity and variation among different sites. Two kinds of FB models were developed: (1) Poisson-LogNormal distribution (PLN) models that account for heterogeneity; and (2) PLN models with random intercept that account for heterogeneity and site effect.

The following sections in this chapter provide a detailed description of the data and traffic conflict indicators used to develop the safety models; the FB analysis applied to consider the unobserved heterogeneity; the results of the developed safety models; and the conflict frequency and severity investigation.

4.2 Study Locations and Video Data Collection

The video-data described in detail in chapter 3 of this thesis were used in the analysis. The data were recorded from six signalized intersections in two cities in Canada: Edmonton and Surrey. More details about the selected study locations and the video data are provided in Figures 3.1-3.2 and Table 3.1.

4.3 Full Bayesian SPFs at the Signal Cycle Level

4.3.1 Traffic Characteristics

The dynamic cycle-related traffic parameters described in chapter 3 were considered as explanatory variables in the developed FB real-time safety models. These parameters are: (1) shock wave area (A); (2) traffic volume (vehicles/lane/cycle) (V); (3) backward-moving shock wave speed (S12); (4) platoon ratio (P); and (5) maximum queue length (Q). It should be noted that all the aforementioned traffic characteristics were measured only for cycles that are under-
saturated. Over-saturated cycles, where a vehicle can stay in the same approach for more than one cycle, were neglected in this research.

4.3.2 Number of Traffic Conflicts per Cycle (The Model Response)

This study focuses only on rear-end conflicts at signalized intersections. Multiple rear-end conflict indicators were considered. The following sections explain more details about these indicators.

4.3.2.1 Time to Collision (TTC)

The TTC is generally recognized as the most frequently used indicator to identify rear-end conflicts. The TTC is defined as “the time required for two vehicles to collide if they continue at their present speeds and on the same path” [31]. For each constitutive vehicle trajectories moving in the same lane, the TTC can be continuously estimated over time using the following equation.

\[
TTC_t = \frac{X_{L,t} - X_{F,t} - D_L}{V_{F,t} - V_{L,t}} ; \forall (V_{F,t} - V_{L,t}) > 0
\]  

Eq. (4.1)

Where:

\( t \): Time interval;
\( L \): Leading vehicle;
\( F \): Following vehicle;
\( X \): Vehicle position;
\( V \): Vehicle speed;
\( D \): Vehicle length.

Using the minimum TTC of each conflict, the number of rear-end conflicts was determined for each signal cycle at several TTC thresholds. The main reason behind using several TTC thresholds is to provide multiple SPFs that can address different conflict-severity levels. The selected TTC thresholds range from 1 to 3 seconds with an interval of 0.5 seconds.
4.3.2.2 Modified Time to Collision (MTTC)

The definition of TTC is functional in defining conflicts only if the speed of the following vehicle is higher than the speed of the leading vehicle. However, this definition ignores many potential conflicts that can occur due to acceleration or deceleration discrepancies [32]. Therefore, Ozbay et al. [32] proposed another rear-end conflict indicator (Modified-TTC or MTTC) that considers relative positions, relative speeds, and relative accelerations of the conflicting vehicles. For each constitutive vehicle trajectories moving in the same lane, the MTTC can be continuously estimated over time using the following equation.

\[
MTTC_t = \frac{\Delta V_t \pm \sqrt{\Delta V_t^2 + 2\Delta A_t(\Delta X_t - D_t)}}{\Delta A_t}
\]

Eq. (4.2)

Where:

\( t \): Time interval;
\( L \): Leading vehicle;
\( F \): Following vehicle;
\( X \): Vehicle position;
\( V \): Vehicle speed;
\( D \): Vehicle length;
\( A \): Vehicle acceleration;
\( \Delta X = X_L - X_F \): Relative position;
\( \Delta V = V_F - V_L \): Relative speed;
\( \Delta A = A_F - A_L \): Relative acceleration.

Eq. (4.2) has two outcomes with regard to MTTC. If the two outcomes are positive, the minimum of them is considered to be the MTTC value. If one outcome is positive while the other is negative,
the positive outcome is considered to be the MTTC value. Like the TTC, the minimum MTTC value was used to determine the number of rear-end conflicts for each cycle at several thresholds (1 to 3 seconds with an interval of 0.5 seconds).

### 4.3.2.3 Deceleration Rate to Avoid Crash (DRAC)

The DRAC can be defined as the rate at which a vehicle must decelerate to avoid the collision with another conflicting vehicle [35] [36]. For each constitutive vehicle trajectories moving in the same lane, the DRAC can be continuously estimated over time using the following equation.

\[
DRAC_{F,t} = \frac{(V_{F,t} - V_{L,t})^2}{2[(X_{L,t} - X_{F,t}) - D_L]}
\]

**Eq. (4.3)**

Where:

- \( t \): Time interval;
- \( L \): Leading vehicle;
- \( F \): Following vehicle;
- \( X \): Vehicle position;
- \( V \): Vehicle speed;
- \( D \): Vehicle length.

Using the maximum DRAC of each conflict, the number of rear-end conflicts was determined for each signal cycle at different DRAC thresholds. Four DRAC thresholds were chosen to address different severity levels [106]: 6m/s\(^2\) (the most severe), 4.5m/s\(^2\), 3m/s\(^2\), and 1.5 m/s\(^2\). It is also noteworthy that the ability of the DRAC to accurately reflect traffic conflicts and potential crash situation has been criticized by some researchers. Their main argument was that the DRAC does not consider the vehicle braking capability (e.g. a given DRAC value under wet pavement conditions is more critical to safety than the same value under dry pavement conditions). However,
studies involving this safety measure that explores these aspects are not commonly found in the literature [107] [91]. Future research is recommended in order to consider these aspects.

4.3.3 Video Analysis

The main objective of the video-data analysis was to extract traffic data from the video recordings. The video-analysis procedure is based on a set of MATLAB codes. The procedure started with identifying actual traffic signal timing and cycles for each intersection by detecting the changes in the signal colors from video scenes. Afterwards, moving vehicles in through lanes were tracked (exclusive left-turn and right-turn lanes were excluded), and the space-time diagram for each cycle was plotted. The whole video-analysis procedure is described in details in chapter 3 (section 3.3.2). Figure 4.1 shows samples of the space-time diagram results for 32 traffic signal cycles extracted from videos for one of the study locations.
Figure 4.1 Samples of space-time diagram results (32 traffic signal cycles)
Using the space-time diagram, a computer code was developed to compute various traffic parameters and conflict indicators for each cycle. Thus, the outputs of the video-data analysis for each cycle were: 1) shock wave area ($A$); 2) traffic volume (vehicles/lane/cycle) ($V$); 3) backward-moving shock wave speed ($S_{12}$); 4) platoon ratio ($P$); 5) maximum queue length ($Q$); 6) number of rear-end conflicts at different TTC thresholds; 7) number of rear-end conflicts at different MTTC thresholds; and 8) number of rear-end conflicts at different DRAC thresholds. With regard to the calculated TTC and MTTC, it should be noted that the values of the TTC and the MTTC estimated from Eq. (4.1) and Eq. (4.2) are instantaneous values. The TTC and MTTC values were calculated in the analysis at each video frame (one second = 29.97 frames), which provides an adequate level of accuracy. **Figure 4.2** illustrates the outputs (measurements) of the video data analysis process.

![Figure 4.2 Measurements (outputs) of video data analysis process](image-url)
4.3.4 Summary of Data Statistics

The video analysis outputs described above were obtained for the six study locations. Table 4.1 provides summary statistics of the measured data. The covariates A, Q, S12, and P have good correlations with the number of rear-end conflicts, indicating that they can provide a better conflict prediction if they are incorporated in the conflict-based SPFs.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>V</td>
<td>Traffic Volume per lane per cycle</td>
<td>---</td>
<td>11.58</td>
<td>3.56</td>
<td>2</td>
<td>22</td>
</tr>
<tr>
<td>A</td>
<td>Shock wave area</td>
<td>km. seconds</td>
<td>1.05</td>
<td>0.96</td>
<td>0</td>
<td>3.93</td>
</tr>
<tr>
<td>Q</td>
<td>Maximum queue length</td>
<td>meter</td>
<td>40.42</td>
<td>24.54</td>
<td>0</td>
<td>97.46</td>
</tr>
<tr>
<td>S12</td>
<td>Backward-moving shock wave speed</td>
<td>meter/second</td>
<td>-2.07</td>
<td>2.65</td>
<td>-27.2</td>
<td>0</td>
</tr>
<tr>
<td>P</td>
<td>Platoon ratio</td>
<td>---</td>
<td>1.26</td>
<td>0.40</td>
<td>0</td>
<td>2.27</td>
</tr>
<tr>
<td>TTC1</td>
<td>Number of rear-end conflicts (TTC≤ 1.0sec)</td>
<td>---</td>
<td>0.97</td>
<td>1.40</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>TTC1.5</td>
<td>Number of rear-end conflicts (TTC≤ 1.5sec)</td>
<td>---</td>
<td>1.88</td>
<td>1.88</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>TTC2</td>
<td>Number of rear-end conflicts (TTC≤ 2.0sec)</td>
<td>---</td>
<td>2.97</td>
<td>2.30</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>TTC2.5</td>
<td>Number of rear-end conflicts (TTC≤ 2.5sec)</td>
<td>---</td>
<td>3.82</td>
<td>2.57</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>TTC3</td>
<td>Number of rear-end conflicts (TTC≤ 3.0sec)</td>
<td>---</td>
<td>4.25</td>
<td>2.73</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>MTTC1</td>
<td>Number of rear-end conflicts (MTTC≤ 1.0sec)</td>
<td>---</td>
<td>2.60</td>
<td>2.35</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>MTTC1.5</td>
<td>Number of rear-end conflicts (MTTC≤ 1.5sec)</td>
<td>---</td>
<td>4.61</td>
<td>3.12</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>MTTC2</td>
<td>Number of rear-end conflicts (MTTC≤ 2.0sec)</td>
<td>---</td>
<td>5.38</td>
<td>3.37</td>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>MTTC2.5</td>
<td>Number of rear-end conflicts (MTTC≤ 2.5sec)</td>
<td>---</td>
<td>5.88</td>
<td>3.53</td>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>MTTC3</td>
<td>Number of rear-end conflicts (MTTC≤ 3.0sec)</td>
<td>---</td>
<td>6.02</td>
<td>3.64</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td>DRAC6</td>
<td>Number of rear-end conflicts (DRAC≥ 6.0m/s²)</td>
<td>---</td>
<td>0.41</td>
<td>0.77</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>DRAC4.5</td>
<td>Number of rear-end conflicts (DRAC≥ 4.5m/s²)</td>
<td>---</td>
<td>0.57</td>
<td>0.93</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>DRAC3</td>
<td>Number of rear-end conflicts (DRAC≥ 3.0m/s²)</td>
<td>---</td>
<td>1.00</td>
<td>1.29</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>DRAC1.5</td>
<td>Number of rear-end conflicts (DRAC≥ 1.5m/s²)</td>
<td>---</td>
<td>2.92</td>
<td>2.21</td>
<td>0</td>
<td>11</td>
</tr>
</tbody>
</table>

Table 4.1 Summary of data statistics

4.3.5 Full Bayesian (FB) Analysis

After obtaining the aforementioned measurements, the next step was to develop conflict-based SPFs that relate different traffic characteristics of each cycle to the number of rear-end conflicts that occurred at the same cycle. The SPFs were developed using the FB approach to account for unmeasured or unobserved heterogeneity in the traffic conflict data. The FB approach has been widely used in literature for the development of collision/conflict prediction models (e.g., [182], [187], [188], [39]). The FB approach has a potential advantage of specifying very complex model forms, as well as the flexibility to accommodate various distributions such as the Poisson-Gamma
distribution and the Poisson-LogNormal distribution (PLN). In addition, the FB approach has the ability of using prior information for any unknown parameters, and then it can provide more accurate measures of uncertainty on the posterior distributions of their estimates [182] [187] [188] [39].

Various models were developed using different combinations of the explanatory variables (V, A, Q, S12, and P). The procedure recommended by Sawalha and Sayed [181] to add explanatory variables into the model was utilized. The procedure is a forward procedure that seeks parsimonious models. In this procedure, the variables are added to a model one by one, and the decision on whether a variable is to be retained in the model is based on: 1) the significance of the estimated coefficient of this variable (t-ratio), and 2) the improvement in the goodness of fit of the model caused by adding this variable. Also, variables that represent exposure (e.g. traffic volume (V)) must be included first [181] [184].

4.3.5.1 PLN Models

The PLN model is commonly used to address over-dispersion for unobserved heterogeneity. The PLN model was shown to be better than the Poisson-Gamma model when modeling traffic collisions with the presence of outliers [187]. The main reason is that the tails of the PLN model are known to be heavier than those of the gamma distribution. The main limitation that makes the PLN model less popular is that the model requires more computational efforts. However, this is not an issue with the advanced computational capabilities of computer algorithms and the introduction of numerical methods in Bayesian statistics. This has allowed the application of the PLN model to analyze collision or conflict data with reasonable accuracy [109].
To account for over-dispersion for unobserved or unmeasured heterogeneity, FB PLN models were developed in this study following the FB procedure presented in a previous study by El-Basyouny and Sayed [187]. Let $Y_i$ denotes the number of conflicts at signal cycle $i$ ($i = 1, 2... n$). It was assumed that conflicts at the $n$ signal cycles are independent and that:

$$Y_i|\theta_i \sim \text{Poisson}(\theta_i)$$  \hspace{1cm} \text{Eq. (4.4)}

To address over-dispersion for unobserved or unmeasured heterogeneity, it was assumed that:

$$\theta_i = \mu_i \exp(u_i)$$  \hspace{1cm} \text{Eq. (4.5)}

And:

$$\ln \mu_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_m X_{im}$$  \hspace{1cm} \text{Eq. (4.6)}

Where:

$X_{i1}$: The covariates representing the traffic characteristics (e.g. $\ln(V)$, $A$, $Q$, $P$, $S_{12}$);

$\beta_0, \beta_1, ..., \beta_m$: The model parameters;

$\exp(u_i)$: A multiplicative random effect.

The PLN regression model was obtained by the assumption:

$$\exp(u_i) \sim \text{Lognormal}(0, \sigma_u^2) \quad \text{or} \quad u_i \sim N(0, \sigma_u^2)$$  \hspace{1cm} \text{Eq. (4.7)}

Where $(\sigma_u^2)$ denotes the extra Poisson variance that addressing unmeasured or unobserved heterogeneity.

### 4.3.5.2 PLN Models with Random Intercept

Because the rear-end conflict data was measured at six different intersections, an additional variance component was added to the PLN models to account for the possibility that different sites can have different conflict risks due to the variation of traffic, geometric, driving behavior, and environmental conditions across sites. Hence, the PLN models were developed in such a way that the intercept can vary from site to site. Typically, the $n$ signal cycles belong to $k$ mutually
exclusive sites. It was assumed that the \( i \)th cycle belongs to site \( s(i) \) where \( s(i) \in \{1, 2, \ldots, k\} \), then the model can be expressed as follows:

\[
\ln \mu_i = \beta_{s(i),0} + \beta_1 X_{i1} + \cdots + \beta_m X_{im} \quad \text{Eq. (4.8)}
\]

Where:

\[
\beta_{s(i),0} = \beta_0 + \omega_{s(i)} \quad \text{Eq. (4.9)}
\]

And:

\[
\omega_{s(i)} \sim N(0, \sigma_s^2) \quad \text{Eq. (4.10)}
\]

Where: \( \sigma_s^2 \) represents the additional variance component that addressing the variation among different sites. This means that the model is equivalent to a PLN model with a random intercept that varies at each site.

### 4.3.5.3 Prior Distributions

The formulation of FB models requires a prior distribution for each unknown parameter. A prior distribution reflects to some extent any prior knowledge about the parameter of interest. If such prior information is available before observing any data, it should be used to formulate the so-called informative priors; otherwise non-informative (vague) priors are usually used to reflect the lack of prior information [187]. In this thesis, prior distributions for all parameters \( (\beta_0, \beta_1, \ldots, \beta_m) \) and all hyper-parameters \( (\sigma_u^2, \sigma_s^2) \) were assumed as non-informative due to the lack of prior knowledge of their values. Following the most commonly used vague prior distributions, the prior distributions used in this thesis were diffused normal distributions (with zero mean and large variance) for the regression parameters \( (\beta_u, \beta_1, \ldots, \beta_m) \), and Gamma \( (1, \epsilon) \) for the hyper-parameters \( (\sigma_u^2, \sigma_s^2) \), where \( \epsilon \) is a small number (e.g. 0.001) [187].
4.3.5.4 Full Bayes Estimation

The posterior distributions of the model parameters needed in the FB approach can be obtained using Markov Chain Monte Carlo (MCMC) sampling techniques. MCMC techniques are used to repeatedly sample from the joint posterior distribution. The techniques generate chains of random points, whose distributions converge to the target posterior distributions. Usually, a sub-sample is used to monitor convergence and then discarded as a burn-in sample. The remaining iterations are used for parameter estimation, performance evaluation and inference. Monitoring convergence is essential because it ensures that the posterior distribution has been found in order to begin parameters sampling [187].

Therefore, in this study two independent Markov chains were used to run each model for 20,000 iterations that were discarded as burn in samples to reach convergence. Afterwards, the summary statistics of each chain were estimated, and the convergences of the developed models were checked. To check convergence, Brooks–Gelman–Rubin (BGR) statistic was used; where a value of the BGR statistic less than 1.2 indicates convergence. As well, the ratios of the Monte Carlo errors relative to the respective standard deviations of the estimates were estimated to ensure convergence. Generally, the convergence occurs if these ratios are around or less than (0.05). Moreover, the convergence was monitored throughout visual approaches such as observing trace plots of the estimated parameters [187] [189] [109]. Finally, after obtaining convergence, additional 20,000 iterations were performed for each chain and the significance of the parameter estimates was tested using the 95% confidence intervals. The free statistical software (WinBUGS) [190] was used in this study to perform MCMC sampling and to obtain estimates of the parameters for the developed FB models.
4.3.5.5 Model Comparison and Goodness-of-Fit

The deviance information criterion (DIC) was used as a statistical goodness-of-fit measure to compare between the developed FB models. The DIC, proposed by Spiegelhalter et al. [191], penalizes the model that has larger number of parameters (complexity of a model) as follows:

\[
DIC = \bar{D} + PD = \bar{D} + 2\times PD
\]

\[
\bar{D} = -2 \times \text{Log (Likelihood)} , \text{Likelihood is defined as } P(y|\theta)
\]

\[
\bar{D} = -2 \times \text{Log (Likelihood)} , \text{Likelihood is defined as } P(y|\bar{\theta})
\]

Where:

\(\bar{D}\): The posterior mean of the unstandardized deviance of the model;

\(\bar{D}\): The point estimate of the deviance obtained by substituting the posterior means of the model’s parameters in the unstandardized deviance;

\(PD\): The effective number of parameters (the posterior mean of the deviance minus the deviance of the posterior means or \((PD = \bar{D} - \bar{D})\)) [192].

When comparing different models, the best model is the one with the minimum DIC value. It is difficult to determine what would constitute an important difference in DIC [191] [192]. However, it is roughly assumed that a difference of more than 10 in the value of DIC might rule out the model with higher DIC. Differences between 5 and 10 are substantial. Also, it could be misleading to report the model with the lowest DIC if the difference is less than 5 and the models make very different inferences [187].

4.3.6 Model Estimates

Various SPF s were developed in this study considering different conflict indicators (TTC, MTT, and DRAC), various critical thresholds, different combinations of the covariates (A, Q, S12, and P), and different cases of the model intercept (with or without a random intercept). A total of 28
models were developed. Table 4.2 shows the PLN models that account for the heterogeneity, and Table 4.3 shows PLN models that account for both the heterogeneity and the site effect (models with random intercept). The mathematical format, the estimates and the Bayesian confidence interval of all explanatory variables, the goodness-of-fit statistic (DIC), and the variances that address the heterogeneity and/or the variation among sites ($\sigma_u^2, \sigma_s^2$) for all models are provided in these tables. For all models, the response ($Y$) denotes the number of rear-end conflicts per traffic signal cycle. Also, it is noteworthy to mention that the maximum queue length ($Q$) was excluded from the developed models due to the strong correlation between $A$ and $Q$, or in other words, the multicollinearity effect. In addition, considering that the data were collected sequentially in time, the assumption that the error in the developed models is independent might not be appropriate. Therefore, the serial correlation between the observed conflicts in consecutive signal cycles at each location was estimated using the Durbin-Waston (DW) statistic. The results showed that the serial correlation had low insignificant values and should have little impact on the results.
Model Format: $\ln(Y) = \beta_0 + \beta_1 \ln(V) + \beta_2 A + \beta_3 P + \beta_4 S_{12} + u_i$; where: $u_i \sim N(0, \sigma_u^2)$

<table>
<thead>
<tr>
<th>Conflict Indicator</th>
<th>Y: Number of rear-end conflicts per cycle where</th>
<th>$\beta_0$ Estimate (2.5%, 97.5% Bayesian C.I.)</th>
<th>$\beta_1$ Estimate (2.5%, 97.5% Bayesian C.I.)</th>
<th>$\beta_2$ Estimate (2.5%, 97.5% Bayesian C.I.)</th>
<th>$\beta_3$ Estimate (2.5%, 97.5% Bayesian C.I.)</th>
<th>$\beta_4$ Estimate (2.5%, 97.5% Bayesian C.I.)</th>
<th>$\sigma_u^2$ Estimate** (2.5%, 97.5% Bayesian C.I.)</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>TTC ≤ 1.0 sec</td>
<td>$-0.503 (-0.734, -0.302)$</td>
<td>$1.503 (0.872, 2.144)$</td>
<td>$0.353 (0.168, 0.541)$</td>
<td>$-1.145 (-1.636, -0.655)$</td>
<td>$0.313 (0.183, 0.455)$</td>
<td>$0.030 (0.0003, 0.270)$</td>
<td>521</td>
<td></td>
</tr>
<tr>
<td>TTC ≤ 1.5 sec</td>
<td>$0.349 (0.224, 0.469)$</td>
<td>$1.250 (0.827, 1.686)$</td>
<td>$0.296 (0.166, 0.422)$</td>
<td>$-0.83 (-1.182, -0.484)$</td>
<td>$0.122 (0.055, 0.197)$</td>
<td>$0.003 (0.0003, 0.019)$</td>
<td>674</td>
<td></td>
</tr>
<tr>
<td>TTC ≤ 2.0 sec</td>
<td>$0.884 (0.790, 0.975)$</td>
<td>$1.178 (0.850, 1.511)$</td>
<td>$0.205 (0.101, 0.307)$</td>
<td>$-0.765 (-1.038, -0.493)$</td>
<td>$0.088 (0.040, 0.141)$</td>
<td>$0.002 (0.0003, 0.008)$</td>
<td>770</td>
<td></td>
</tr>
<tr>
<td>TTC ≤ 2.5 sec</td>
<td>$1.184 (1.105, 1.261)$</td>
<td>$0.993 (0.712, 1.276)$</td>
<td>$0.162 (0.070, 0.253)$</td>
<td>$-0.749 (-0.989, -0.510)$</td>
<td>$0.051 (0.014, 0.091)$</td>
<td>$0.002 (0.0003, +0.0006)$</td>
<td>838</td>
<td></td>
</tr>
<tr>
<td>TTC ≤ 3.0 sec</td>
<td>$1.302 (1.228, 1.375)$</td>
<td>$0.998 (0.737, 1.266)$</td>
<td>$0.150 (0.063, 0.236)$</td>
<td>$-0.713 (-0.939, -0.489)$</td>
<td>$0.040 (0.008, 0.076)$</td>
<td>$0.002 (0.0002, 0.007)$</td>
<td>860</td>
<td></td>
</tr>
<tr>
<td>MTTC ≤ 1.0 sec</td>
<td>$0.722 (0.620, 0.821)$</td>
<td>$1.239 (0.900, 1.583)$</td>
<td>$0.220 (0.111, 0.329)$</td>
<td>$-0.790 (-1.082, -0.498)$</td>
<td>---*</td>
<td>$0.003 (0.0003, 0.012)$</td>
<td>755</td>
<td></td>
</tr>
<tr>
<td>MTTC ≤ 1.5 sec</td>
<td>$1.376 (1.305, 1.447)$</td>
<td>$1.073 (0.824, 1.326)$</td>
<td>$0.142 (0.059, 0.225)$</td>
<td>$-0.677 (-0.891, -0.463)$</td>
<td>---*</td>
<td>$0.003 (0.0003, 0.007)$</td>
<td>907</td>
<td></td>
</tr>
<tr>
<td>MTTC ≤ 2.0 sec</td>
<td>$1.559 (1.494, 1.623)$</td>
<td>$1.024 (0.792, 1.257)$</td>
<td>$0.128 (0.050, 0.207)$</td>
<td>$-0.553 (-0.750, -0.354)$</td>
<td>---*</td>
<td>$0.002 (0.0002, 0.010)$</td>
<td>959</td>
<td></td>
</tr>
<tr>
<td>MTTC ≤ 2.5 sec</td>
<td>$1.663 (1.602, 1.722)$</td>
<td>$0.975 (0.754, 1.197)$</td>
<td>$0.139 (0.062, 0.213)$</td>
<td>$-0.413 (-0.601, -0.227)$</td>
<td>---*</td>
<td>$0.003 (0.0003, 0.012)$</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>MTTC ≤ 3.0 sec</td>
<td>$1.687 (1.627, 1.746)$</td>
<td>$0.984 (0.768, 1.203)$</td>
<td>$0.144 (0.070, 0.218)$</td>
<td>$-0.366 (-0.552, -0.179)$</td>
<td>---*</td>
<td>$0.003 (0.0003, 0.013)$</td>
<td>1016</td>
<td></td>
</tr>
<tr>
<td>DRAC ≥ 6.0 m/s²</td>
<td>$-1.556 (-1.911, -1.231)$</td>
<td>$1.884 (0.893, 2.904)$</td>
<td>$0.391 (0.119, 0.658)$</td>
<td>$-1.518 (-2.290, -0.762)$</td>
<td>$0.287 (0.101, 0.501)$</td>
<td>$0.007 (0.0003, 0.053)$</td>
<td>305</td>
<td></td>
</tr>
<tr>
<td>DRAC ≥ 4.5 m/s²</td>
<td>$-1.134 (-1.419, -0.870)$</td>
<td>$2.110 (1.278, 2.963)$</td>
<td>$0.297 (0.065, 0.528)$</td>
<td>$-1.412 (-2.069, -0.748)$</td>
<td>$0.257 (0.105, 0.430)$</td>
<td>$0.003 (0.0003, 0.016)$</td>
<td>375</td>
<td></td>
</tr>
<tr>
<td>DRAC ≥ 3.0 m/s²</td>
<td>$-0.368 (-0.555, -0.19)$</td>
<td>$1.522 (0.920, 2.137)$</td>
<td>$0.336 (0.162, 0.508)$</td>
<td>$-0.870 (-1.353, -0.398)$</td>
<td>$0.172 (0.071, 0.285)$</td>
<td>$0.005 (0.0003, 0.037)$</td>
<td>522</td>
<td></td>
</tr>
<tr>
<td>DRAC ≥ 1.5 m/s²</td>
<td>$0.909 (0.818, 0.998)$</td>
<td>$1.097 (0.774, 1.426)$</td>
<td>$0.119 (0.013, 0.224)$</td>
<td>$-0.858 (-1.135, -0.584)$</td>
<td>$0.054 (0.013, 0.100)$</td>
<td>$0.002 (0.0003, 0.010)$</td>
<td>794</td>
<td></td>
</tr>
</tbody>
</table>

* The explanatory variable $S_{12}$ was removed from this model as its coefficient was not found to be significant at 95% confidence level

** $\sigma_u^2$ is the extra Poisson variance that addressing unmeasured or unobserved heterogeneity in the Full Bayes models

Table 4.2 PLN Models for different conflict indicators
Model Format: \( \ln(Y) = \beta_0 + \beta_1 \ln(V) + \beta_2 A + \beta_3 P + \beta_4 S_{12} + u_i + w_{s(i)} \); where: \( u_i \sim N(0, \sigma_u^2) \) & \( w_{s(i)} \sim N(0, \sigma_s^2) \)

<table>
<thead>
<tr>
<th>Conflict Indicator</th>
<th>( Y ): Number of rear-end conflicts per cycle where</th>
<th>( \beta_0 ) Estimate</th>
<th>( \beta_1 ) Estimate</th>
<th>( \beta_2 ) Estimate</th>
<th>( \beta_3 ) Estimate</th>
<th>( \beta_4 ) Estimate</th>
<th>( \sigma_u^2 ) Estimate**</th>
<th>( \sigma_s^2 ) Estimate***</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>PPCM ≤ 1.0 sec</td>
<td>TTC ≤ 1.0 sec</td>
<td>-0.484 (-1.135, 0.116)</td>
<td>1.749 (1.063, 2.457)</td>
<td>0.315 (0.101, 0.529)</td>
<td>-0.861 (-1.374, -0.343)</td>
<td>0.180 (0.054, 0.325)</td>
<td>0.005 (0.0003, 0.037)</td>
<td>0.560 (0.128, 1.795)</td>
<td>463</td>
</tr>
<tr>
<td></td>
<td>TTC ≤ 1.5 sec</td>
<td>0.376 (0.076, 0.669)</td>
<td>1.449 (0.981, 1.929)</td>
<td>0.268 (0.121, 0.411)</td>
<td>-0.789 (-1.156, -0.424)</td>
<td>0.072 (0.007, 0.145)</td>
<td>0.003 (0.0003, 0.015)</td>
<td>0.111 (0.020, 0.376)</td>
<td>643</td>
</tr>
<tr>
<td></td>
<td>TTC ≤ 2.0 sec</td>
<td>0.886 (0.757, 1.013)</td>
<td>1.227 (0.883, 1.579)</td>
<td>0.190 (0.078, 0.298)</td>
<td>-0.760 (-1.044, -0.482)</td>
<td>0.083 (0.033, 0.137)</td>
<td>0.002 (0.0003, 0.007)</td>
<td>0.011 (0.0004, 0.057)</td>
<td>767</td>
</tr>
<tr>
<td></td>
<td>TTC ≤ 2.5 sec</td>
<td>1.175 (1.065, 1.276)</td>
<td>1.022 (0.730, 1.316)</td>
<td>0.150 (0.052, 0.244)</td>
<td>-0.744 (-0.990, -0.498)</td>
<td>0.052 (0.015, 0.093)</td>
<td>0.002 (0.0003, 0.007)</td>
<td>0.006 (0.0003, 0.031)</td>
<td>835</td>
</tr>
<tr>
<td></td>
<td>TTC ≤ 3.0 sec</td>
<td>1.291 (1.188, 1.386)</td>
<td>1.032 (0.758, 1.319)</td>
<td>0.136 (0.042, 0.226)</td>
<td>-0.716 (-0.951, -0.486)</td>
<td>0.041 (0.007, 0.078)</td>
<td>0.001 (0.0003, 0.006)</td>
<td>0.006 (0.0004, 0.028)</td>
<td>857</td>
</tr>
<tr>
<td></td>
<td>MTTC ≤ 1.0 sec</td>
<td>0.728 (0.567, 0.894)</td>
<td>1.355 (0.974, 1.757)</td>
<td>0.189 (0.066, 0.308)</td>
<td>-0.805 (-1.110, -0.502)</td>
<td>***</td>
<td></td>
<td>0.023 (0.0003, 0.011)</td>
<td>0.023 (0.0005, 0.105)</td>
</tr>
<tr>
<td></td>
<td>MTTC ≤ 1.5 sec</td>
<td>1.331 (1.182, 1.456)</td>
<td>1.126 (0.856, 1.401)</td>
<td>0.111 (0.019, 0.202)</td>
<td>-0.698 (-0.933, -0.466)</td>
<td>***</td>
<td></td>
<td>0.002 (0.0003, 0.009)</td>
<td>0.018 (0.001, 0.069)</td>
</tr>
<tr>
<td></td>
<td>MTTC ≤ 2.0 sec</td>
<td>1.484 (1.313, 1.636)</td>
<td>1.093 (0.840, 1.350)</td>
<td>0.091 (0.005, 0.176)</td>
<td>-0.603 (-0.824, -0.385)</td>
<td>***</td>
<td></td>
<td>0.002 (0.0002, 0.007)</td>
<td>0.032 (0.005, 0.112)</td>
</tr>
<tr>
<td></td>
<td>MTTC ≤ 2.5 sec</td>
<td>1.574 (1.384, 1.742)</td>
<td>1.062 (0.819, 1.307)</td>
<td>0.097 (0.014, 0.178)</td>
<td>-0.483 (-0.698, -0.274)</td>
<td>***</td>
<td></td>
<td>0.002 (0.0002, 0.006)</td>
<td>0.041 (0.007, 0.140)</td>
</tr>
<tr>
<td></td>
<td>MTTC ≤ 3.0 sec</td>
<td>1.594 (1.399, 1.773)</td>
<td>1.079 (0.840, 1.322)</td>
<td>0.096 (0.016, 0.177)</td>
<td>-0.429 (-0.641, -0.220)</td>
<td>***</td>
<td></td>
<td>0.002 (0.0003, 0.0065)</td>
<td>0.047 (0.010, 0.156)</td>
</tr>
<tr>
<td></td>
<td>DRAC ≥ 6.0 m/s²</td>
<td>-1.547 (-1.921, -1.199)</td>
<td>1.855 (0.841, 2.888)</td>
<td>0.405 (0.132, 0.688)</td>
<td>-1.474 (-2.271, -0.680)</td>
<td>0.282 (0.094, 0.496)</td>
<td>0.007 (0.0003, 0.057)</td>
<td>0.022 (0.0003, 0.191)</td>
<td>304</td>
</tr>
<tr>
<td></td>
<td>DRAC ≥ 4.5 m/s²</td>
<td>-1.101 (-1.484, -0.704)</td>
<td>2.043 (1.180, 2.921)</td>
<td>0.324 (0.078, 0.574)</td>
<td>-1.259 (-1.975, -0.523)</td>
<td>0.244 (0.086, 0.422)</td>
<td>0.003 (0.0003, 0.015)</td>
<td>0.100 (0.0004, 0.583)</td>
<td>370</td>
</tr>
<tr>
<td></td>
<td>DRAC ≥ 3.0 m/s²</td>
<td>-0.332 (-0.569, -0.060)</td>
<td>1.527 (0.905, 2.152)</td>
<td>0.337 (0.153, 0.518)</td>
<td>-0.784 (-1.300, -0.262)</td>
<td>0.158 (0.053, 0.273)</td>
<td>0.003 (0.0002, 0.015)</td>
<td>0.037 (0.0004, 0.222)</td>
<td>518</td>
</tr>
<tr>
<td></td>
<td>DRAC ≥ 1.5 m/s²</td>
<td>0.906 (0.785, 1.024)</td>
<td>1.109 (0.780, 1.446)</td>
<td>0.105****</td>
<td>-0.820 (-1.108, -0.529)</td>
<td>0.057 (0.014, 0.105)</td>
<td>0.002 (0.0003, 0.011)</td>
<td>0.008 (0.0004, 0.045)</td>
<td>791</td>
</tr>
</tbody>
</table>

* Not significant at 95% confidence level ** \( \sigma_u^2 \) is the extra Poisson variance that addressing unobserved heterogeneity in the Full Bayes models *** \( \sigma_s^2 \) is the additional variance component that addressing the variation among different sites

Table 4.3 PLN models with random intercept (incorporating site effect) for different conflict indicators
Overall, all the developed models provided in Tables 4.2 and 4.3 show good fit and all the explanatory variables are statistically significant according the Bayesian confidence interval at the 95% level. All the covariates’ coefficients have logical signs. In other words, higher conflict occurrence is expected during the signal cycles that have bigger shock waves. On the other hand, the higher platoon ratio means that more vehicles arrive during the green time leading to a better arrival type and lower chances of conflict occurrence during the cycle.

During the development of each model with a specific conflict indicator and at a specific threshold, the explanatory variables were added to the model one by one. It was noted that the DIC value, the heterogeneity effect ($\sigma_u^2$), and the site variation effect ($\sigma_s^2$) steadily decreased when adding more explanatory variables to the model. This is reasonable as the additional variables improved the model fit and explained some of the unmeasured heterogeneity and unmeasured variation across sites. This emphasizes the important effect of the selected variables (i.e. A, P, and S12) in providing a better prediction of the conflict occurrence beyond what can be expected from the exposure only (i.e. V).

As shown in Table 4.3, the models with the random intercept statistically have better fit than their counterparts in Table 4.2 with a singular intercept. Considering the site variation effect ($\sigma_s^2$) decreases the DIC value significantly and improves the model fit. For example, the DIC value of the first model ($\text{TTC} \leq 1 \text{ s}$) decreased from 521 in Table 4.2 to 463 in Table 4.3. This is expected because the conflict data in this study was measured at six different intersections, and the random intercept (i.e. the additional variance component ($\sigma_s^2$)) accounts for the possibility that different sites can have different conflict risks due to the variation of traffic, geometric, driving behavior,
and environmental conditions across sites. For the TTC models shown in Table 4.3, it can be noted that the random term ($\sigma_s^2$) at lower TTC thresholds is particularly stronger than that at higher TTC thresholds. This is mainly attributed to the strong effect of the site specificity on the occurrence of high severe conflicts.

### 4.4 Conflict Frequency and Severity

#### 4.4.1 Conflict Frequency Distribution

The temporal distribution of rear-end conflicts presented in chapter 3 showed that most of conflicts occur usually during the yellow time (the start of the red time), the red time (the area of the shock wave), and the end of the red time (the start of releasing the traffic queue at the beginning of the green time). The work in this chapter additionally considers various conflict indicators with multiple thresholds to address the severity of traffic conflicts. The conflict events obtained from all locations were divided into 21 bins based on the relation of the recorded conflict time to the signal time. To account for different signal timings (especially green and red durations) between cycles and sites, the conflict time was represented as a percentage with regard to the signal timing (e.g. a conflict occurs at 15% of the red time). Both green and red times were divided into 10 bins (i.e. 0-10%, 10-20%… 90-100%). The yellow time, which is 4 seconds for all locations, contained only one bin. Using the conflict time (as a percentage) and the TTC value, temporal distributions of conflict frequency were developed at different severity levels. Figure 4.3 shows the conflict distribution based on different TTC thresholds.
As shown in Figure 4.3, the maximum conflict frequency usually exists at the start of the green time. This is mainly attributed to the variation in speeds at the start of the traffic queue release. The stopped flow starts to discharge gradually at low speed while other vehicles are arriving at higher speeds to the end of the queue. However, most of these conflicts have a low severity (higher values of TTC). If a higher severity level is considered, another conflict frequency peak can be noticed at the first third of the red-light duration. These conflicts can be attributed to the dilemma zone where the traffic signal indication changes from green to yellow to red.

In addition, it is noteworthy to mention that the MTTC identified higher frequencies of rear-end conflicts than the TTC. This can be attributed to inclusion of vehicle accelerations in MTTC calculation which may result in recognizing more conflicts than TTC. Basically, some situations that are not possible to produce TTC conflicts can produce possible MTTC conflicts. For example, when the speed of the leading vehicle is higher than the following vehicle, it is not possible to have
a TTC conflict. However, in case of MTTC, there is a chance of having a conflict if the acceleration of the following vehicle is higher than the leading vehicle [32].

4.4.2 Conflict Severity Distribution

In addition to the frequency distribution, the severity distribution of the identified conflicts was also investigated. The Severity Index (SI) [50] based on the minimum TTC values was calculated following the formula provided in a previous study by Saunier and Sayed [50]. Only through lanes were selected for analysis (i.e. exclusive right-turn and left-turn lanes were excluded). Therefore, the SI formula can be expressed as follows:

\[ SI = \exp\left(-\frac{TTC_{\text{min}}^2}{2\sigma^2}\right) ; \forall (TTC) > 0 \]  \hspace{1cm} \text{Eq. (4.12)}

Where:

\( SI \): Severity index;

\( TTC_{\text{min}} \): Minimum value of time to collision;

\( \sigma \): Normalizing constant.

The normalizing constant \( \sigma \) was chosen to be equal to an average age user reaction time (1.50 seconds) [50]. Figures 4.4 and 4.5 show the minimum TTC distribution and the SI distribution, respectively.
As shown in Figures 4.4 and 4.5, the highest conflict severity (the lowest TTC values) exists at the first third of the red-light duration. Again, this is attributed to the dilemma zone where the traffic signal indication changes from green to yellow to red. Also, although the beginning of the
green time has the highest conflict frequency, it shows less conflict severity than the yellow and
the red times.

### 4.4.3 Extended Time to Collision Measures

Minderhoud and Bovy [37] introduced two traffic conflict measures based on extensions of the
TTC: Time Exposed Time-to-collision (TET) and Time Integrated Time-to-collision (TIT). These
measures can take the full course of vehicles over space and time into account and can give a more
comprehensive picture of the safety level on a specific section of road during a specific period of
time [37]. TET and TIT were estimated for each signal cycle. Also, the effects of the shock wave
area and the platoon ratio on the TET and the TIT values at the signal cycle level were investigated.
The following sections provide more detail about TET and TIT.

#### 4.4.3.1 Time Exposed to Collision (TET)

The TET measure expresses the exposition time to safety-critical approach situations (in seconds).
It is a summation of all moments (over the considered time period) that a driver approaches a front
vehicle with a TTC-value below the critical TTC threshold that discriminates between conflict and
non-conflict events. Thus, the lower the TET value, the safer the situation (on average over the
considered time period) [37]. Based on the aforementioned definition, the TET value was
calculated for each signal cycle as per the following formula [37].

\[
TET^* = \sum_{i=1}^{N} TET_i^*
\]

\[
TET_i^* = \sum_{t=0}^{T} \delta_i(t) \cdot \tau_{sc}
\]

\[
\delta_i(t) = \begin{cases} 
0 & \forall \ 0 < TTC_i(t) < TTC^* \\
1 & else
\end{cases}
\]
Where:

\( TET^* \): TET (in seconds) for the signal cycle at a specific TTC threshold*;

\( N \): Total number of vehicles at the signal cycle;

\( \tau_{sc} \): Time step (video frame is 1/29.97 second);

\( t \): Time instants (0, 1, 2, ...T);

\[ T = \frac{\text{total cycle length in seconds}}{\tau_{sc}} \]: Number of video frames per cycle;

\( TTC_i(t) \): Instantaneous TTC, from Eq. (4.1).

After estimating the TET value for each cycle at different TTC thresholds, the relationship between the cycle parameters and the TET was investigated. Figure 4.6 shows the TET relationships with the shock wave and the platoon ratio.
Figure 4.6 indicates that the TET value is positively correlated with the shock wave area at all TTC thresholds. This conforms to the positive sign of the shock wave coefficient in the SPFs provided in Tables 4.2 and 4.3. On the other hand, the TET value is inversely correlated with the platoon ratio at all TTC thresholds. This is also conforming to the negative sign of the platoon ratio coefficient in the developed SPFs.

4.4.3.2 Integrated Time to Collision (TIT)

The TIT measure expresses the integral of the time-to-collision profile of drivers to express the level of safety (in $s^2$) [37]. Unlike the TET, the TIT measure considers the TTC-values during the...
critical events. Basically, the TIT integrates the difference between the TTC value and the critical TTC threshold over all time periods that the TTC is below this threshold. Thus, the lower the TIT value, the safer the situation (on average over the considered time period). The TIT value for each signal cycle was estimated as per the following formula [37].

\[
TIT^* = \sum_{i=1}^{N} TIT_i^* \tag{4.14}
\]

\[
TIT_i^* = \sum_{t=0}^{T} [TTC^* - TTC_i(t)] \cdot \tau_{sc} ; \quad \forall \ 0 < TTC_i(t) < TTC^*
\]

Where:

- \(TIT^*\): TIT, in squared second, for the signal cycle at a specific critical TTC threshold*;
- \(N\): Total number of vehicles at the signal cycle;
- \(\tau_{sc}\): Time step (video frame is 1/29.97 second);
- \(t\): Time instants (0, 1, 2, ...T);
- \(T = \frac{\text{total cycle length in seconds}}{\tau_{sc}}\): Number of video frames per cycle;
- \(TTC_i(t)\): Instantaneous TTC, from Eq. (4.1).

After estimating the TIT value for each cycle at different TTC thresholds, the relationship between the cycle parameters and the TIT was investigated. Figure 4.7 shows the TIT relationships with the shock wave and the platoon ratio.
Like the TET, the TIT measure is shown in Figure 4.7 to be positively correlated with the shock wave area and inversely correlated with the platoon ratio at all TTC thresholds. Again, this conforms to the signs of the shock wave and the platoon ratio coefficients in the SPFs developed earlier. This also emphasizes the importance of including these cycle parameters in real-time safety evaluation of signalized intersections.

4.5 Summary and Conclusion

The work presented in this chapter develops Full Bayes SPFs of signalized intersections at the cycle level using multiple traffic conflict indicators. Traffic video-data collected from six
signalized intersections was used in the analysis. The developed SPFs relate various dynamic traffic parameters to the number of rear-end conflicts at the signal cycle. The measured traffic parameters at each cycle were: traffic volume, maximum queue length, shock wave area, shock wave backward-moving speed, and platoon ratio. The TTC, the MTTC, and the DRAC were used as traffic conflict indicators. The SPFs were developed using the FB approach to address the unobserved heterogeneity and the variation among different sites. Two kinds of FB models were developed: 1) PLN models that account for heterogeneity; and 2) PLN models with random intercept that account for heterogeneity and site effect.

Overall, the results showed that all the developed models have good fit and all the explanatory variables are statistically significant. Also, all the covariate coefficients have logical signs. In other words, the number of traffic conflicts is expected to increase during the signal cycles that have bigger shock waves, and lower platoon ratios. The deviance information criterion (DIC) was used as a statistical goodness-of-fit measure to compare different models. It was noted that the DIC value, the heterogeneity effect ($\sigma_u^2$), and the site variation effect ($\sigma_s^2$) steadily decreased when adding more explanatory variables to the model. This is reasonable as the additional variables improved the model fit and explained some of the unmeasured heterogeneity and unmeasured variation across sites. This emphasizes the important effect of the selected traffic variables in providing a better prediction of the conflict occurrence beyond what can be expected from the exposure only. Moreover, the models with the random intercept are statistically better than their counterparts with a singular intercept. This is expected because the conflict data in this study was measured at six different intersections, and the random intercept accounts for the possibility that
different sites can have different conflict risks due to the variation of traffic, geometric, driving behavior, and environmental conditions across sites.

Furthermore, the conflict frequency and severity distributions along the signal cycle were investigated. The results indicated that the highest conflict frequency exists at the beginning of the green time due to the variation in speeds at the start of the traffic queue release. On the other hand, the highest conflict severity exists at the beginning of the red time due to the dilemma zone where the traffic signal indication changes from green to yellow to red.

Lastly, two extended time to collision measures (TET and TIT) were investigated at the cycle level. The results showed that both TET and TIT are positively correlated with the shock wave area and inversely correlated with the platoon ratio at all TTC thresholds. This conforms to the signs of the shock wave and the platoon ratio coefficients in the developed SPFs. This also emphasizes the importance of including these cycle parameters in real-time safety evaluation of signalized intersections.

Of the SPFs provided in this chapter, it was difficult to recommend a specific model to estimate traffic conflicts at the cycle level. This is due to the lack of agreement in the literature on the critical threshold value, for each conflict indicator, that can be used to discriminate between conflict and non-conflict events. Hence, estimating conflicts at different thresholds using multiple SPFs is generally recommended when comparing safety levels of different signal design alternatives. Finally, the results of presented in this chapter can have a potential implementation in real-time safety optimization of signalized intersection in the CVs environment.
Chapter 5: Transferability of Real-time Safety Models for Signalized Intersections

5.1 Background

The signalized-intersections safety models, presented in the third chapter of this thesis, relate various dynamic traffic parameters to the number of rear-end traffic conflicts at the signal cycle level. These models enable the real-time safety evaluation for signalized intersections and provide insight into how real-time changes in the signal design and the traffic flow condition can affect safety. For a wider application of these real-time safety models, their transferability needs to be examined. Therefore, the work presented in this chapter aims to investigate the models’ transferability to other jurisdictions. Two corridors of signalized intersections in California and Atlanta States, USA, were used in the analysis as destination jurisdictions. Detailed vehicle trajectories for these corridors were obtained from the Next Generation Simulation (NGSIM) data [51]. Several conventional measures of transferability and goodness-of-fit were estimated. Moreover, the real-time safety models were locally calibrated at the new jurisdictions and their transferability was re-evaluated after the calibration process. The overall goal was to test the validity of using those models for real-time safety evaluation at signalized intersections.

The following sections in this chapter provide a detailed description of the data used for investigating the transferability of the real-time safety models; various measures and approaches that were applied to conduct the transferability analysis; and lastly the most recommended real-time safety model.
5.2 Data Preparation

Three datasets were prepared and used to investigate the transferability of the real-time conflict-based safety models (SPFs) from their base jurisdiction to two destination jurisdictions. The datasets consist of hundreds of traffic signal cycles. At each signal cycle, the space-time diagram was plotted using real vehicle trajectories and actual signal timings; then various dynamic traffic parameters were extracted. The extracted traffic parameters include: (1) shock wave area \((A)\); (2) traffic volume \((V)\); (3) backward-moving shock wave speed \((S_{12})\); (4) platoon ratio \((P)\); (5) maximum queue length \((Q)\); (6) number of rear-end conflicts that have TTC equals or less than 1.5 seconds. Figure 5.1 shows an example of the space-time diagram of one signal cycle and illustrates the extracted traffic parameters.

![Image of a space-time diagram for one cycle with traffic characteristics selected for the SPFs]

**Figure 5.1 Example of the space-time diagram for one cycle with traffic characteristics selected for the SPFs**

5.2.1 Base Jurisdiction Dataset

The video-data described in detail in chapter 3 of this thesis were utilized as the base jurisdiction for the transferability analysis. The data were recorded from six signalized intersections in two
cities in Canada: Edmonton and Surrey. More details about the selected study locations and the video data are provided in Figures 3.1-3.2 and Table 3.1. The video data were analyzed to track vehicles and extract their trajectories from the video recordings. The whole video-analysis procedure is described in details in chapter 3 (section 3.3.2) of this thesis. The procedure is based on a set of MATLAB codes. The procedure started with identifying actual traffic signal timing and cycles for each intersection by detecting the changes in the signal colors from video scenes. Afterwards, moving vehicles in through lanes were tracked (exclusive left-turn and right-turn lanes were excluded), and the space-time diagram for each cycle was plotted. From the space-time diagram, various traffic parameters and the number of rear-end conflicts at each cycle were estimated. Table 5.1 provides a summary of statistics of the base jurisdiction dataset used in the transferability analysis.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>V</td>
<td>Volume per lane per cycle</td>
<td>---</td>
<td>11.58</td>
<td>3.56</td>
<td>2</td>
<td>22</td>
</tr>
<tr>
<td>A</td>
<td>Shock wave area</td>
<td>km. seconds</td>
<td>1.05</td>
<td>0.96</td>
<td>0</td>
<td>3.93</td>
</tr>
<tr>
<td>Q</td>
<td>Maximum queue length</td>
<td>meter</td>
<td>40.42</td>
<td>24.54</td>
<td>0</td>
<td>97.46</td>
</tr>
<tr>
<td>S12</td>
<td>Backward-moving shock wave speed</td>
<td>meter/second</td>
<td>-2.07</td>
<td>2.65</td>
<td>-27.2</td>
<td>0</td>
</tr>
<tr>
<td>P</td>
<td>Platoon ratio</td>
<td>---</td>
<td>1.26</td>
<td>0.40</td>
<td>0</td>
<td>2.27</td>
</tr>
<tr>
<td>TTC1.5</td>
<td>Number of rear-end conflicts (TTC≤ 1.5sec)</td>
<td>---</td>
<td>1.88</td>
<td>1.88</td>
<td>0</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 5.1 Summary of statistics - base jurisdiction dataset (Canada)

5.2.2 Destination Jurisdiction Datasets

Two different datasets, from two corridors of signalized intersections in California and Atlanta in USA, were used as destination jurisdictions for the transferability analysis. For each corridor, detailed traffic data were obtained from the NGSIM vehicle trajectories and supporting data provided online by the United States Department of Transportation [51]. The first corridor is Lankershim Boulevard, an arterial in Los Angeles, California, USA. Vehicle trajectories for three main intersections along this corridor were analyzed. The second corridor is Peachtree Street, an arterial in Atlanta, Georgia, USA. Vehicle trajectories for four main intersections along this
corridor were analyzed. **Figure 5.2** shows the location and the selected intersections of both corridors. Details on the selected intersections along each corridor are provided in **Table 5.2**. This includes: the intersected roads, the date and time of data collection, the selected approaches, the number of lanes per approach, and the signal timing.

- The left image shows the first destination Jurisdiction (Lankershim Blvd., Los Angeles, California, USA)
- The right image shows the second destination jurisdiction (Peachtree St., Georgia, Atlanta, USA)

**Figure 5.2 Destination jurisdictions**
<table>
<thead>
<tr>
<th>Site #</th>
<th>City (State)</th>
<th>Intersected roads</th>
<th>Video-data was recorded in</th>
<th>Selected approaches</th>
<th>Number of Lanes per approach</th>
<th>Traffic signal timing (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Los Angeles (California)</td>
<td>Lankershim Blvd. &amp; Lankershim Blvd. Ramp</td>
<td>June 16th, 2005 (8:28 – 9:00 am)</td>
<td>Lankershim Blvd. (Southbound)</td>
<td>3 (Through)</td>
<td>15 to 30 3 65 to 85</td>
</tr>
<tr>
<td>2</td>
<td>Los Angeles (California)</td>
<td>Lankershim Blvd. &amp; Universal Hollywood Dr.</td>
<td>June 16th, 2005 (8:28 – 9:00 am)</td>
<td>Lankershim Blvd. (Northbound &amp; Southbound)</td>
<td>1 NB or 2 SB (Left) 3 (Through) 1 (Right)</td>
<td>32 to 77 3 30 to 70</td>
</tr>
<tr>
<td>3</td>
<td>Los Angeles (California)</td>
<td>Lankershim Blvd. &amp; Main St.</td>
<td>June 16th, 2005 (8:28 – 9:00 am)</td>
<td>Lankershim Blvd. (Northbound &amp; Southbound)</td>
<td>1 (Left) 3 (Through) 1 (Right)</td>
<td>17 to 33 3 59 to 120</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Site #</th>
<th>City (State)</th>
<th>Intersected roads</th>
<th>Video-data was recorded in</th>
<th>Selected approaches</th>
<th>Number of Lanes per approach</th>
<th>Traffic signal timing (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Atlanta (Georgia)</td>
<td>Peachtree St. &amp; 10\textsuperscript{th} St. NE</td>
<td>November 8\textsuperscript{th}, 2006 (12:45 – 1:00 pm) (4:15 – 4:30 pm)</td>
<td>Peachtree St. (Southbound)</td>
<td>1 (Left) 1 (Through) 1 (Through + Right)</td>
<td>45 to 63 4 30 to 44</td>
</tr>
<tr>
<td>2</td>
<td>Atlanta (Georgia)</td>
<td>Peachtree St. &amp; 11\textsuperscript{th} St. NE</td>
<td>November 8\textsuperscript{th}, 2006 (12:45 – 1:00 pm) (4:15 – 4:30 pm)</td>
<td>Peachtree St. (Northbound &amp; Southbound)</td>
<td>1 (Left) 1 (Through) 1 (Through + Right)</td>
<td>15 to 52 4 40 to 88</td>
</tr>
<tr>
<td>3</td>
<td>Atlanta (Georgia)</td>
<td>Peachtree St. &amp; 12\textsuperscript{th} St. NE</td>
<td>November 8\textsuperscript{th}, 2006 (12:45 – 1:00 pm) (4:15 – 4:30 pm)</td>
<td>Peachtree St. (Northbound &amp; Southbound)</td>
<td>1 (Left) 1 (Through) 1 (Through + Right)</td>
<td>16 to 33 4 60 to 89</td>
</tr>
<tr>
<td>4</td>
<td>Atlanta (Georgia)</td>
<td>Peachtree St. &amp; 14\textsuperscript{th} St. NE</td>
<td>November 8\textsuperscript{th}, 2006 (12:45 – 1:00 pm) (4:15 – 4:30 pm)</td>
<td>Peachtree St. (Northbound)</td>
<td>1 (Left) 1 (Through) 1 (Through + Right)</td>
<td>14 to 59 4 31 to 84</td>
</tr>
</tbody>
</table>

**Table 5.2 Location of the two destination jurisdictions**

The NGSIM data were originally collected by researchers for the NGSIM program through a network of synchronized digital video cameras. NGVIDEO, a customized software application developed for the NGSIM program, transcribed the vehicle trajectory data from the video [51]. For the analysis of this study, the trajectory data for each of the selected corridors was downloaded from [51] as a spreadsheet. The spreadsheet includes vehicles’ identification number, position, length, occupied lane number, speed, direction, and acceleration at each 0.1 second for 30-minutes period. A MATLAB code was developed to filter the NGSIM data for each intersection approach.
and divide it into cycles. For each cycle, the code plots the space-time diagram to determine different traffic characteristics and the number of rear-end conflicts. Detailed trajectories of more than 2100 vehicles were extracted and analyzed. Table 5.3 provides a summary of statistics of the first and the second destination jurisdiction datasets.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>V</td>
<td>Traffic Volume per lane per cycle</td>
<td>---</td>
<td>12.70</td>
<td>4.04</td>
<td>3</td>
<td>26</td>
</tr>
<tr>
<td>A</td>
<td>Shock wave area</td>
<td>km. seconds</td>
<td>1.45</td>
<td>1.16</td>
<td>0</td>
<td>4.41</td>
</tr>
<tr>
<td>Q</td>
<td>Maximum queue length</td>
<td>meter</td>
<td>44.26</td>
<td>26.75</td>
<td>0</td>
<td>113.63</td>
</tr>
<tr>
<td>S12</td>
<td>Backward-moving shock wave speed</td>
<td>meter/second</td>
<td>-1.54</td>
<td>1.22</td>
<td>-7.60</td>
<td>0</td>
</tr>
<tr>
<td>P</td>
<td>Platoon ratio</td>
<td>---</td>
<td>1.11</td>
<td>0.38</td>
<td>0.31</td>
<td>2.83</td>
</tr>
<tr>
<td>TTC1.5</td>
<td>Number of rear-end conflicts (TTC≤ 1.5sec)</td>
<td>---</td>
<td>2.95</td>
<td>2.51</td>
<td>0</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 5.3 Summary of statistics - destination jurisdiction datasets (USA)

5.3 Base Models (Canada)

The real-time safety models (SPFs) presented in chapter 3 were used as the base models whose transferability needs to be investigated. These SPFs are six different models developed from the base jurisdiction dataset (Canada) using different combinations of the explanatory variables (V, A, Q, S12, and P). The models’ development is described in details in section 3.3.3. Table 5.4 provides a summary of these models (i.e., the base jurisdiction models).
As per Table 5.4, the base models show good fit with all the explanatory variables are statistically significant. Based on the estimated value of the dispersion parameter (\( \sigma_d \)), the error structure was assumed to follow Negative Binomial distribution for four models, and Poisson distribution for two models. The shock wave area, the maximum queue length, the shock wave speed, and the platoon ratio were shown to be important characteristics that affect the number of rear-end conflicts at the signal cycle. Incorporating one of these characteristics or a combination of them, along with the traffic volume, in the conflict-based SPFs improves the model fit and provides a better prediction of the conflict occurrence beyond what can be expected from the traffic volume only.

### 5.4 Transferability Analysis

#### 5.4.1 Statistical Measures to Test Transferability

The transferability of the base models was investigated using the data obtained from the destination jurisdictions. To assess the transferability of each model, the transfer index (TI) measure [193] was estimated. The Transfer Index (TI) is a relative measure that indicates how well a transferred model performs in predicting the application dataset relative to a model locally-estimated at the application context [193]. The index has been applied in several studies to perform transferability.
analysis (e.g., [80] [194] [77] [75]). The upper bound of TI is 1, which means the transferred model performs on the new jurisdiction dataset (the application dataset) as good as the locally-estimated model. Negative values of TI indicate that the transferred model is worse than the local constant model. The TI can be expressed as follows [193] [80]:

\[
TI = \frac{L_j(\hat{\theta}_I) - L_j(\hat{c})}{L_j(\hat{\theta}_j) - L_j(\hat{c})}
\]

Eq. (5.1)

Where:

TI: Transfer index;

\(L_j(\hat{\theta}_I)\): Log-likelihood in application context \(j\) using model from context \(I\);

\(L_j(\hat{\theta}_j)\): Log-likelihood given by application context model \(j\);

\(L_j(\hat{c})\): Log-likelihood given by constant model estimated in application context \(j\).

In addition to the TI, several goodness-of-fit (GOF) measures were calculated to assess the ability of the transferred models to predict traffic conflicts at the new jurisdictions (the application jurisdictions). This includes: (1) Akaike’s Information Criterion (AIC) [185]; (2) Pearson’s product moment correlation coefficient (r); (3) Mean prediction bias (MPB); (4) Mean absolute deviation (MAD); (5) Mean absolute percentage error (MAPD); (6) Pearson chi-squared (\(\chi^2\)) [195]; and (7) Z-score [196]. All of these measures compare the predicted conflicts obtained from the model with the observed ones at the new jurisdictions.

The AIC of the transferred model can be estimated using Eq. (5.2) by getting the log-likelihood in the application context (the new jurisdiction dataset) using the model from the base context. The AIC measure is used to compare models that have the same dependent variable (the same response). For a certain dataset, the model that has the lowest AIC value is the best [185].
\[ AIC = 2p - 2(\text{LogLik}_{\text{full}}) \]  
\textbf{Eq. (5.2)}

Where:

- \( p \): The number of model parameters;
- \( \text{LogLik}_{\text{full}} \): Log-likelihood for the full model.

The Pearson’s product moment correlation coefficient (\( r \)) between the observed and the predicted conflicts provides an indication on how well the model predicts the observed conflicts. The \( r \) values can range from -1 to +1. The ideal model gives \( r \) value of 1 which indicates a perfect fit. The mean prediction bias (MPB) describes the magnitude and direction of the average bias in the subject model. The closer to zero the value of the MPB is, the better the model predicts the observed data. Positive values of MPB indicate that the model under-predicts the observed conflicts, and vice versa. The MPB can be expressed mathematically as follows:

\[ MPB = \frac{\sum_{i=1}^{n} y_i - E(Y_i)}{n} \]  
\textbf{Eq. (5.3)}

Where:

- \( y_i \): The observed number of rear-end conflicts at cycle (\( i \)) in the new jurisdiction dataset;
- \( E(Y_i) \): The predicted frequency of rear-end conflicts at cycle (\( i \)) in the new jurisdiction dataset as obtained from the conflict prediction model;
- \( n \): The sample size of the new jurisdiction dataset.

The mean absolute deviation (MAD) describes the average prediction error of the model. MAD values close to zero indicate that the model on average predicts the observed data well. The MAD can be defined as follows:
\[ MAD = \frac{1}{n} \sum_{i=1}^{n} |y_i - E(Y_i)| \]  
\text{Eq. (5.4)}

The mean absolute percentage error (MAPD) describes the absolute prediction error of the model as a percentage of the total number of the observed conflict. The MAPD value close to zero indicates a good prediction of the subject model. The MAPD can be defined as follows:

\[ MAPD = \frac{\sum_{i=1}^{n} |y_i - E(Y_i)|}{\sum_{i=1}^{n} y_i} \]  
\text{Eq. (5.5)}

The Pearson chi-squared statistic (\( \chi^2 \)), given in Eq. (5.6), is a measure of the goodness of fit of a model to any dataset. Therefore, it can be used to test whether a certain model, developed at the base jurisdiction, can provide reliable predictions at a new jurisdiction [72] [196].

\[ Pearson \chi^2 = \sum_{i=1}^{n} \frac{[y_i - E(Y_i)]^2}{Var(Y_i)} \]  
\text{Eq. (5.6)}

Where:

\( y_i \): The observed number of rear-end conflicts at cycle \((i)\) in the new jurisdiction dataset;

\( E(Y_i) \): The predicted frequency of rear-end conflicts at cycle \((i)\) in the new jurisdiction dataset as obtained from the conflict prediction model;

\( Var(Y_i) \): The variance of conflict frequency for the cycle \((i)\).

The Z-score measures how far the calculated \( \chi^2 \) statistic is from its expected value. Z-score values close to zero indicate that the transferred model predicts the new observed data well. The Z-score can be defined as follows [72] [196]:

\[ Z_{Score} = \frac{\chi^2 - E(\chi^2)}{\sigma(\chi^2)} \]  
\text{Eq. (5.7)}
Where:

\[ E(\chi^2) \]: The expected value of \( \chi^2 \) (the number of observations in the new dataset (n));

\[ \sigma(\chi^2) \]: The standard deviation of \( \chi^2 \).

In addition to the previous GOF measures, the HSM calibration factor (C), defined in Eq. (5.8), was estimated for each model to compare the total number of the predicted conflicts with the total number of the observed conflicts. C values higher than 1 indicate that the model generally underestimate the number of conflicts, and vice versa. However, this factor is used in this research as a GOF measure not as a calibration factor to calibrate the SPFs.

\[ C = \frac{\sum \text{Observed Conflicts}}{\sum \text{Predicted Conflicts}} \]  
Eq. (5.8)

5.4.2 Transferability Analysis Approaches

Generally, there are two approaches for analyzing the transferability of a specific model: (1) the application-based approach, and (2) the estimation-based approach. In the application-based approach, the base model developed from the base jurisdiction is applied with no change (without calibration) to the destination jurisdiction (the application context) to assess how well the model predicts at the new region. In the estimation-based approach, the base model parameters estimated from the base jurisdiction data are recalibrated using the destination jurisdiction data to test whether each parameter in the model is transferable [72] [194]. In this thesis, both approaches were applied to investigate the transferability of the base SPFs.

5.4.2.1 Application-based Approach

In this approach, the six base SPFs, developed at the base jurisdiction (Canada), were transferred as they are with no change to the new jurisdictions (California and Atlanta). The transfer index
and the GOF measures were estimated for each model. Table 5.5 provides the results obtained from the transferred models at each destination jurisdiction.

| Base Models (Canada’s Models) Transferred without Calibration to the First Destination Jurisdiction (California – USA) |  |
|---|---|---|---|---|---|---|---|---|
| Model # | TI | AIC | r | MPB | MAD | MAPD | $\chi^2$ | Z Score | C |
| Model 1 | 0.984 | 517 | 0.34 | 0.75 | 1.91 | 0.65 | 175 | 2.72 | 1.344 |
| Model 2 | 0.986 | 503 | 0.48 | 0.34 | 1.71 | 0.58 | 215 | 5.48 | 1.130 |
| Model 3 | 0.909 | 490 | 0.77 | 0.65 | 1.36 | 0.46 | 133 | 0.97 | 1.284 |
| Model 4 | 0.987 | 516 | 0.36 | 0.70 | 1.88 | 0.64 | 165 | 2.26 | 1.310 |
| Model 5 | 0.956 | 523 | 0.47 | 0.26 | 1.77 | 0.60 | 305 | 10.7 | 1.097 |
| Model 6 | 0.980 | 509 | 0.50 | -0.01 | 1.79 | 0.61 | 235 | 6.98 | 0.997 |

| Base Models (Canada’s Models) Transferred without Calibration to the Second Destination Jurisdiction (Atlanta – USA) |  |
|---|---|---|---|---|---|---|---|---|
| Model # | TI | AIC | r | MPB | MAD | MAPD | $\chi^2$ | Z Score | C |
| Model 1 | 0.916 | 328 | 0.44 | 1.19 | 1.53 | 0.64 | 189 | 5.8 | 1.982 |
| Model 2 | 0.953 | 312 | 0.52 | 0.95 | 1.31 | 0.55 | 158 | 5.32 | 1.654 |
| Model 3 | 0.920 | 310 | 0.74 | 1.10 | 1.31 | 0.55 | 138 | 3.8 | 1.858 |
| Model 4 | 0.892 | 336 | 0.37 | 1.20 | 1.57 | 0.66 | 214 | 7.07 | 2.011 |
| Model 5 | 0.733 | 378 | 0.54 | 1.12 | 1.38 | 0.58 | 1379 | 57.59 | 1.877 |
| Model 6 | 0.857 | 352 | 0.47 | 1.16 | 1.49 | 0.62 | 577 | 28.29 | 1.944 |

Table 5.5 Transferring the base SPF’s to the destination jurisdictions without calibration

The results in Table 5.5 show that the transferred models have high values of TI that range from 0.73 to 0.987. This reveals that the base SPF’s developed at the cycle level are fairly transferable to other jurisdictions. The MPB and C results indicate that all models generally underestimate the observed conflicts. One exception of that is model 6, which slightly overestimates the number of conflicts at the first destination jurisdiction. The results also show medium to high correlation (r) between predicted and observed conflicts. In addition, Pearson chi-squared and Z-score values support the transferred models, except for models 5 and 6 at the second destination jurisdiction. In fact, it is very difficult to determine the best model of the six base SPF’s when all the GOF measures provided in Table 5.5 are considered. However, it can be noticed that models 2, 3, and 6 have the best performance at the first destination jurisdiction. At the second destination jurisdiction, models 2 and 3 provide the best data fitting.
5.4.2.2  Estimation-based Approach

In this approach, the base model parameters estimated from the base jurisdiction data are recalibrated using the destination jurisdiction data. Two methods of calibration were considered herein. The first method comprises the calibration of the model intercept and the shape parameter only, while the second method considers the calibration of all the model parameters.

5.4.2.2.1  Intercept and Shape Parameter Calibration

In this section, the base SPFs, developed at the base jurisdiction (Canada), were transferred to the new jurisdictions (California and Atlanta) after calibrating both the model intercept and the shape parameter, following the calibration procedure proposed by Sawalha and Sayed [72]. For each model, a new intercept and shape parameter for each model were determined using the method of maximum likelihood. The statistical analysis software “R” was used to perform the GLM regression and the maximum likelihood calculations. The coefficients of all the explanatory variables were forced to their original values obtained from the base jurisdiction. The “offset” command within the GLM regression functions in “R” was applied to perform this process. Afterwards, the transfer index and the GOF measures were estimated for each model. Table 5.6 provides the results obtained from the transferred models at each destination jurisdiction after the calibration process.
The results in Table 5.6 show that there is a notable improvement in the GOF measures for all models in general after calibrating the intercept and the shape parameter. Specifically, the measures TI, AIC, $\chi^2$ and Z-Score were significantly improved. This is expected as the local calibration of the intercept and the shape parameter allows the transferred models to better suit local conditions at the destination jurisdictions. The intercept usually accounts for most factors outside the explanatory variables. On the other hand, for negative binomial models, the shape parameter (k) of the model determines the variability of the data around the model regression hyper-surface. This variability for the new jurisdiction dataset might be different than that for the original dataset. Furthermore, $\chi^2$ and Z-Score values are dependent upon the shape parameter. Therefore, the shape parameter calibration is necessary and expected to improve the fit of the transferred models [72].

<table>
<thead>
<tr>
<th>Model #</th>
<th>$a_0$ $c^*$</th>
<th>$K$ $c^{**}$</th>
<th>TI</th>
<th>AIC</th>
<th>$r$</th>
<th>MPB</th>
<th>MAD</th>
<th>MAPD</th>
<th>$\chi^2$</th>
<th>Z Score</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>-2.899</td>
<td>3.13</td>
<td>0.998</td>
<td>486</td>
<td>0.34</td>
<td>-0.11</td>
<td>1.95</td>
<td>0.66</td>
<td>97</td>
<td>-0.79</td>
<td>0.964</td>
</tr>
<tr>
<td>Model 2</td>
<td>-1.58</td>
<td>3.98</td>
<td>0.996</td>
<td>471</td>
<td>0.48</td>
<td>-0.29</td>
<td>1.86</td>
<td>0.63</td>
<td>112</td>
<td>-0.08</td>
<td>0.910</td>
</tr>
<tr>
<td>Model 3</td>
<td>-1.796</td>
<td>Poisson</td>
<td>0.968</td>
<td>417</td>
<td>0.77</td>
<td>0.00</td>
<td>1.30</td>
<td>0.44</td>
<td>110</td>
<td>-0.22</td>
<td>1.000</td>
</tr>
<tr>
<td>Model 4</td>
<td>-3.013</td>
<td>3.27</td>
<td>0.997</td>
<td>486</td>
<td>0.36</td>
<td>-0.10</td>
<td>1.92</td>
<td>0.65</td>
<td>98</td>
<td>-0.75</td>
<td>0.968</td>
</tr>
<tr>
<td>Model 5</td>
<td>-1.599</td>
<td>2.96</td>
<td>0.967</td>
<td>501</td>
<td>0.47</td>
<td>-0.29</td>
<td>1.91</td>
<td>0.65</td>
<td>156</td>
<td>1.85</td>
<td>0.910</td>
</tr>
<tr>
<td>Model 6</td>
<td>-1.522</td>
<td>3.74</td>
<td>0.983</td>
<td>482</td>
<td>0.50</td>
<td>-0.33</td>
<td>1.90</td>
<td>0.64</td>
<td>125</td>
<td>0.53</td>
<td>0.900</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model #</th>
<th>$a_0$ $c^*$</th>
<th>$K$ $c^{**}$</th>
<th>TI</th>
<th>AIC</th>
<th>$r$</th>
<th>MPB</th>
<th>MAD</th>
<th>MAPD</th>
<th>$\chi^2$</th>
<th>Z Score</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>-2.525</td>
<td>10.59</td>
<td>0.998</td>
<td>271</td>
<td>0.44</td>
<td>-0.05</td>
<td>1.26</td>
<td>0.53</td>
<td>69</td>
<td>-0.33</td>
<td>0.979</td>
</tr>
<tr>
<td>Model 2</td>
<td>-1.273</td>
<td>16.92</td>
<td>0.999</td>
<td>261</td>
<td>0.52</td>
<td>-0.05</td>
<td>1.25</td>
<td>0.52</td>
<td>65</td>
<td>-0.62</td>
<td>0.979</td>
</tr>
<tr>
<td>Model 3</td>
<td>-1.427</td>
<td>Poisson</td>
<td>0.999</td>
<td>236</td>
<td>0.74</td>
<td>0.00</td>
<td>0.95</td>
<td>0.40</td>
<td>48</td>
<td>-1.84</td>
<td>1.000</td>
</tr>
<tr>
<td>Model 4</td>
<td>-2.576</td>
<td>6.80</td>
<td>0.982</td>
<td>280</td>
<td>0.37</td>
<td>-0.10</td>
<td>1.36</td>
<td>0.57</td>
<td>69</td>
<td>-0.3</td>
<td>0.960</td>
</tr>
<tr>
<td>Model 5</td>
<td>-1.008</td>
<td>3.85</td>
<td>0.874</td>
<td>324</td>
<td>0.54</td>
<td>-0.38</td>
<td>1.50</td>
<td>0.63</td>
<td>557</td>
<td>23.67</td>
<td>0.863</td>
</tr>
<tr>
<td>Model 6</td>
<td>-0.894</td>
<td>7.16</td>
<td>0.948</td>
<td>294</td>
<td>0.47</td>
<td>-0.16</td>
<td>1.28</td>
<td>0.54</td>
<td>213</td>
<td>8.27</td>
<td>0.937</td>
</tr>
</tbody>
</table>

*a_0^c*: Model intercept calibrated at the new jurisdiction  
**K^c**: Model shape parameter calibrated at the new jurisdiction

Table 5.6 Transferring the base SPF to the destination jurisdictions with calibration of the model intercept and the shape parameter
As shown in Table 5.6, the TI values of the transferred models are much closer to 1. The TI values range from 0.874 to 0.999. This confirms that the base SPFs are considerably transferable to other jurisdictions if the intercept and the shape parameter are locally-calibrated. The MPB and C values became much closer to zero and one, respectively. The correlation (r) values are the same as Table 5.5. This is because the coefficients of all the explanatory variables were forced to their original values during the calibration process. Pearson chi-squared and Z-score values support the transferred models, except for models 5 and 6 at the second destination jurisdiction. It is still difficult to determine the best model of the six base SPFs when all the GOF measures provided in Table 5.6 are considered. However, it can be noticed again that models 2, 3, and 6 have the best performance at the first destination jurisdiction. At the second destination jurisdiction, models 2 and 3 provide the best data fitting.

5.4.2.2.2 Full Model Calibration

In this section, the six SPFs (shown in Table 5.4) were redeveloped at the two new jurisdictions: California and Atlanta, using the same procedure described earlier. The main goal is to confirm that the selected explanatory variables (V, A, Q, P, S\textsubscript{i2}) are important characteristics that affect the number of rear-end conflicts at the signal cycle and can provide a better prediction of the conflict occurrence beyond what can be expected from the traffic volume only. In addition, developing these models using different datasets can help in recommending the best one of them to be used for real-time safety evaluation. Table 5.7 (a, b) provides a summary of the SPFs redeveloped using the two destination jurisdiction datasets.
Overall, the redeveloped models at the two new jurisdictions, shown in Table 5.7, show good fit with almost all the explanatory variables are statistically significant. Based on the estimated value of the dispersion parameter \((\sigma_d)\), the error structure was assumed to follow Negative Binomial distribution for all models except two models whose error structure follows Poisson distribution. The redeveloped models emphasize that the shock wave area, the maximum queue length, the shock wave speed, and the platoon ratio are important covariates that affect the number of rear-end conflicts. Incorporating one of these covariates or a combination of them, along with the traffic volume, in the SPFs improves the model fit and provides a better conflict prediction. This can be noticed from the improvement in the AIC value when adding one of these covariates to the traffic volume in the developed SPFs. Moreover, all the covariate coefficients have logical signs that
conform to those of the base models provided in Table 5.4. In other words, the number of conflicts is expected to increase during signal cycles that have higher volumes, longer queues, and bigger shock waves. On the other side, it is intuitive that more vehicle-arrivals on green time lead to higher platoon ratios and less conflict probability.

It should be noted that some models were excluded from Table 5.7, such as models 3a, and 4b-6b. Basically, a model is excluded either because the model does not show an AIC value better than that obtained from another model with a smaller number of covariates, or because some covariates in the model are not statistically significant at 95% confidence level. This insignificance is usually due to the correlation between the model covariates (the multicollinearity effect). One factor that may contribute to the multicollinearity effect in the excluded models is the existing signal coordination along the selected corridors (Lankershim Boulevard and Peachtree Street). Future research is recommended to incorporate the effect of the signal coordination into real-time SPFs. After redeveloping the SPFs at the new jurisdictions, the GOF measures were estimated for each model. Table 5.8 provides the GOF results for each model at each destination jurisdiction.
Table 5.8 Goodness-of-fit measures of SPF s developed at the destination jurisdictions

The results in Table 5.8 indicate that the GOF measures, especially AIC, r, and Z-Score, were improved after redeveloping the SPF s. Since the new models are locally developed by maximizing the likelihood function at the new jurisdictions, they are expected to provide a better fit to the new data. However, comparing to Table 5.6, the improvement in the GOF measures in Table 5.8 is slight. This means that the prediction performance of the models in Table 5.6 at the new jurisdictions is still good. Therefore, calibrating only the intercept and the shape parameter seems sufficient to transfer the base SPF s to new jurisdictions. With regard to the models shown in Tables 5.7 and 5.8, it can be noticed that models 2 and 6 have the best performance at the first destination jurisdiction; while models 2 and 3 provide the best data fitting at the second destination jurisdiction.

5.5 Recommended Real-time Safety Evaluation Model

Although all the developed SPF s show a good fit with statistically significant explanatory variables and high transfer indices, it is useful to recommend a specific model for real-time safety evaluation. Based on the transferability analysis results and considering the base jurisdiction as well as the two destination jurisdictions, model 2 is the most recommended model. Model 2 includes two
explanatory variables to predict rear-end conflicts: the traffic volume ($V$), and the shock wave area ($A$). The model is recommended due to several reasons. First, the inclusion of the shock wave area as an explanatory variable in the SPF is logical. Considering the shock wave area enables the SPF to discriminate between different cycles even if the traffic volume is the same. Basically, at a specific traffic volume, cycles with bigger shock waves most likely are expected to cause more conflicts. In addition, the shock wave area can describe, indirectly, the maximum queue length and the vehicle arrival pattern. Most importantly, the shock wave area is affected by the signal timing. Therefore, the effects of real-time signal changes on traffic conflicts can be captured in the real-time SPF through the shock wave area.

Second, model 2 shows a good fit at the three studied jurisdictions. The explanatory variables of the model ($V$ and $A$) are statistically significant at 95% confidence level. The model has AIC value that is significantly lower than that of the exposure-only model (model 1). This means that the model provides a better prediction of the conflict occurrence beyond what can be expected from the traffic volume only.

Third, model 2 shows high transfer indices, 0.986 and 0.953, at the two new jurisdictions. These indices have further improved to 0.996 and 0.999 after calibrating the intercept and the shape parameter. The high values of the TI confirm the transferability of the model among different contexts. Furthermore, the other GOF measures of model 2 at the new jurisdictions affirm the model transferability. As shown in Tables 5.6-5.8, the model shows $r$ values range from 0.48 to 0.59, $Z$ scores range from -0.62 to 5.48, $C$ values close to 1, scaled deviance and $\chi^2$ values close to the degree of freedom, and MPB and MAD values close to zero. However, it should be noted
that calibrating the intercept and the shape parameter is important to improve the model fit when transferring to new jurisdictions.

Finally, the regression results of model 2 are consistent at the three jurisdictions (Table 5.4 and Table 5.7) in terms of the sign and the value of the model parameters. As logically-expected, the signs of the traffic volume (V) and the shock wave area (A) coefficients are positive when model 2 is developed at any of the three jurisdictions. The coefficient of the traffic volume (\(a_1\)) is 0.706, 0.625, and 0.924 at the base jurisdiction, the first destination jurisdiction, and the second destination jurisdiction, respectively. All the \((a_1)\) values are consentient to be less than 1, meaning that the projection of the model function in the Y-V plane concaves down. The coefficient of the shock wave area \((a_2)\) has consistent positive values that range from 0.307 to 0.501.

5.6 Summary and Conclusion

This work presented in this chapter investigates the transferability of the conflict-based real-time SPFs of signalized intersections that were provided in chapter three. The SPFs relate various dynamic traffic parameters to the number of rear-end conflicts at the signal cycle level. The traffic parameters include: the traffic volume, the maximum queue length, the shock wave speed and area, and the platoon ratio. To investigate the models’ transferability, two corridors of signalized intersections in California and Atlanta states were used in the analysis as destination jurisdictions. Detailed vehicle trajectories for these corridors were obtained from the NGSIM data. Two transferability analysis approaches were applied: (1) the application-based approach, and (2) the estimation-based approach. In the first approach, the base models were applied with no change (without calibration) to the destination jurisdictions to assess how well the models predict in the new region. In the second approach, the model parameters estimated from the base jurisdiction
data were recalibrated using the destination jurisdiction data. Two methods of calibration were conducted. The first method comprises the calibration of the model intercept and the shape parameter only, while the second method considers the calibration of all the model parameters.

In both transferability approaches, the transfer index (TI) measure was estimated to test the transferability of the base SPFs. Additionally, several goodness-of-fit (GOF) measures were examined to assess and compare the prediction performances of the transferred models at the destination jurisdictions. The applied GOF measures are: (1) Akaike’s Information Criterion (AIC); (2) Pearson’s product moment correlation coefficient (r); (3) Mean prediction bias (MPB); (4) Mean absolute deviation (MAD); (5) Mean absolute percentage error (MAPD); (6) Pearson chi-squared ($\chi^2$); and (7) Z-score.

Overall, the results showed that the conflict-based real-time SPFs are fairly transferable among different sites. The transfer index ranged from 0.73 to 0.987 when the base SPFs were transferred without calibration and from 0.874 to 0.999 when the intercept and the shape parameter were calibrated. Also, the transferred SPFs generally, with and without calibration, were shown to have a good fit for the destination jurisdiction datasets. The GOF results indicated medium to high correlation between the predicted conflicts and the observed ones, small Z scores, and MPB and MAD values close to zero. However, there was a notable improvement in the GOF measures for all models in general after calibrating the intercept and the shape parameter. Specifically, the measures AIC, $\chi^2$ and Z-Score were significantly improved. This is expected as the local calibration of the intercept and the shape parameter allows the transferred models to better suit local conditions at the destination jurisdictions.
In the second calibration method, the base SPFs were redeveloped at the destination jurisdictions. All the model parameters were estimated by the GLM approach using the new jurisdictions datasets. The results showed that the redeveloped models have good fit with almost all the explanatory variables are statistically significant. The redeveloped models emphasize that the shock wave area, the maximum queue length, the shock wave speed, and the platoon ratio are important covariates that affect the number of rear-end conflicts. Incorporating one of these covariates or a combination of them, along with the traffic volume, in the SPFs improves the model fit and provides a better conflict prediction. Moreover, all the covariate coefficients had logical signs; this means the number of conflicts is expected to increase during signal cycles that have higher volumes, longer queues, bigger shock waves, and lower platoon ratios.

The GOF measures, especially AIC, r, and Z-Score, were improved after redeveloping the SPFs in the second calibration method. This is reasonable because the new models are locally developed by maximizing the likelihood function using the new data from the destination jurisdictions, which leads to a better fit. However, comparing to the first calibration method, the improvement in the GOF measures was slight. This means that calibrating only the intercept and the shape parameter seems sufficient to transfer the base SPFs to new jurisdictions.

The last contribution of this chapter was to recommend one of the studied SPFs for real-time safety evaluation. Based on the transferability analysis results and considering the base jurisdiction as well as the two destination jurisdictions, the model that combined the traffic volume and the shock wave area was the most recommended model due to several reasons. First, the inclusion of the shock wave area as an explanatory variable in the SPF is logically valid. The covariate shock wave
area enables the SPF to discriminate between different cycles even at the same traffic volume, and describes indirectly the maximum queue length and the vehicle arrival pattern. Most importantly, the effects of real-time signal changes on traffic conflicts can be captured in the real-time SPF through the shock wave area. Second, the recommended model showed a good fit at the three studied jurisdictions. The explanatory variables of the model are statistically significant at 95% confidence level. The model has AIC value that is significantly lower than that of the exposure-only model. Third, the recommend model shows high transfer indices, 0.986 and 0.953, at the two destination jurisdictions. These indices have further improved to 0.996 and 0.999 after calibrating the intercept and the shape parameter. Furthermore, the GOF measures at the new jurisdictions affirm the model transferability. Finally, the regression results of the recommended model are consistent at the three jurisdictions in terms of the sign and the value of each model parameter.

In conclusion, the results presented in this chapter confirm the validity of using the developed conflict-based real-time SPFs for real-time safety evaluation of signalized intersections. This paves the way for several applications in the CVs environment, where real-time information on vehicle positions and trajectories will be available. One of these applications is the real-time safety optimization of traffic signals. In such an application, CVs data can be used to adapt signal controllers in real time to minimize traffic conflicts and maximize safety. Developing a methodology for such a real-time safety optimization process will be discussed in the seventh chapter of this thesis.
Chapter 6: Real-time Safety Models in Traffic Microsimulation

6.1 Background

Using traffic simulation for safety analysis is a promising approach that has been recently proposed ([45] [46]) and increasingly applied ([111] [112] [107] [47] [113] [114] [115] [116] [117]). In this approach, vehicle trajectories extracted from traffic simulation models are usually analyzed using the Surrogate Safety Assessment Model (SSAM) [46]. The SSAM tool has recently been developed to estimate traffic conflicts from four commonly-used microscopic simulation models: VISSIM, AIMSUN, PARAMICS, and TEXAS. The SSAM can estimate several traffic conflict indicators as surrogate measures of safety, such as TTC, PET, deceleration rate, and speed differential. The estimated conflicts can also be classified into three maneuver types: rear-end, lane-change, and crossing [46].

Conducting safety analysis using traffic simulation models can have several advantages. First, using traffic conflicts [85] overcomes the well-recognized quality and quantity limitations of collision data [27]. Second, simulation models and SSAM can be used to estimate simulated conflicts easily without actually observing them in the field. Third and most importantly, traffic simulation is the simplest way to investigate new designs and innovative applications before implementing them in the real world. For example, most of connected-vehicles (CVs) applications, proposed in recent research (e.g., [13] [14] [118] [11] [119]), were developed and tested using simulation models to evaluate their potential mobility and/or safety benefits without actual field implementation. Lastly, simulation models are extremely valuable in assessing the relative performance of one design versus another [46].
Despite the aforementioned advantages, various concerns about using traffic simulation models in safety studies have been raised. First, all simulation models were originally designed with the assumption that drivers behave in a safe manner \[45\] \[44\]. Thus, vehicles in simulation models follow specific rules (i.e., car-following models, gap acceptance rules, lane-changing behavior) that aim to produce a crash-free environment. Using these safe-moving vehicles to evaluate conflicts and near-misses may lead to inaccurate results \[47\]. Second, every simulation model has many input parameters. Changing the value of these parameters can have a significant impact on road user behavior in the simulation model and subsequently on the estimated number of traffic conflicts. Third, there are usually many assumptions and different ways to model traffic in simulation models (e.g., priority rules, conflicts areas, traffic distribution). The results of simulated conflicts can vary significantly depending on the approach used in modelling \[46\] \[48\] \[47\]. Moreover, unrealistic crashes and abnormal movements are often recorded in traffic simulations, most likely due to an insufficient minimum gap size, a failure to yield to a priority rule, an abrupt lane change of a vehicle in an intersection or during queuing, or an irregular queuing up at left/right turn bay tapers \[44\] \[45\] \[46\].

Despite the existing research efforts on calibrating simulation models for safety analysis (e.g., \[47\] \[48\] \[49\] \[107\] \[112\] \[113\] \[114\] \[115\] \[121\] \[122\]), several major issues regarding the application of simulated traffic conflicts remain unsolved. The first issue is the complexity of the calibration process of the simulation model. While it is necessary for obtaining reliable conflict results, the calibration process is time consuming and usually requires real conflict/crash data to be collected \[48\]. Secondly, the results of simulated conflicts are highly sensitive to many parameters in the simulation model. The analysis mainly ends up with a wide range of the estimated number of
conflicts, leading to poor conflict prediction and less reliability. The third issue is the remarked discrepancies between simulated and field-observed conflicts. Although high correlation values between simulated and field-observed conflicts was obtained in previous studies, systematic overestimation or underestimation of the real number of conflicts were also found. Furthermore, major differences between simulated and field-observed conflicts in spatial distribution were detected ( [47] [48] [49] [115]). These discrepancies suggest that the high correlation between simulated and field-observed conflicts/crashes might come from the exposure dependency (i.e., both simulated and field-observed conflicts/crashes are correlated with traffic volume), not from the ability of simulation models to capture the real driving behavior and the actual conflict mechanism. All of these issues highlight the need for more research on using simulation models for safety analysis.

In this chapter, a new procedure, alternative to SSAM, for evaluating the safety of signalized intersections from traffic simulation is proposed. Specifically, the procedure combines simulated vehicle trajectories with real-time safety models, provided in chapter three, to predict rear-end conflicts at the intersection’s approaches. The conflict prediction is based on dynamic traffic parameters, such as traffic volume and shock wave characteristics, repeatedly measured over a short time interval (e.g. a few seconds). The proposed procedure benefits from the simulation models’ ability to provide reliable estimates of these dynamic parameters. The proposed procedure was validated using real-world traffic conflict data extracted from two signalized intersections in the city of Surrey, British Columbia. In addition, as an illustrative case study, the proposed procedure was applied to evaluate the safety impact of a recently-developed real-time adaptive
traffic signal control (ATSC) algorithm, which aims to minimize total delays in the CVs environment.

The following sections in this chapter provide a detailed description of the proposed safety evaluation procedure that integrates real-time safety models with traffic simulation; the validation process using real-world data; and the selected case study.

6.2 The Proposed Safety Evaluation Procedure

The safety evaluation procedure, proposed in this chapter, predicts the number of rear-end conflicts at signalized intersections. To predict the number of traffic conflicts, the procedure combines simulated vehicle trajectories extracted from traffic microsimulation models with the real-time safety models described in chapter 3. Figure 6.1 shows the overall scheme of the proposed safety evaluation procedure.
As shown in Figure 6.1, the proposed procedure includes seven main steps toward conflict’s prediction at a specific intersection. First, the examined intersection is modeled in a traffic microsimulation program (e.g., VISSIM). The microsimulation model is built accurately to match field conditions, including the intersection geometry, the traffic volume, the actual signal timing, the priority rules, and the desired speed distribution. Second, detailed simulated traffic data are continuously recorded at a very short time step (e.g., every second of simulation). These data
include position and speed of every vehicle, vehicle types, and status of all signal heads. The data recording can be obtained using an external program that controls the simulation model via a programmable platform (e.g., COM interface). To account for the stochastic nature of traffic, the simulation model should be run for multiple random seeds, at least two seeds. In addition, visual inspection needs to be performed to ensure that there are no abnormal movements of the simulated vehicles.

After running the simulation and recording detailed traffic data, the third step is to determine signal cycles for each approach of the intersection. Signal cycles for each approach can be determined using the recorded status of the approach signal head. Fourth, recorded vehicle trajectories are filtered by time and space to specify vehicle trajectories for each lane per each signal cycle. Fifth, for each lane, the space-time diagram for each signal cycle can be obtained using both the filtered trajectories and the cycle timing (Figure 3.5). This space-time diagram can then be used to calculate various traffic parameters at the signal-cycle level, including traffic volume, shock wave area, shock wave speed, queue length, and platoon ratio. Sixth, the estimated cycle-related parameters are inputted into the real-time safety models, presented in Table 3.3, to predict the number of rear-end conflicts at the cycle level. Finally, the number of conflicts for each approach per each hour can be estimated by aggregating the number of conflicts predicted from all cycles and all lanes of this approach, as per the following equation.

\[
Y = \sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij}
\]  

Eq. (6.1)
Where:

\( Y \): The predicted number of rear-end conflicts for approach per hour;

\( N \): The number of lanes per approach;

\( C \): The number of signal cycles per lane;

\( y_{ij} \): The predicted number of rear-conflicts from real-time safety models for cycle \( j \) in lane \( i \).

6.3 Validation Using Field-measured Traffic Data

The proposed safety evaluation process was validated using field-measured traffic data obtained from two urban signalized intersections in the city of Surrey, British Columbia. The validation process comprised a comparison between the number of predicted conflicts and the number of field-measured conflicts at the selected intersections. Field-measured conflicts and traffic characteristics for both intersections were extracted from video recordings, as described in details in previous studies ([47] [48] [49] [197]). The following subsections describe briefly the site characteristics, the recorded video data, the field-measured conflict extraction, the simulation model, and the conflict prediction for the selected intersections.

6.3.1 Study Locations and Video Data

The two selected intersections are located on 72nd Avenue in the city of Surrey, British Columbia, Canada (Figure 6.2). Both intersections are urban signalized intersections with 4 protected-permissive left-turns. At the first intersection, 72nd Avenue and 128 Street, traffic videos were recorded using 8 high-resolution cameras (29.97 frames per second) distributed to cover the four approaches (i.e. two cameras for each approach). Seventy-two hours of recorded video data were analyzed to estimate rear-end conflicts at this intersection (i.e., 9 hours * 4 approaches * 2 cameras). At the second intersection, 72nd Avenue and 132 Street, traffic videos were recorded
using 4 high-resolution cameras (29.97 frames per second) distributed to cover the two approaches located on the 72nd avenue (i.e. two cameras for each approach). A total of thirty-six hours of video recordings (i.e. 9 hours * 2 approaches * 2 cameras) were analyzed to estimate traffic conflicts at this intersection. Figure 6.2 shows the locations of the intersections, the selected approaches, and the recorded video scenes.

![Figure 6.2 Study locations and video scenes](image)

Real-world traffic data for each approach for each hour were extracted from the video recordings. These data include the actual signal program, the traffic volume of all movements, the number of vehicles arriving on green, the traffic composition, and the desired speed distribution.

6.3.2 Field-Measured Traffic Conflicts

The feature-based tracking and video analysis process, presented in previous studies ([197] [94] [100] [50] [101] [198]), was applied to track vehicles in the recorded videos and analyze traffic conflicts. This included five main steps, as shown in Figure 6.3. First, camera calibration was carried out to identify a mapping between the three-dimensional image (video scene) and the two-dimensional image (orthogonal Google map) [179]. Second, distinguishable points (features) on moving objects were tracked [101]. Third, the tracked features that move at similar speed and
satisfy other spatial proximity and common motion constraints were grouped to create objects, and the trajectories of these objects were recorded. The fourth step was to generate a group of motion patterns (prototypes) that define the set of movements carried out by vehicles in the video scene. Vehicle trajectories were then matched to those prototypes, providing a set of predicted future positions with associated probabilities of occurrence. Fifth, conflicts between vehicles were determined by evaluating if any of these future positions coincide spatially and temporally with other vehicles. The conflict analysis involved the calculation of the Time-to-Collision (TTC) as a conflict indicator. The TTC is generally recognized as the most frequently used indicator to identify rear-end conflicts.

Figure 6.3 Computer vision video-analysis process
Using the video analysis process, the number of rear-end conflicts was determined for each approach for nine hours, resulting in a total of 54 datapoints (9 hours * 6 approaches). The TTC threshold of 1.50 second was used to discriminate between conflict and non-conflict events. Also, only through lanes were considered in the conflict analysis. Thus, the conflict results obtained from the video analysis can be compared with the conflict results that would be estimated from the real-time safety models provided in Table 3.3.

6.3.3 Microsimulation Model

The traffic microsimulation model VISSIM (v7.00-16) was used in this research. VISSIM is a time-step and behavior-based model developed to simulate traffic and depends on a psycho-physical car-following model that is based on Wiedemann’s model [199] [52]. The Wiedemann model assumes that the driver can have one of four driving modes: free driving, approaching, following, and braking [52].

VISSIM models of the two selected intersections came from previous studies [47] [48]. The VISSIM models were built accurately to match actual field conditions in terms of intersection geometry, traffic volumes, traffic composition, traffic signal settings. Visual inspection was performed to ensure that there are no abnormal movements of the simulated vehicles. The VISSIM models were also calibrated in previous studies [47] [48] [49] using a two-step calibration procedure. The first calibration step aimed to match the simulated delay times with the field-observed delay times. This was achieved by matching the arrive type and desired speed to the field conditions. The second calibration step aimed at enhancing the correlation between field-observed and simulated conflicts by calibrating the VISSIM parameters. Firstly, important VISSIM parameters that had the most significant effect on the simulated conflicts were determined through
a sensitivity analysis. Subsequently, a Genetic Algorithm (GA) was applied to estimate the best values of these parameters with the objective of enhancing correlation between field-observed and simulated conflicts. Table 6.1 shows the selected VISSIM parameters and their calibrated values at each intersection [47] [48]. It is noteworthy that the calibration process is not within the scope of this thesis. For more details about the VISSIM calibration process, the readers can refer to previous studies [47] [48] [49].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
<th>Default Value</th>
<th>Calibrated Value (128 St &amp; Ave)</th>
<th>Calibrated Value (132 St &amp; Ave)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standstill distance</td>
<td>The desired distance between stopped vehicles</td>
<td>m</td>
<td>1.50</td>
<td>2.50</td>
<td>2.10</td>
</tr>
<tr>
<td>Headway time</td>
<td>The time that a driver wants to keep</td>
<td>s</td>
<td>0.90</td>
<td>1.3</td>
<td>1.3</td>
</tr>
<tr>
<td>Following thresholds</td>
<td>The thresholds which control the speed differences during the 'Following' state</td>
<td></td>
<td>±0.35</td>
<td>±0.25</td>
<td>±1.10</td>
</tr>
<tr>
<td>Reduction factor for safety distance</td>
<td>This reduction factor defines the vehicle behavior close to stop line at signalized intersections</td>
<td></td>
<td>0.60</td>
<td>0.75</td>
<td>0.60</td>
</tr>
<tr>
<td>Start upstream of stop line</td>
<td>Distance upstream of the stop line of signalized intersection</td>
<td>m</td>
<td>100</td>
<td>110</td>
<td>100</td>
</tr>
<tr>
<td>Desired deceleration</td>
<td>Desired deceleration is used as the maximum for: the deceleration caused by a desired speed decision; the deceleration in case of Stop &amp; Go traffic, when closing up to a preceding vehicle; the deceleration toward an emergency stop position (route); and for co-operative braking</td>
<td>m/s^2</td>
<td>-2.80</td>
<td>-2.80</td>
<td>-2.80</td>
</tr>
</tbody>
</table>

Table 6.1 Calibrated VISSIM parameters [47] [48]

In this research, three scenarios for the VISSIM models were analyzed: (1) before calibration (default VISSIM), (2) after first calibration, and (3) after second calibration. The simulation model was run for each intersection at the three scenarios at two different random seeds. The conflict results of the two random seeds for each scenario were then averaged.
6.3.4 Traffic Conflict Estimation from Simulation Models

Simulated vehicle trajectories were analyzed to estimate the number of rear-end conflicts at each intersection. Two different methods were applied: (1) the SSAM method and (2) the real-time safety models’ method (i.e., the proposed safety evaluation procedure described earlier).

6.3.4.1 SSAM

Trajectory files were exported from VISSIM and processed in SSAM to estimate the simulated rear-end conflicts for 36 hours (9 hours * 4 approaches) at the first intersection, and 18 hours (9 hours * 2 approaches) at the second intersection. The TTC threshold in SSAM was set to 1.5 second. To overcome the problem of having any abnormal traffic situations in VISSIM, rear-end conflicts that have TTC values less than zero were excluded. The SSAM output was then filtered using both the conflict time and the conflict location (i.e. coordinates). Only through lanes were considered in the conflict analysis. SSAM conflicts were estimated for the three simulation scenarios: before calibration, after first calibration, and after second calibration. A total of 54 datapoints (9 hours * 6 approaches) were produced for each scenario.

6.3.4.2 Real-time Safety Models

The safety evaluation procedure described earlier was applied to estimate the number of rear-end conflicts at the selected intersections. Simulated vehicle trajectories extracted from VISSIM were filtered by time and location; and the cycle-related parameters were calculated for each signal cycle at each lane of each approach. Only through lanes were considered in the conflict analysis. The real-time safety models provided in chapter 3 (Table 3.3) were then applied to predict the number of rear-end conflicts. Specifically, model 2 in Table 3.3 was used, as recommended by the transferability analysis described in chapter 5. The model predicts the number of conflicts per a signal cycle using the traffic volume and the shock wave area of this cycle. Rear-end conflicts for
36 hours (9 hours * 4 approaches) at the first intersection, and 18 hours (9 hours * 2 approaches) at the second intersection were estimated. Rear-end conflicts were predicted for the three simulation scenarios: before calibration, after first calibration, and after second calibration. A total of 54 datapoints (9 hours * 6 approaches) were produced for each scenario.

### 6.4 Results and Discussion

The simulated conflict results estimated from SSAM and the real-time safety models were compared with the field-measured conflicts estimated from video analysis. Scatter plots of the simulated conflicts versus the field-measured conflicts for the default scenario, the after first calibration scenario, and the after second calibration scenario were developed (Figure 6.4). In addition, the mean absolute percentage error (MAPE) was estimated. The MAPE describes the absolute prediction error of the simulated conflicts as a percentage of the total number of the field-measured conflicts. The MAPE value close to zero indicates a good prediction of the subject procedure. The MAPE can be defined as follows:

\[
MAPE = \frac{\sum_{i=1}^{n} |y_i - E(Y_i)|}{\sum_{i=1}^{n} y_i} \quad \text{Eq. (6.2)}
\]

Where:

- \(y_i\): The number of field-measured conflicts at the datapoint (i) (i.e. conflicts for one approach for one hour);
- \(E(Y_i)\): The number of simulated conflicts, predicted by SSAM or real-time safety models, at the datapoint (i) (i.e. conflicts for one approach for one hour);
- \(n\): The sample size, 54 datapoints (9 hours * 6 approaches).
The number of field-measured and simulated conflicts were estimated using TTC threshold of 1.5 seconds.

As shown in Figure 6.4 (a, b, c), SSAM systematically underestimated the number of field-measured conflicts, while the proposed procedure provided a better prediction of them. The proposed procedure also led to MAPE values smaller than those estimated from SSAM. Specifically, the estimated MAPE values of SSAM were 86.5%, 57.8%, and 54.7% for the default scenario, the after first calibration scenario, and the after second calibration scenario,
respectively. On the other hand, the MAPE values of the proposed procedure were 28.9%, 19.1%, and 19.2% for the same three scenarios.

The comparison results suggest that the proposed procedure outperforms SSAM in predicting field-measured conflicts. This can be interpreted by several reasons. First, SSAM analyses simulated trajectories at a microscopic level. Subsequently, the SSAM results depend on the driving behavior in the simulation model, which, in many cases, is considerably different from the actual driving behavior. On the other side, the proposed procedure predicts conflicts using dynamic traffic characteristics, such as traffic volume and shock waves. In most cases, these dynamic traffic characteristics can be generated from traffic simulation with reasonable accuracy. Secondly, simulation models are based on specific car-following rules that aim to produce safe traffic movements by avoiding collisions between simulated vehicles. Using these safe-moving vehicles by SSAM to evaluate conflicts and near-misses may lead to inaccurate results. In contrast, the proposed procedure estimates the number of conflicts based on various traffic parameters, using statistical models that were originally developed from real-world traffic data.

It should also be noted that the SSAM results were significantly enhanced by the two calibration steps of the simulation model. The MAPE value of SSAM decreased from 86.5% before calibration to 54.7% after calibration. The first calibration step controls the vehicle arrival pattern and affects the number of interactions between vehicles. The second calibration step mainly affects vehicle behavior in the simulation model by calibrating the values of the safety-related parameters. Although the two calibration steps improved the SSAM results, the first step is shown to have the most significant impact. This is similar to recent findings from previous studies ([47] [48] [49]).
Regarding the proposed conflict prediction procedure, interestingly, only the first calibration step enhanced the conflict results. Specifically, the MAPE deceased from 28.9% before calibration to 19.1% after the first calibration. This is reasonable because calibrating the arrival pattern directly affects the estimated shock wave area which is a covariate in the conflict prediction model. On the other side, the second calibration step was shown to have little effect on the results. This is also expected as the second calibration step enhances the correlation between SSAM estimated conflicts and field-measured conflicts and does not consider the conflicts obtained from the real-time safety models.

For further investigation of the simulation model’s ability to generate reasonable cycle-related parameters (e.g., traffic volume and shock wave area), samples of field-measured and simulated signal cycles were analyzed and compared. The selected samples of signal cycles constitute four hours of traffic data of the eastbound approach at the first intersection. The selected hours represent peak and non-peak hours. The traffic volume and the shock wave area for all field-measured and simulated cycles (before and after calibration) were recorded. Figure 6.5 shows the volume-shock wave area relationship for both field-measured and simulated cycles. The figure also shows a contour visualization of model 2 in Table 3.3. The contour lines represent the number of rear-end conflicts predicted from the real-time safety model (model 2), given traffic volume and shock wave area of the signal cycle. In the contour visualization, it is noteworthy that the worst-case scenario occurs when the signal cycle has high traffic volume associated with big shock wave areas (the upper right corner). On the other hand, the most optimized scenario, the lower right corner, is when the cycle has high traffic volume and small shock wave area. This means that most of vehicles arrive on green time which leads to a smaller number of rear-end conflicts.
From Figure 6.5, it is noticeable that the simulation model generated volumes and shock waves at the signal cycle level are comparable to those measured in the field. The calibration process, especially the first calibration step, resulted in considerable improvement of the simulated measures. This is attributed to the arrival pattern calibration which directly affects simulated shock waves.
Contour lines represent the number of rear-end conflicts predicted from the real-time safety model (model 2) given the traffic volume and the shock wave area of the signal cycle.

* Figure 6.5: Cycle parameters (shock wave area and traffic volume) estimated from field-measured trajectories and simulated trajectories (before and after calibration) for 4 hours at the eastbound approach of the first intersection.
Since simulation models can generate reasonable values of traffic volumes and shock waves, the proposed safety procedure that combines simulated trajectories and real-time safety models is a promising approach to predict the number of rear-end conflicts at signalized intersections. However, it should be noted that calibrating the arrival pattern in the simulation model to match the field conditions should further improve the conflict-prediction accuracy. Lastly, the validation results showed that the proposed procedure outperforms SSAM in two aspects. The first is the accuracy of the predicted number of conflicts (i.e., MAPE of 19.1% versus MAPE 54.7%). The second point is that the proposed procedure lessens the inevitability of the calibration process. Without calibration, the proposed procedure resulted in MAPE of 28.9% which is less than the MAPE of SSAM after calibration (i.e., 54.7%). Also, the second calibration step seems unnecessary when the proposed procedure was applied.

6.5 Case Study

The proposed safety evaluation procedure (Figure 6.1) can be applied to evaluate the safety impacts of CVs-based applications related to signalized intersections, such as adaptive traffic signal control algorithms. Most of these algorithms are developed and tested using traffic simulation models, since the CVs technology is not fully deployed to existing road networks. Traffic simulation models can easily be programmed to emulate a CVs environment representing real-time traffic connectivity (e.g., V2V and V2I communications). Using CVs trajectories and signal timings recorded from simulation models, the safety evaluation procedure proposed in this chapter can be applied to estimate the number of rear-end conflicts at the intersection’s approaches. Subsequently, the safety impacts of CVs adaptive traffic signal control algorithms can be predicted.
This section presents a case study of using the proposed safety evaluation procedure (Figure 6.1) to evaluate the safety impact of the cumulative travel time responsive (CTR) real-time intersection control algorithm developed by Lee et al. [13]. The CTR algorithm adapts traffic signals in real time using CVs data to minimize the total travel time at an isolated signalized intersection [13]. It is worth noting that the safety impact of this algorithm has been evaluated in a previous study using SSAM [200].

6.5.1 CTR Signal Control Algorithm

In the CTR algorithm [13], the cumulative travel time (CTT) is the real-time measure. The CTT of an approach link at a specific moment is defined as the time spent on the approach link by vehicles that exist on this link at this moment. Capturing CTTs in real-time for all approaches is possible in the CVs environment since real-time information about vehicle positions is available. The CTT can be updated in a short time interval (e.g., 5 seconds), which enables the CTR algorithm to rapidly respond to dynamic variations in traffic. The CTR algorithm estimates the CTT for each of all possible NEMA phase combinations (i.e., 8 phase combinations of the National Electrical Manufacturers Association). Then, the phase with the highest CTT value is selected. If the selected phase is the same as the current green phase, the current green phase is extended for a duration of the update time interval. Otherwise, the current green phase is switched to the selected phase (the highest CTT phase) after applying both yellow and all-red intervals [13].

6.5.2 Mobility and Safety Impacts of CTR

In this study, the CTR algorithm was applied to the calibrated VISSIM models of the two signalized intersections described earlier. Using VISSIM COM interface [201], a set of MATLAB codes were developed to control VISSIM, extract CTTs every 5 seconds, determine the next green phase combination, and apply the required real-time signal changes. For each intersection, 9 hours
of simulation were run at two random seeds (the results were then averaged). Simulated vehicle trajectories were recorded second by second. The total travel time for all approaches were calculated. The proposed safety evaluation procedure was then applied to estimate rear-end conflicts for all approaches (through lanes only). Multiple market penetration rates (MPR) of CVs were considered. The MPR ranges from 0% (the base condition without CTR) to 100% with 10% interval. For each MPR, the total travel time and the total rear-end conflicts were calculated and compared with the base condition (MPR 0%). Table 6.2 shows the mobility and safety impacts of CTR at the selected intersections.

**TABLE 3 Mobility and Safety Impacts of CTR at the Selected Intersection**

<table>
<thead>
<tr>
<th>Intersection</th>
<th>MPR</th>
<th>% change in the total travel time*</th>
<th>% change in the total number of rear-end conflicts*</th>
</tr>
</thead>
<tbody>
<tr>
<td>72nd Ave and 128 St.</td>
<td>0</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>+1%</td>
<td>+10%</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>-21%</td>
<td>-8%</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>-24%</td>
<td>-9%</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>-26%</td>
<td>-11%</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>-26%</td>
<td>-11%</td>
</tr>
<tr>
<td></td>
<td>60</td>
<td>-27%</td>
<td>-11%</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>-27%</td>
<td>-11%</td>
</tr>
<tr>
<td></td>
<td>80</td>
<td>-27%</td>
<td>-11%</td>
</tr>
<tr>
<td></td>
<td>90</td>
<td>-28%</td>
<td>-12%</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>-29%</td>
<td>-12%</td>
</tr>
<tr>
<td>72nd Ave and 132 St.</td>
<td>0</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>+11%</td>
<td>-30%</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>-27%</td>
<td>-21%</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>-34%</td>
<td>-29%</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>-36%</td>
<td>-32%</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>-38%</td>
<td>-34%</td>
</tr>
<tr>
<td></td>
<td>60</td>
<td>-38%</td>
<td>-34%</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>-39%</td>
<td>-35%</td>
</tr>
<tr>
<td></td>
<td>80</td>
<td>-39%</td>
<td>-34%</td>
</tr>
<tr>
<td></td>
<td>90</td>
<td>-40%</td>
<td>-35%</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>-40%</td>
<td>-36%</td>
</tr>
</tbody>
</table>

* Positive values indicate increase and negative values indicate reduction

Table 6.2 Mobility and safety impacts of CTR at the selected intersection

As shown in Table 6.2, the CTR algorithm led to positive mobility and safety impacts on signalized intersections. Generally, the mobility and safety improvements were directly
proportional to the MPR value. However, most of safety and mobility benefits were achieved at MPR of 40% or higher. It should also be noted that the percentages mentioned in Table 6.2 were derived based on existing field conditions and specific traffic volumes of the selected intersections. These percentages may vary if other intersections or different traffic volumes are investigated. It is also noteworthy to mention that the improvement in mobility at all MPR values was more significant than the improvement in safety. This is expected because the main optimization objective of the CTR algorithm is to minimize the total travel time (i.e. improving mobility). Developing new optimization procedures that consider safety as a primary objective can lead to higher safety improvement levels. Also, considering multi-objective optimization procedures that consider both safety and mobility is recommended as future research.

6.6 Summary and Conclusion

This chapter presents a new procedure, alternative to SSAM, for evaluating the safety of signalized intersections using traffic simulation models. The procedure combines simulated vehicle trajectories with real-time safety models to predict rear-end conflicts at the intersection’s approaches. The conflict prediction is based on dynamic traffic parameters, such as traffic volume and shock wave, repeatedly measured over a short time interval (i.e. the signal cycle length). To validate the proposed procedure, its performance in predicting traffic conflicts extracted from 54 hours of real-world video data at two signalized intersections in the city of Surrey, Canada was investigated. The predicted conflict results were then compared with SSAM.

Overall, the validation results showed that the proposed procedure outperforms SSAM in predicting rear-end conflicts from traffic simulation. For the analyzed intersections, the proposed procedure predicted rear-end conflicts with MAPE values of 28.9% and 19.1% before and after
calibrating the arrival pattern in the simulation model, respectively. On the other hand, the MAPE of SSAM ranged from 86.5%, before calibration, to 54.7% after calibration. The outperformance of the proposed procedure can be attributed to two main reasons. First, the SSAM results depend on the driving behavior in the simulation model, which, in many cases, is considerably different from the actual driving behavior. On the other side, the proposed procedure predicts conflicts using dynamic traffic characteristics, such as traffic volume and shock waves. In most cases, these dynamic characteristics can be generated from traffic simulation with reasonable accuracy. Second, simulation models are based on specific car-following rules that aim to produce safe traffic movements by avoiding collisions between simulated vehicles. Using these safe-moving vehicles by SSAM to evaluate conflicts and near-misses may lead to inaccurate results. On the contrary, the proposed procedure estimates the number of conflicts based on various traffic parameters, using statistical models that were originally developed from real-world traffic data.

Moreover, this chapter presents a case study of using the proposed procedure to evaluate the effects of real-time CVs-based applications on safety. Specifically, the CTR real-time intersection control algorithm developed by Lee et al. [13] was applied to the two aforementioned intersections through traffic simulation. The safety impact of the CTR algorithm was then evaluated at multiple MPRs of CVs, using the proposed safety evaluation procedure. The results demonstrated that the CTR algorithm led to positive mobility and safety impacts on signalized intersections, especially at MPR of 40% or higher. Unsurprisingly, the improvement in mobility at all MPR values was more significant than the improvement in safety, because the main optimization objective of the algorithm was to minimize the total travel time. Developing new optimization procedures that consider safety as a primary objective may lead to higher safety improvement levels.
In conclusion, the safety evaluation procedure presented in this chapter can be useful in predicting rear-end conflicts at signalized intersections from traffic simulation with reasonable accuracy. This can be useful in investigating the safety impacts of various CVs-based applications at signalized intersections prior to their real-world implementation. However, before using the proposed safety evaluation procedure for signalized intersections in a specific region, it is important to assure that the real-time safety models (Table 3.3) statistically fit that region.
Chapter 7: Self-learning Adaptive Traffic Signal Control for Real-time Safety Optimization

7.1 Background

Real-time optimization of traffic signals has recently received increasing interest among researchers and practitioners, especially with the availability of real-time traffic data from emerging technologies such as connected vehicles (CVs) [7] and innovative video detection techniques ([202] [203] [204] [205] [206]). Over the past few decades, adaptive traffic signal control (ATSC) systems have shown considerable advances. Several ATSC algorithms have been developed and implemented (e.g., [157] [158] [159] [160] [161]), while numerous have been proposed (e.g., [56] [167] [169] [170] [144] [174] [14] [16] [18] [19]). The common objective of these algorithms is to accommodate real-time traffic conditions and optimize traffic efficiency by maximizing throughput capacity, minimizing traffic delay, and/or reducing queue lengths. Compared to the traditional fixed-time or actuated signals, ATSC algorithms have shown a significant improvement in traffic efficiency at signalized intersections.

However, despite the aforementioned mobility benefits, the safety impact of the existing ATSC algorithms remains unclear. Some studies showed that mobility-oriented ATSC algorithms can improve safety and significantly reduce traffic collisions ([207] [208] [209]) or traffic conflicts ([210] [200]). Meanwhile, other studies indicated that implementing ATSC algorithms either leads to insignificant reduction in traffic collisions ([211] [212]) or increases traffic conflicts significantly and worsens traffic safety [197]. This inconsistency in the safety impact of existing ATSC algorithms may be related to that these algorithms do not consider optimizing traffic safety
as a primary objective. More importantly, optimizing mobility does not necessarily mean optimizing safety [162]. For example, an ATSC algorithm might tend to minimize the total delay by generating many stops, each with a short duration. Although this might lead to improved mobility, generating many stops can increase the potential risk of collision and deteriorate safety.

A few studies ([213] [150] [149]) have attempted to optimize safety of signalized intersections using traffic simulation and the Surrogate Safety Assessment Model (SSAM) [46]. The safety optimization process comprises tuning various signal timing parameters (e.g., cycle length, offset, and phase change interval) to minimize the number of traffic conflicts. Multiple signal designs were tested offline and their corresponding safety levels were evaluated using SSAM. However, the optimization algorithms in these studies are not as practically effective as self-learning ATSC algorithms, in terms of responding instantaneously to real-time traffic changes and covering all possible traffic conditions. Besides, using SSAM to evaluate traffic safety has generally been criticized due to several concerns. First, vehicles in simulation models follow specific rules that aim to produce a crash-free environment. Using these safe-moving vehicles to evaluate conflicts and near-misses may lead to inaccurate results. Second, the SSAM results can vary significantly depending on the assumed values of the simulation model parameters and the approach used in modelling. Finally, unrealistic crashes and unusual movements are often recorded in traffic simulations, most likely due to an insufficient minimum gap size, a failure to yield to a priority rule, an abrupt lane change of a vehicle, or an irregular queuing up at left/right turn bay tapers ([45] [44] [46] [47]).

Despite the importance of the real-time safety optimization, it has generally been disregarded in existing ATSC algorithms, most likely due to the lack of tools to evaluate safety of signalized
intersections in real time. Unlike vehicle delay and travel time, the safety level of signalized intersections cannot be directly estimated from real-time traffic data. However, as presented in chapters 3 to 5 in this thesis, various real-time safety models for signalized intersections were developed and validated. These models relate the number of traffic conflicts to various dynamic traffic parameters at a very short time period (i.e., a few seconds). The dynamic traffic parameters include traffic volume, shock wave area, shock wave speed, queue length, and platoon ratio. These models can be used to evaluate safety in real time; subsequently, they can enable developing ATSC strategies for real-time safety optimization.

This chapter presents a novel self-learning adaptive traffic signal control algorithm to optimize traffic safety in real time using CVs data. The algorithm is referred to as RS-ATSC (Real-time Safety-optimized Adaptive Traffic Signal Control). The RS-ATSC algorithm has several advantages. First, the safety evaluation is not based on simulated conflicts which were shown not to well represent actual-field conflicts and crashes ([47] [48] [53]). Rather, the optimization is based on real-time safety models that were originally developed and validated using real-world traffic data. Second, the algorithm is developed using the Reinforcement Learning (RL) technique as an efficient approach to solving the ATSC problem considering real-time and stochastic traffic changes ([55] [56] [57]). Third, the algorithm is practical since it respects all traffic signal operation standards, including the phasing sequence, the minimum/maximum green time, and the intersection clearance time. Fourth, the algorithm is validated using real-world traffic data obtained from two signalized intersections. Fifth, the presented algorithm is found to be effective and feasible under low market penetration rates of CVs. Lastly, to the best of the author’s knowledge,
this is the first self-learning ATSC algorithm that optimizes traffic safety in real time (i.e., safety is evaluated and optimized over a very short time period, a few seconds).

7.2 The Proposed RS-ATSC Algorithm

This section includes the methodology of developing the proposed RS-ATSC algorithm. First, the real-time safety models, on which the algorithm is based, are described. Second, an overview of both the reinforcement learning (RL) technique and the method selected to solve the RL problem is provided. Third, the formulation of the RL problem for the proposed RS-ATSC is presented. This includes the state, action, and reward definitions; the learning and discount rates; and the trade-off between exploration and exploitation. Lastly, details on modeling the environment and training the algorithm are elaborated.

7.2.1 Real-time safety models

The proposed RS-ATSC algorithm is based on the real-time safety models presented in chapter 3 of this thesis. These models relate various dynamic traffic parameters to the number of rear-end conflicts at the signal-cycle level. The Time-to-Collision (TTC) [31] was used as a traffic conflict indicator. The traffic parameters (Figure 3.5) include traffic volume (V), shock wave area (A), shock wave speed (S_{12}), queue length (Q), and platoon ratio (P). The models were originally developed using real-world traffic data obtained from several signalized intersections. The models have good fit and all the explanatory variables are statistically significant (Table 3.3).

7.2.2 Reinforcement Learning

The Reinforcement Learning (RL) technique was applied to develop the proposed RS-ATSC algorithm. RL is an area of machine learning that has widely been applied in the literature for self-learning ATSC algorithms (e.g., [166] [56] [167] [214] [168] [169] [170] [171] [57] [19] [18]). In RL, the agent or the decision-maker (e.g., the signal controller) dynamically interacts with its
surrounding environment (e.g., the traffic network). The agent iteratively observes the state of the environment, takes an action accordingly (e.g., determining which signal phase will be green), and receives a reward or an evaluative feedback (Figure 7.1). Unlike the supervised machine learning paradigm, the RL agent is not told which actions to take. Instead, it learns and discovers which actions yield the maximum reward over time. In other words, RL is a goal-directed learning, in which, the agent learns how to map states and actions to achieve a specific goal (i.e., maximizing the total cumulative reward). This state-action mapping is called the control policy. The agent tries to learn the optimal control policy by iteration (i.e., trial-and-error search). It should also be noted that actions may affect not only the immediate reward but also the next state and subsequently the future rewards. Thus, RL has two main distinguishing characteristics: trial-and-error search and delayed reward [54].

![Figure 7.1 The agent–environment interaction in reinforcement learning](image)

7.2.3 Q-learning

Solving the RL problem requires computing the optimal control policy. However, it should be noted that the expression “optimal control policy” came from the theoretical definition of the RL technique. Practically, there is no solution that is optimal under all conditions, and the optimality case cannot be defined. Therefore, in this research, the control policy is optimized but not necessarily optimal.
There are numerous methods to solve the RL problem. Generally, the RL methods can be classified into three main classes: dynamic programming (DP) methods, Monte Carlo (MC) techniques, and temporal difference (TD) learning methods. TD learning methods are recommended as the most relevant to the ATSC problem [57] [55]. TD methods have an advantage over DP methods. Unlike DP methods, TD methods do not require a model of the environment dynamics. Instead, the agent learns directly through interaction with the environment. TD methods also have an advantage over MC methods. While MC methods require waiting until the end of an episode to find out the return, TD methods require waiting for only one time-step [54] [55].

There are several TD methods, including the SARSA method, the Q-learning method, and the n-step difference learning method. A previous study by El-Tantawy et al. [57] has compared the performance of these methods in solving the ATSC problem. The results showed that SARSA and Q-learning lead to the same results and outperform the n-step difference method. This outperformance may be attributed to the nature of the ATSC problem. The control task in ATSC algorithms is a continuing task (i.e., not a finite episode) with a discounted reward in which looking ahead to future steps is less important compared to a finite episodic task with undiscounted reward [57]. Numerous studies have succeeded in solving the ATSC problem using the Q-learning method (e.g., [56] [167] [168] [169] [170] [171] [57]). Therefore, this method was selected in this research to develop the proposed RS-ATSC algorithm.

The Q-learning [215] [216] is an off-policy TD method, in which the algorithm uses the experience of each state transition to update one element of a table called Q-table. The Q-table is a matrix in which each row represents a specific state and each column represents a specific action. Each cell
in this matrix represents a Q-value for a specific state-action pair \( Q(s,a) \) [54]. The Q-value in general is used to compare various actions at a specific state. Given a specific state (specific row), the best action (column) is that with the highest Q. To train the algorithm, the Q-table is usually initiated with all values set to zero. Then, the Bellman’s equation (Eq. (7.1)) is used to update these values every time-step (\( \Delta t \)). The Q-value for a specific state-action pair \( Q(s,a) \) depends on the reward of taking that action at that state. The Q-value also depends on the new state that is achieved as a result of taking this action. Two factors are also considered when updating the Q-value: the discount rate (\( \gamma \)) and the learning rate (\( \alpha^{t+1} \)). The unit of the Q-value is the same as that for the reward, since all other factors are unitless. When the agent performs action \( a^t \) at state \( s^t \), leading to a new state \( s^{t+1} \) and a reward \( r^{t+1} \), the Q-learning algorithm improves its policy by updating the Q-table according to Bellman’s equation as follows:

\[
Q^{t+1}(s^t, a^t) = Q^t(s^t, a^t) + \alpha^{t+1} \left[ r^{t+1} + \gamma \max_{a \in A} Q^t(s^{t+1}, a^{t+1}) - Q^t(s^t, a^t) \right]
\]

Eq. (7.1)

Where:

- \( s^t, a^t \): the current state and the selected action at the current state;
- \( Q^{t+1}, Q^t \): the updated and the old Q-value;
- \( r^{t+1} \): the reward of applying action \( a^t \) at state \( s^t \);
- \( s^{t+1}, a^{t+1} \): the new state and the best action at the new state;
- \( \alpha^{t+1} \): the learning rate;
- \( \gamma \): the discount rate;
- \( A \): the action’s space.
7.2.4 State Representation

One of the main challenges in the Q-learning method is the use of the tabular form of the Q-matrix to represent realistic environments that have a very large or infinite number of states. Including large number of states in the Q-matrix can result in most states being not experienced by the agent. This issue exists in the ATSC problem, where the continuous and stochastic nature of traffic leads to an infinite number of possible states (i.e., various vehicle positions and speeds). To overcome this issue, there are typically two ways. The first is to enable generalization among states by representing Q-values not as a table but as a trainable parameterized function. Such a generalization is called “function approximation” because it takes examples from a desired function and attempts to generalize from them to construct an approximation of the entire function. There are many methods for the function approximation, such as artificial neural networks and statistical curve fitting [54]. However, due to its imperfect value estimations, the function approximation can have many consequences that can affect the quality of the solution, such as the divergence of Q-estimates [55]. Another simpler way, that overcomes the problem of having a very large number of states, is to discretize all possible states into ranges and define only these ranges in the Q-matrix. Since Q-matrix with discretized ranges of states was successfully applied in previous studies for the ATSC problem (e.g., [56] [167] [168] [169] [170] [171] [57]), this method was selected for the state representation in the proposed RS-ATSC.

In the proposed RS-ATSC, the state is represented by the current green phase as well as the status of existing vehicles in each approach within the V2I Dedicated Short-Range Communications (DSRC) domain upstream the stop line. Specifically, the state vector consists of 5 elements, assuming a 4 approach intersection. The first element is the current green phase represented by a
phase index (the length of the current phase is not included), while the other four elements represent the current traffic status of each approach.

Representing the current traffic status at each approach took several forms in the literature. This includes the number of existing vehicles [167] [169], the queue length [56] [57], the number of arriving vehicles to the current green phase and the queue length at the red phase [57], the cumulative delay [57] [168], the relative delay [171], and the detectors status [214]. In this thesis, the objective of the RS-ATSC algorithm is to improve safety by minimizing the rear-end conflict rate at the intersection’s approaches. Therefore, the current traffic status for an approach is represented by the number of rear-end conflicts per second (i.e., the current rear-end conflict rate) at that approach.

The number of rear-end conflicts for each lane at the signal cycle level can be estimated from the real-time safety models presented in Table 3.3, using dynamic traffic variables. Of the six real-time safety models shown in Table 3.3, model 6 is used since it shows the best statistical fit with all variables being significant (i.e., V, A, S₁₂, P). The predicted number of conflicts at each lane at the signal cycle level is then normalized by the cycle length (C) to obtain the conflict rate (conflicts/second). Since signal cycles can have different lengths, the cycle length (C) is dynamically updated in the algorithm every time-step (Δt) to be the length of the last cycle. Lastly, the conflict rate at each approach is calculated as the summation of conflict rates from all lanes, as follows:
\[ C_{r(App)} = \sum_{i=1}^{N} \frac{Y_i}{C} \]  

Eq. (7.2)

Where:

\( C_{r(App)} \): the rear-end conflict rate for the approach (number of conflicts/second);

\( Y_i \): the number of rear-end conflicts at the signal cycle level for lane \( i \);

\( N \): the number of lanes at the approach;

\( C \): the signal cycle length in seconds.

To obtain a discretized Q-matrix with all possible states, the calculated conflict rate per approach is discretized into specific ranges. The discretization method involves determining the minimum and the maximum value of the conflict rate as well as specifying the range width. The minimum conflict rate was set to zero (i.e., no vehicles exist at the cycle). On the other hand, the maximum conflict rate was calculated given: (1) the maximum number of vehicles that can exist within the V2I DSRC domain upstream the stop line; (2) the number of lanes per approach; and (3) the minimum cycle length (i.e., corresponding to the maximum conflict rate given a specific number of conflicts). The minimum cycle length equals the summation of the minimum green times plus yellow and all-red times for all phases. The range width was set to be increasing uniformly with the range number. This means the first range (i.e., the range that starts from the minimum conflict rate) has the lowest width, while the last range (i.e., the range that ends with the maximum conflict rate) has the largest width. Hypothetical simulation runs were performed for several hours considering many different scenarios (various traffic volumes and various cycle lengths) to validate the reasonability of the discretized ranges before training the Q-learning algorithm.
7.2.5 Action Representation

In RL-based ATSC algorithms, the action, taken by the agent at each decision point, is to determine the next green phase. The size of the action space (i.e., the number of possible actions) depends on the phasing sequence. If the phasing sequence is variable, the action space typically includes n actions; where n is the number of phases. If the phasing sequence is fixed, the action space has only two actions: (1) extending the current green phase, and (2) switching the green light to the following phase. Several previous studies have applied the variable phasing sequence (e.g., [166] [214] [169] [171] [57] [19] [175]), while others have used the fixed phasing sequence (e.g., [56] [167] [168] [170] [57]).

The variable phasing sequence could theoretically lead to a better performance, since it gives the RL agent more actions to investigate. However, it is generally recommended to prohibit ATSC systems from changing the phase sequence [217] for several safety and mobility concerns. The variable phasing sequence may confuse road-users, leading to unsafe traffic movements. For example, at 4-leg intersections with protected-permissive left turns, varying the phasing sequence could cause a yellow trap (i.e., a condition that leads the left-turning user into the intersection believing the opposing user is seeing a yellow). In addition, when the next green phase is not expected, road-users tend not to react quickly to the green indication. This could increase the start-up lost time causing additional delays [217]. The fixed phasing sequence, on the other hand, meets the road-users’ expectation, providing a safer traffic environment without unnecessary start-up delays. Furthermore, having only two possible actions in the fixed phasing sequence, instead of n actions, decreases the Q-matrix size dramatically, which enables faster convergence of the RL algorithm to the optimized policy.
Therefore, the fixed phasing sequence was adopted for the proposed RS-ATSC algorithm. The RS-ATSC agent performs one of the two following actions: (1) extending the current green phase (A1); and (2) switching the green light to the next phase (A2). If action A1 is selected, the current green phase will be extended by a specific time interval (assumed to be 5 seconds). On the other hand, if action A2 is selected, the yellow (Y) and the all-red (AR) times will be applied before switching the green light to the next phase and applying its minimum green time ($G_{min}$). Thus, the update time interval $\Delta t$ (i.e., the time between decision points) for the RS-ATSC algorithm can be expressed as follows:

$$\Delta t = \begin{cases} 
5 & \text{if } a^t = A1 \\
Y + AR + G_{min} & \text{if } a^t = A2 
\end{cases} \quad \text{Eq. (7.3)}$$

Where:

- $\Delta t$: the update time interval in seconds for the RS-ATSC algorithm;
- $Y$: the yellow time in seconds;
- $AR$: the all-red time in seconds;
- $G_{min}$: the minimum green time in seconds.

The proposed RS-ATSC algorithm also applies the maximum green time as a fundamental constraint. This constraint defines the maximum length of time that a phase can be green in the presence of a conflicting call. If the maximum green time is reached, the RS-ATSC agent is prohibited from extending the green time of the current phase (i.e., action A1 cannot be applied). A typical value of 70s is assumed for the maximum green time [217].

### 7.2.6 Reward Representation

Since the main objective of the proposed RS-ATSC is to optimize traffic safety, the reward for each state-action pair in the RS-ATSC algorithm is defined by the rear-end conflict rate estimated
from all approaches as a penalty. The conflict rate for each lane at each approach is estimated at every decision point. Then, the reward value $r^{t+1}$ for performing action $a^t$ at state $s^t$ can be defined as follows:

$$r^{t+1} = -\sum_{i=1}^{M} \sum_{j=1}^{N} \frac{Y_{ij}}{C}$$

Eq. (7.4)

Where:

$r^{t+1}$: the reward value for the state-action pair $(a^t, s^t)$ estimated at state $s^{t+1}$;

$N$: the number of lanes per approach;

$M$: the number of approaches at the signalized intersection;

$Y_{ij}$: the number of rear-end conflicts at the signal cycle level for lane $j$ in approach $i$ (model 6 in Table 3.3);

$C$: the signal cycle length in seconds.

7.2.7 Learning Rate and Discount Rate

The learning rate $\alpha^{t+1}$ in Eq. (7.1) is determined every time-step as the reciprocal of the number of visits by the agent to the state-action pair $(s^t, a^t)$ as follows [54] [57]:

$$\alpha^{t+1} = \frac{1}{V^{t+1}(s^t, a^t)}$$

Eq. (7.5)

Where: $V^{t+1}(s^t, a^t)$: the number of visits by the agent to the state-action pair $(s^t, a^t)$.

In addition, the discount rate $\gamma$ in Eq. (7.1), which considers the long-run reward, is assumed to be 0.5.

7.2.8 Exploration Versus Exploitation

The trade-off between exploration and exploitation is one of the main challenges in RL. While the agent must exploit the most effective experienced actions to obtain a lot of reward, it must also
explore new actions in order to make better action selections in the future. To obtain the optimized policy, neither exploitation nor exploration can be followed exclusively. Rather, an action selection strategy should be applied to balance the exploration and exploitation. The typical action selection strategies used in the literature are $\epsilon$-greedy and softmax [54].

In this research, the $\epsilon$-greedy method is adopted as the action selection strategy. This means the RS-ATSC agent selects, in each iteration, the greedy action most of the time except for $\epsilon$ amount of time, when it selects a random action uniformly. The rate of exploration $\epsilon$ is assumed to decrease gradually with the number of iterations (i.e., the age of the agent). The highest exploration occurs at the beginning of the learning, since the agent does not have much experience. At the end of the learning, the lowest exploration occurs, and more exploitation takes place as the agent converges to the optimized policy [54]. The gradual decreasing rate of exploration $\epsilon$ can be represented as follows [57]:

$$
\epsilon = e^{-En}
$$

Eq. (7.6)

Where: $E$ is a constant and $n$ is the iteration number.

7.2.9 Modeling the Environment

The traffic microsimulation model VISSIM (v7.00.16) [52] was utilized in this study. VISSIM is a time-step and behavior-based model developed to simulate traffic and depends on a psycho-physical car-following model that is based on Wiedemann’s model [199] [52]. The Wiedemann model assumes that the driver can have one of four driving modes: free driving, approaching, following, and braking [52].
An isolated signalized intersection was modeled in VISSIM, representing a connected-vehicle environment for the proposed RS-ATSC algorithm. The modeled intersection has four approaches with two through lanes and a single left-turn lane. The traffic control unit, the agent, receives real-time V2I information from all CVs that exist within a specific distance from the stop lines. This distance virtually represents the standard V2I DSRC domain. Since the standard V2I DSRC domain roughly ranges from 150 to 300 meters [7], the distance was assumed to be 225m (i.e., the average). Furthermore, various market penetration rates of CVs were represented in the VISSIM model by creating a new vehicle class called “connected vehicle” and varying traffic composition percentages of each traffic input point. In addition to CVs, loop detectors installed at each lane are assumed to provide real-time traffic information to the traffic controller. Two types of loop detectors were considered: traffic counting detectors at through lanes and left-turn detectors at the beginning and the end of each left-turn bay (Figure 7.2).

To simulate the CVs environment and the RS-ATSC algorithm, an external MATLAB code was developed to control the VISSIM model through its COM interface [201]. The MATLAB code can run/pause simulation at any time using the “sim-break-at” function, record detailed information on traffic signals and vehicles (i.e., vehicle identification number, class, position, and speed), and apply any required real-time changes to traffic signal heads in VISSIM. Thus, this code represents the agent (i.e., the traffic controller) for the Q-learning, since it is able to receive the environment’s state and take various actions.
7.2.10 Training the Algorithm

The RS-ATSC algorithm was trained by running the VISSIM simulation model of the isolated intersection depicted in Figure 7.2. The simulation was run for 420 episodes. Each episode included 20,000 simulation seconds divided into 1500s as a warming-up period, 500s as a cooling-down period, and 18000s (i.e., 5 hours) to train the algorithm. During the training period of each episode, the simulation was paused every $\Delta t$ seconds (Eq. (7.3)), the state was defined, the next action was selected and applied, the reward was calculated, and lastly, the Q-matrix was updated. To account for the stochastic nature of traffic, various random seeds were considered in VISSIM. Additionally, to allow the algorithm to visit as many states as possible, the traffic volume entering
each approach was uniformly randomized between 200 vehicle/hour to 1600 vehicle/hour. Traffic volumes were determined by assuming random values, from 0.1 to 1, of the volume to capacity ratio (V/C). These values correspond to undersaturation flow conditions where the real-time safety models presented in Table 3.3 can be applied.

When training such a RL-based algorithm, observing the learning progress of the agent and assuring the algorithm’s convergence to the optimized policy are essential. In general, the theoretical definition of convergence to the optimal policy is that the agent visited each state-action pair an infinite number of times. Since this is not feasible, the learning progress of the agent was observed after each episode using two measures: (1) the number of visited state-action pairs and (2) the minimum conflict rate (conflicts/exposure) resulted from all episodes. Figure 7.3 illustrates the learning progress of the agent represented by the number of traffic conflicts normalized by the traffic volume (conflicts/exposure). After about 200 episodes, most state-action pairs were visited many times by the agent and the minimum conflict rate was not changed throughout the next episodes (i.e., episodes 201 to 420). Therefore, it was considered that the agent converged to the optimized policy. The conflict rate was reduced from approximately 0.18 conflict/vehicle at the beginning of the learning process to 0.11 conflict/vehicle when the convergence was reached.
7.3 Validation Using Real-world Traffic Data

The proposed RS-ATSC algorithm was validated using real-world traffic data obtained from two signalized intersections in the city of Surrey, British Columbia, Canada. For both intersections, the real-world signal control is a typical fully actuated signal control with stop-line and extension detectors. The real-world actuated signal control was set as a benchmark to evaluate the effectiveness of the RS-ATSC. For each intersection, both the trained RS-ATSC and the real-world benchmark actuated signal control (ASC) were implemented in a calibrated VISSIM model. The safety and operational performances of both signal controllers were then observed and compared.

7.3.1 Real-world Traffic Data

The first selected intersection is 72nd Avenue and 128 Street, while the second selected intersection is 72nd Avenue and 132 Street. At each intersection, video data were collected using 8 high-resolution cameras (29.97 frames per second) distributed to cover the four approaches (i.e. two cameras for each approach). The data were collected during a weekday from 9:00 am to 6:00 pm, to cover both peak and off-peak hours. Thus, the total amount of the collected data is 144
video-hours (8 cameras * 9 hours * 2 intersections). Figure 7.4 shows the location of the selected intersections, the selected approaches, and the recorded video scenes.

Figure 7.4 Study locations and video scenes

Detailed real-world traffic data at each approach for each hour were extracted from the video recordings. These data include the actual signal program, the traffic volume of all movements, the number of vehicles arriving on green, the average platoon ratio, the average delay time, the desired speed distribution, and the traffic composition. The traffic composition includes percentages of passenger cars, trucks, and buses. Motorcycles were neglected as they were rarely found in the videos.

### 7.3.2 Calibrated Simulation Models

VISSIM models of the two selected intersections came from previous studies ([47] [48] [49]). The VISSIM models were built accurately to match actual field conditions in terms of intersection geometry, traffic volumes, traffic composition, traffic signal settings. The real-world ASC were defined in VISSIM using the Ring Barrier Controller (RBC) module [52]. Visual inspection was also performed to ensure that there are no abnormal movements of the simulated vehicles. In
addition, the VISSIM models were precisely calibrated in previous studies ([47] [48] [49]) using a comprehensive two-step calibration procedure. The first calibration step aimed to match the simulated delay times with the field-observed delay times. This was achieved by matching the arrival pattern and the desired speed to the field conditions. The second calibration step aimed at enhancing the correlation between field-observed and simulated traffic conflicts by calibrating the VISSIM parameters. Firstly, important VISSIM parameters that had the most significant effect on the simulated conflicts were determined through a sensitivity analysis. Subsequently, a Genetic Algorithm was applied to estimate the best values of these parameters with the objective of enhancing correlation between field-observed and simulated conflicts. Table 7.1 shows the selected VISSIM parameters and their calibrated values at each intersection ([47] [48]).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
<th>Default Value</th>
<th>Calibrated Value (128 St &amp; 72 Ave)</th>
<th>Calibrated Value (132 St &amp; 72 Ave)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standstill distance</td>
<td>The desired distance between stopped vehicles</td>
<td>m</td>
<td>1.50</td>
<td>2.50</td>
<td>2.10</td>
</tr>
<tr>
<td>Headway time</td>
<td>The time that a driver wants to keep</td>
<td>s</td>
<td>0.90</td>
<td>1.3</td>
<td>1.30</td>
</tr>
<tr>
<td>Following thresholds</td>
<td>The thresholds which control the speed differences during the ‘Following’ state</td>
<td>—</td>
<td>±0.35</td>
<td>±0.25</td>
<td>±1.10</td>
</tr>
<tr>
<td>Reduction factor for safety distance closed to stop line</td>
<td>This reduction factor defines the vehicle behavior close to stop line at signalized intersections</td>
<td>—</td>
<td>0.60</td>
<td>0.75</td>
<td>0.60</td>
</tr>
<tr>
<td>Start upstream of stop line</td>
<td>Distance upstream of the stop line of signalized intersection</td>
<td>m</td>
<td>100</td>
<td>110</td>
<td>100</td>
</tr>
<tr>
<td>Desired deceleration</td>
<td>Desired deceleration is used as the maximum for: the deceleration caused by a desired speed decision; the deceleration in case of Stop &amp; Go traffic, when closing up to a preceding vehicle; the deceleration toward an emergency stop position (route); and for co-operative braking</td>
<td>m/s²</td>
<td>-2.80</td>
<td>-2.80</td>
<td>-2.80</td>
</tr>
</tbody>
</table>

Table 7.1 Calibrated VISSIM parameters [47] [48]
To validate the proposed RS-ATSC, its performance was compared with the benchmark ASC. The number of rear-end traffic conflict occurred at the intersection approaches was considered as a measure of safety performance. Other measures of operational performance were also considered, including the number of stops, the maximum queue length, the 95th percentile of queue length, and the average delay time per vehicle. To evaluate these measures, the calibrated VISSIM model for each intersection was run for a 9-hour period (i.e., 9:00 am to 6:00 pm). For each hour, two signal controllers in VISSIM were simulated separately: (1) the RBC module that represents the real-world benchmark ASC, and (2) an external real-time MATLAB code that represents the trained RS-ATSC. For each signal controller, 10 different random seeds were applied, and the results were then averaged. The minimum required number of random seeds to compare the performance measures of the two alternatives (i.e., the proposed RS-ATSC and the ASC benchmark) was estimated, following the methodology provided by Dowling et al. [218]. The statistical analysis showed that 10 simulation runs are sufficient to reject the null hypothesis at 95% confidence level. This means the differences in the performance measures are caused by using two different alternatives and not just a result of using different random seeds.

During each simulation run, detailed simulated traffic data were continuously recorded at a very short time step (e.g., every second of simulation). These data included position and speed of every vehicle, vehicle types, and status of all signal heads. The data recording was obtained using an external program that controls the simulation model via the VISSIM COM interface [201]. After running the simulation and recording detailed traffic data, the procedure proposed in chapter 6 were applied to estimate dynamic traffic parameters (i.e., V, A, S_{12}, P) and evaluate safety (i.e.,
predict the number of conflicts) (Figure 6.1). First, signal cycles for each approach of the intersection were determined using the recorded status of the approach signal head. Second, recorded vehicle trajectories were filtered by time and space to specify vehicle trajectories for each lane per each signal cycle. Third, for each lane, the space-time diagram for each signal cycle (Figure 3.5) was obtained using both the filtered trajectories and the cycle timing. This space-time diagram was then used to calculate various traffic parameters at the signal-cycle level, including traffic volume, shock wave area, shock wave speed, and platoon ratio. Lastly, the estimated cycle-related parameters were inputted into a real-time safety model (i.e., model 6 in Table 3.3) to predict the number of rear-end conflicts at the cycle level. The model predicts the number of conflicts per a signal cycle using the traffic volume, the shock wave area, the shock wave speed, and the platoon ratio of this cycle.

7.3.4 Validation Results

The aforementioned dynamic traffic parameters as well as the number of rear-end conflicts were extracted from simulation at each of the selected intersections for the 9-hour analysis period (9:00 am to 6:00 pm). The safety performance of the trained RS-ATSC was compared with that of the real-world benchmark ASC. Overall, the RS-ATSC led to positive safety impacts in terms of reducing rear-end conflicts. Figures 7.5 shows the conflict rate for each hour at the two selected intersections with both ASC and RS-ATSC. As shown in the figure, when the RS-ATSC was implemented instead of the ASC, the average conflict rate was decreased from 0.165 to 0.08 conflict/vehicle/hour at the first intersection and from 0.17 to 0.11 conflict/vehicle/hour at the second intersection.
The real-time variation of traffic conflicts was also investigated at each approach of both intersections. The number of rear-end conflicts were estimated for each lane per each signal cycle from model 6 in Table 3.3. The conflict rate (conflict/second) was then estimated by dividing the number of conflicts at each cycle by the cycle length. Figures 7.6 and 7.7 show the real-time variation of the conflict rate for each approach at the first and the second intersection, respectively. Moreover, the cumulative numbers of rear-end conflicts throughout the 9-hour analysis period for both intersections are shown in Figures 7.8 and 7.9. Compared to the benchmark ASC, the proposed RS-ATSC reduced the number of rear-end conflicts significantly at both intersections. The magnitude of reduction in the rear-end conflicts was not the same for all approaches. Some approaches experienced higher reduction in the number of conflicts, such as the southbound approach at the first intersection (Figures 7.6 and 7.8) and the westbound approach at the second intersection (Figures 7.7 and 7.9). At the same time, some approaches showed less reduction in the number of conflicts, such as the southbound approach at the second intersection (Figures 7.7 and 7.9). More importantly, the results do not indicate any increase in the cumulative number of conflicts at any approach. This means that the RS-ATSC not only improved the overall safety level of each intersection, but also it did not deteriorate the safety level of any individual approach.
Figure 7.6 Real-time variation of the conflict rate at each approach of the first intersection (72 Ave and 128 St) before and after implementing the proposed RS-ATSC

Figure 7.7 Real-time variation of the conflict rate at each approach of the second intersection (72 Ave and 132 St) before and after implementing the proposed RS-ATSC
Figure 7.8 Cumulative traffic conflicts each approach of the first intersection (72 Ave and 128 St) before and after implementing the proposed RS-ATSC

Figure 7.9 Cumulative traffic conflicts each approach of the second intersection (72 Ave and 132 St) before and after implementing the proposed RS-ATSC
The overall comparison of the performance of the proposed RS-ATSC to the benchmark ASC is reported in Table 7.2. For the 9-hour analysis period, the RS-ATSC led to a significant improvement in the safety level of both analyzed intersections. The overall rate of rear-end conflicts (i.e., the total number of conflicts normalized by the exposure) was reduced by 49% and 37% at the first and the second intersection, respectively. The proposed algorithm also improved the operational performance of the analyzed intersections. Compared to the benchmark ASC, the RS-ATSC reduced the average delay time by 12% and 23% for the first and the second intersection, respectively. The number of stops, the maximum queue length, and the 95th percentile of queue length were also reduced by 47%, 23%, and 51% at the first intersection; and by 27%, 17%, and 28% at the second intersection, respectively.

It is noteworthy that the performance results provided in Table 7.2 were derived based on the geometric and traffic characteristics of the selected intersections. These results can vary if the algorithm is implemented to other intersections with different characteristics. It should also be noted that the V2I DSRC domain was assumed to be 225 meters. Using a higher value of this domain can potentially improve the algorithm’s performance. In addition, the algorithm’s performance was evaluated with the assumption that the V2X communication system is ideal. Practically, several sources of error may exist in connected systems, including position error, packet delay, and packet loss. These connectivity error sources can impact the algorithm’s performance.
The reduction in the conflict rate confirms the positive safety impact of the proposed RS-ATSC algorithm. In addition, the improvement in the average delay time, the number of stops, and the queue length indicates that the algorithm has a positive mobility impact. Thus, the proposed RS-ATSC algorithm improves both the safety and the mobility performance of the analyzed intersections. In other words, the algorithm optimizes safety without deteriorating mobility.

<table>
<thead>
<tr>
<th>First intersection (128 St &amp; 72 Ave)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Analysis period of 9 hours in total (9:00 am to 6:00 pm)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Approach*</th>
<th>EB</th>
<th>SB</th>
<th>WB</th>
<th>NB</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traffic Volume</td>
<td>7886</td>
<td>5562</td>
<td>7201</td>
<td>4239</td>
<td>24888</td>
</tr>
<tr>
<td>Rear-end conflicts per exposure (conflict/vehicle)</td>
<td>0.226</td>
<td>0.128</td>
<td>0.169</td>
<td>0.093</td>
<td>0.165</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>-51%</td>
<td>-55%</td>
<td>-44%</td>
<td>-43%</td>
<td>-49%</td>
</tr>
<tr>
<td>Total number of stops</td>
<td>6414</td>
<td>4488</td>
<td>5760</td>
<td>2491</td>
<td>19153</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>-40%</td>
<td>-45%</td>
<td>-57%</td>
<td>-43%</td>
<td>-47%</td>
</tr>
<tr>
<td>Maximum queue length (vehicle)</td>
<td>18.5</td>
<td>12.8</td>
<td>14.5</td>
<td>9.3</td>
<td>18.5</td>
</tr>
<tr>
<td>95th percentile of queue length (vehicle)</td>
<td>15.2</td>
<td>6.6</td>
<td>9.5</td>
<td>5.1</td>
<td>14.3</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>-23%</td>
<td>-16%</td>
<td>-24%</td>
<td>-19%</td>
<td>-23%</td>
</tr>
<tr>
<td>Average delay time per vehicle (second/vehicle)</td>
<td>24.7</td>
<td>17.7</td>
<td>21.6</td>
<td>15</td>
<td>20.5</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>-24%</td>
<td>+12%</td>
<td>-38%</td>
<td>+44%</td>
<td>-12%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Second intersection (132 St &amp; 72 Ave)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Analysis period of 9 hours in total (9:00 am to 6:00 pm)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Approach*</th>
<th>EB</th>
<th>SB</th>
<th>WB</th>
<th>NB</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traffic Volume</td>
<td>7526</td>
<td>3527</td>
<td>7650</td>
<td>3077</td>
<td>21780</td>
</tr>
<tr>
<td>Rear-end conflicts per exposure (conflict/vehicle)</td>
<td>0.142</td>
<td>0.234</td>
<td>0.187</td>
<td>0.141</td>
<td>0.173</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>-30%</td>
<td>-30%</td>
<td>-44%</td>
<td>-39%</td>
<td>-37%</td>
</tr>
<tr>
<td>Total number of stops</td>
<td>5178</td>
<td>5899</td>
<td>5985</td>
<td>2321</td>
<td>19383</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>-32%</td>
<td>-11%</td>
<td>-38%</td>
<td>-27%</td>
<td>-27%</td>
</tr>
<tr>
<td>Maximum queue length (vehicle)</td>
<td>14</td>
<td>23</td>
<td>15.3</td>
<td>16.5</td>
<td>23</td>
</tr>
<tr>
<td>95th percentile of queue length (vehicle)</td>
<td>8.5</td>
<td>22</td>
<td>8.5</td>
<td>10.6</td>
<td>20.3</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>-29%</td>
<td>-27%</td>
<td>-40%</td>
<td>-61%</td>
<td>-28%</td>
</tr>
<tr>
<td>Average delay time per vehicle (second/vehicle)</td>
<td>15.4</td>
<td>64.2</td>
<td>20.7</td>
<td>32.5</td>
<td>28.5</td>
</tr>
<tr>
<td>% Reduction/increase**</td>
<td>+4%</td>
<td>-27%</td>
<td>-25%</td>
<td>-37%</td>
<td>-23%</td>
</tr>
</tbody>
</table>

*EB: eastbound, WB: westbound, NB: northbound, SB: southbound
** Positive values indicate increase and negative values indicate reduction

Table 7.2 Safety optimization results of the proposed RS-ATSC algorithm compared to the ASC

The reduction in the conflict rate confirms the positive safety impact of the proposed RS-ATSC algorithm. In addition, the improvement in the average delay time, the number of stops, and the queue length indicates that the algorithm has a positive mobility impact. Thus, the proposed RS-ATSC algorithm improves both the safety and the mobility performance of the analyzed intersections. In other words, the algorithm optimizes safety without deteriorating mobility.
Given the aforementioned validation results, the proposed RS-ATSC algorithm can be implemented in real-world to optimize the safety of signalized intersections using CVs real-time data. When implemented to a specific intersection, the RS-ATSC algorithm can be designed to continue learning itself using real-world traffic and geometric data of this intersection. The Q-table should be re-trained to properly consider the site characteristics as well as the local driving behavior. Minor modifications should also be applied in the algorithm to match the intersection specifications, such as the number of approaches, the number of lanes, the number of phases, the phase sequence, and the signal timing constraints (e.g., minimum/maximum green time, yellow time, all-red time). Considering these site-specific data can potentially lead to better safety and mobility performances.

7.3.5 Effect of CVs Market Penetration Rate

The CVs technology is supposed to be deployed gradually. A mix of CVs and conventional vehicles is expected to exist in road networks during the transition period that predates the full deployment of CVs technology. Subsequently, it is not feasible to validate any ATSC algorithm assuming that all vehicles are CVs. Rather, various market penetration rates (MPRs) of CVs should be considered. Therefore, in this study, the performance of the proposed RS-ATSC at the two selected intersections was investigated under various MPRs of CVs, ranging from 10% to 100%. Various MPRs of CVs were represented in the VISSIM model by creating a new vehicle class called “connected vehicle” and varying traffic composition percentages of each traffic input point. When implementing the RS-ATSC algorithm with a specific MPR value, instantaneous vehicle information was captured from vehicles with the “connected vehicle” class only. The cycle parameters for each lane was estimated from CVs data. Some of these parameters (e.g., traffic volume per cycle per lane) were multiplied by a correction factor (i.e., magnification factor) to
represent all vehicle classes (CVs and conventional vehicles). This factor equals the reciprocal of the MPR value. The exact MPR value can be estimated in real time, given the number of CVs from the V2I communications and the total traffic counts from the counting detectors upstream each approach of the intersection. The traffic conflict rate and the average delay time were estimated under each MPR and were compared to the benchmark ASC.

Figures 7.10 and 7.11 show the average conflict rate and the average delay time of the analyzed intersections when the RS-ATSC is applied under various MPRs. The benchmark ASC is also illustrated for comparison. As shown in Figure 7.10, the maximum safety benefit of the RS-ATSC is corresponding to the MPR of 100% (i.e., all vehicles are connected). At this MPR, the conflict rate was reduced from 0.165 to 0.084 at the first intersection and from 0.173 to 0.109 at the second intersection. However, it should be noted that 90% of these benefits can be achieved when the MPR is 50%. Moreover, the MPR of 30% seems sufficient to achieve about 50% of the maximum safety benefit. On the other hand, the results of the average delay time (Figure 7.11) emphasize that the RS-ATSC algorithm has a positive mobility impact. This means the algorithm optimizes safety without deteriorating mobility.
For clarity, only MPRs with a considerable change in the conflict rate are shown. For example, MPRs 60-90% almost have the same conflict rate as MPR 50; therefore, they are not shown here.

Figure 7.10 The effect of the CVs MPR value on the average conflict rate at the selected intersections when implementing the proposed RS-ATSC
Figure 7.11 The effect of the CVs MPR value on the average delay time at the selected intersections when implementing the proposed RS-ATSC

Overall, the proposed RS-ATSC algorithm can be very effective when the MPR of CVs is equal to or higher than 30%. The higher the MPR value, the more the safety effectiveness of the algorithm. MPR values less than 20% may not lead to significant safety benefits, since the algorithm cannot define the environment state with a reasonable accuracy due to the lack of real-time information on vehicle positions and speeds.

7.4 Summary and Conclusion

This chapter presents a novel adaptive traffic signal control algorithm (i.e., RS-ATSC) that optimizes safety of signalized intersections in real time using CVs data. The algorithm is based on real-time safety models provided in the third chapter of this thesis. The models use dynamic traffic parameters, such as the platoon ratio and the shock wave characteristics, to predict traffic conflicts and evaluate safety of signalized intersections in real time. To the best of the author’s knowledge,
the presented RS-ATSC is the first self-learning ATSC algorithm that uses CVs data to optimize traffic safety in real time (i.e., safety is evaluated and optimized over a very short time period, a few seconds).

The RS-ATSC algorithm was developed using the RL technique. Specifically, the Q-learning off-policy TD method was applied. In the developed Q-learning algorithm, the state is defined using the rate of rear-end conflicts (number of conflicts per second) upstream each approach within a specific V2I DSRC domain. The action space includes only two actions representing the fixed phasing sequence. Thus, every time step, the RL agent decides whether to extend the current green time or to switch the green light to the next phase. The reward function is defined by the summation of conflict rates estimated from all approaches as a penalty. In addition, several constraints are considered to ensure the feasibility of implementing the proposed algorithm in real-world. This includes accommodating the yellow time, the all-red time, and the minimum/maximum green time, whenever they are necessary.

To train the RS-ATSC algorithm, an isolated intersection was modelled in the simulation platform VISSIM. The VISSIM model was controlled by an external program to emulate the CVs environment as well as real-time signal changes. In the learning process, the simulation model was run using random traffic volumes for 420 episodes, each includes 20,000 seconds. The RS-ATSC agent converged to the optimized policy after about 200 episodes.

The trained RS-ATSC algorithm was validated using real-world traffic data of two signalized intersections in the City of Surrey, British Columbia. The algorithm’s performance was compared
with the performance of the existing fully actuated traffic signal control (ASC). Overall, the validation results showed that the proposed RS-ATSC algorithm outperforms the real-world ASC. When implementing the RS-ATSC, the overall rate of rear-end conflicts (i.e., the total number of conflicts normalized by the exposure) was decreased by 49% and 37% at the first and second intersection, respectively. In addition to these safety benefits, the RS-ATSC has positive mobility impacts. Compared to the benchmark ASC, the RS-ATSC reduced the average delay time by 12% and 23% for the first and second intersection, respectively. The number of stops, the maximum queue length, and the 95th percentile of queue length were also reduced by 47%, 23%, and 51% at the first intersection; and by 27%, 17%, and 28% at the second intersection, respectively.

The RS-ATSC algorithm was also tested under various market penetration rates of CVs. Although the maximum safety benefit is corresponding to the MPR of 100%, the results showed that 90% of this benefit can be achieved when the MPR is 50%. Moreover, the MPR of 30% seems sufficient to achieve about 50% of the maximum safety benefit. MPR values less than 20% may not lead to significant safety benefits, since the algorithm cannot define the environment state with a reasonable accuracy due to the lack of real-time information on vehicle positions and speeds.

In conclusion, the proposed RS-ATSC is a promising and feasible algorithm that can adapt traffic signals to optimize real-time safety in the CVs environment. The algorithm outperforms the traditional actuated traffic signal control in terms of the produced number of rear-end traffic conflicts. The proposed RS-ATSC algorithm can be very effective when the MPR of CVs is equal to or higher than 30%. The higher the MPR value, the more the safety effectiveness of the algorithm. More importantly, when implemented to a specific intersection, the RS-ATSC
algorithm can be designed to continue learning itself using real-world traffic and geometric data of this intersection. The Q-table should be re-trained to properly consider the site characteristics as well as the local driving behavior. Minor modifications should also be applied in the algorithm to match the intersection specifications, such as the number of approaches, the number of lanes, the number of phases, the phase sequence, and the signal timing constraints. Considering these site-specific data can potentially lead to better safety and mobility performances.

It should be noted that although the RS-ATSC algorithm reduces delay times, its mobility performance cannot be considered the optimum. The reason is that the RS-ATSC is a safety-oriented algorithm whose optimized policy is based on minimizing the number of traffic conflicts to optimize safety. Other ATSC algorithms that consider minimizing delay times as a primary objective can lead to better mobility performance. In fact, traffic delays are an essential issue since congestion occurs more frequently and leads to significant economic and environmental costs. Meanwhile, traffic safety is also a fundamental issue due to high collision frequencies and severities at signalized intersections and their associated enormous social and economic costs. Therefore, both mobility and safety should be considered as fundamental optimization objectives in ATSC algorithms. Since previous research has been focused on optimizing delays, the main contribution of this research is to present a new algorithm that optimizes safety without deteriorating mobility (without increasing delays). Based on the results presented in this chapter, safety and mobility of signalized intersections seem to be non-conflicting objectives, although their optimum designs may not be the same.
Chapter 8: Conclusion and Future Research

8.1 Summary and Conclusions

In the era of connected vehicles (CVs), a considerable amount of high-resolution data on vehicle positions and trajectories will be generated in real time. These data can potentially be used for real-time safety and mobility optimization of traffic signals. Existing research has mainly focused on using CVs data for mobility optimization at signalized intersections. Numerous procedures have been proposed in the literature to adapt traffic signal controllers in real time to optimize mobility (i.e., minimize delay time, minimize queue length, or maximize traffic throughput) using vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications. On the other side, the real-time safety optimization of traffic signals has generally been disregarded, despite the potential safety benefits of the emerging CVs technology. This is mainly because safety optimization is generally more complicated than mobility optimization. Unlike vehicle delay and travel time, the safety level of signalized intersections cannot be directly estimated in real time from CVs data. The main challenge is the lack of tools to evaluate the safety of signalized intersections in real time.

This thesis presents several advances toward the real-time safety and mobility optimization of traffic signals in a connected-vehicle environment. Specifically, this thesis has three main contributions. First, new models to evaluate the safety of signalized intersections in real time were developed. These models utilize real-time dynamic traffic parameters to predict the safety level of signalized intersections within a short time-period (i.e., a few seconds). Second, an approach to integrate the developed real-time safety models with traffic microsimulation models was provided.
Third, a novel ATSC algorithm to optimize traffic safety using real-time CVs data was proposed. A summary of these contributions is discussed in the following sections.

8.1.1 Real-time Safety Models for Signalized Intersections

This thesis presents new real-time safety models (i.e., SPFs at the signal cycle level) for signalized intersections. The models relate the number of rear-end conflicts occurring in each signal cycle to dynamic traffic parameters. To develop these models, traffic video-data were recorded for six signalized intersections located in two cities in Canada. A new video analysis procedure was proposed to precisely collect dynamic traffic parameters and estimate traffic conflicts at the signal cycle level. The TTC was used as a traffic conflict indicator. The traffic parameters include traffic volume, maximum queue length, shock wave speed and area, and platoon ratio. Six real-time safety models were developed using the GLM approach. The results show that all models have a good fit and almost all the explanatory variables are statistically significant, leading to a better prediction of conflict occurrence beyond what can be expected from the traffic volume only. Furthermore, space-time conflict heat maps were developed to investigate the distribution of traffic conflicts. The heat maps illustrate graphically the association between rear-end conflicts and various traffic parameters.

Additional real-time safety models (i.e., SPFs at the signal cycle level) were developed to incorporate various traffic conflict indicators (i.e., TTC, MTTC, DRAC) and to account for different severity levels (i.e., several thresholds of TTC, MTTC, and DRAC). The additional real-time safety models were developed using the Full Bayesian (FB) approach to address the unobserved heterogeneity and the variation among different sites. Two kinds of FB models were developed: (1) Poisson-LogNormal distribution (PLN) models that account for the unobserved
heterogeneity; and (2) PLN models with a random intercept that account for the unobserved heterogeneity and site effect. Overall, the results showed that all the additional real-time safety models have a good fit with all explanatory variables being statistically significant. The conflict frequency and severity distributions along the signal cycle were also investigated. The results indicated that the highest conflict frequency exists at the beginning of the green time due to the variation in speeds at the start of the traffic queue release. On the other hand, the highest conflict severity exists at the beginning of the red time due to the dilemma zone where the traffic signal indication changes from green to yellow to red. Furthermore, two extended time to collision measures (TET and TIT) were investigated at the cycle level. The results showed that both TET and TIT are positively correlated with the shock wave area and inversely correlated with the platoon ratio at all TTC thresholds. This conforms to the signs of the shock wave and the platoon ratio coefficients in the developed models. This also emphasizes the importance of including these cycle-related parameters in real-time safety evaluation of signalized intersections.

For a wider application of the developed real-time safety models, their transferability to new jurisdictions was investigated. Two corridors of signalized intersections in California and Atlanta states, USA, were used in the analysis as destination jurisdictions. Detailed vehicle trajectories for these corridors were obtained from the Next Generation Simulation (NGSIM) data [51]. Two transferability analysis approaches were applied: (1) the application-based approach, and (2) the estimation-based approach. In the first approach, the base models were applied with no change (without calibration) to the destination jurisdictions to assess how well the models predict in the new region. In the second approach, the model parameters estimated from the base jurisdiction data were recalibrated using the destination jurisdiction data. Two methods of calibration were
conducted. The first method comprises the calibration of the model intercept and the shape parameter only, while the second method considers the calibration of all the model parameters. In both transferability approaches, the transfer index (TI) measure was estimated to test the transferability of the base SPFs. Additionally, several goodness-of-fit (GOF) measures were examined to assess and compare the prediction performances of the transferred models at the destination jurisdictions. The applied GOF measures are: (1) Akaike’s Information Criterion (AIC); (2) Pearson’s product moment correlation coefficient (r); (3) Mean prediction bias (MPB); (4) Mean absolute deviation (MAD); (5) Mean absolute percentage error (MAPD); (6) Pearson chi-squared ($\chi^2$); and (7) Z-score. The results showed that the real-time safety models are fairly transferable among different sites, which confirms the validity of using them for real-time safety evaluation of signalized intersections.

In conclusion, the real-time safety models developed in this thesis can provide insight into how real-time changes in the signal cycle design affect the safety of signalized intersections. This paves the way for developing new strategies that utilize CVs data to adapt traffic signals in real time (e.g., adaptive traffic signal control algorithms) to optimize traffic safety. The overall goal is to maximize the potential safety benefits of the emerging CVs technology, leading to fewer collisions at signalized intersections.

### 8.1.2 A Procedure to Integrate Real-time Safety Models with Traffic Microsimulation

This thesis presents a new procedure, alternative to SSAM, for evaluating the safety of signalized intersections from traffic simulation. The procedure combines simulated vehicle trajectories with the developed real-time safety models to predict rear-end conflicts at the intersection’s approaches. The conflict prediction is based on dynamic traffic parameters, such as traffic volume and shock
wave characteristics, repeatedly measured over a short time interval (e.g. a few seconds). The proposed procedure benefits from the simulation models’ ability to provide reliable estimates of these dynamic parameters.

The proposed safety evaluation procedure was validated and compared with SSAM, using real-world traffic conflict data extracted from 54 hours of video recordings at two signalized intersections in the city of Surrey, British Columbia. The results showed that the proposed procedure outperforms SSAM in terms of conflict-prediction accuracy. For the two analyzed intersections, the proposed procedure predicted rear-end conflicts with MAPE values of 28.9% and 19.1% before and after calibrating the simulation model, respectively. On the other hand, the MAPE of SSAM ranged from 86.5%, before calibration, to 54.7 % after calibration.

Moreover, as an illustrative case study, the proposed procedure was applied to evaluate the safety impact of a recently-developed real-time adaptive traffic signal control (ATSC) algorithm, which aims to minimize total delays in the CVs environment. Specifically, the CTR real-time intersection control algorithm developed by Lee et al. [13] was applied to the two aforementioned intersections through traffic simulation. The safety impact of the CTR algorithm was then evaluated at multiple MPRs of CVs, using the proposed safety evaluation procedure. The results demonstrated that the CTR algorithm led to positive mobility and safety impacts on signalized intersections, especially at MPR of 40% or higher. Unsurprisingly, the improvement in mobility at all MPR values was more significant than the improvement in safety, because the main optimization objective of the algorithm was to minimize the total travel time.
In conclusion, the safety evaluation procedure presented in this thesis can be useful in predicting rear-end conflicts at signalized intersections from traffic simulation with reasonable accuracy. This can be useful in investigating the safety impacts of various CVs-based applications at signalized intersections prior to their real-world implementation.

8.1.3 Adaptive Traffic Signal Control Algorithm for Real-time Safety Optimization

This thesis presents a novel self-learning ATSC algorithm to optimize the safety of signalized intersections using real-time CVs data. The algorithm is referred to as RS-ATSC (Real-time Safety-optimized Adaptive Traffic Signal Control). The RS-ATSC algorithm has several advantages. First, although the algorithm was developed and trained using the simulation platform VISSIM [52], the safety evaluation is not based on simulated conflicts that were shown not to well represent actual-field conflicts and crashes [47] [48] [53]. Rather, the optimization is based on real-time safety models that were originally developed and validated using real-world traffic data. Second, the algorithm was developed using the Reinforcement Learning (RL) technique [54] as an efficient approach to solving the ATSC problem considering real-time and stochastic traffic changes [55] [56] [57]. Third, the algorithm is practical since it respects all traffic signal operation standards, including the phasing sequence, the minimum/maximum green time, and the intersection clearance time. Lastly, to the best of the author’s knowledge, this is the first self-learning ATSC algorithm that optimizes traffic safety in real time (i.e., safety is evaluated and optimized over a very short time-period, a few seconds).

The RS-ATSC algorithm was validated using real-world traffic data obtained from two signalized intersections in the city of Surrey, British Columbia. Compared to the traditional actuated signal control (ASC) system, the RS-ATSC algorithm reduced traffic conflicts by approximately 40%.
In addition to these safety benefits, the RS-ATSC has positive mobility impacts. Compared to the benchmark ASC, the RS-ATSC reduced the average delay time, the number of stops, the maximum queue length, and the 95th percentile of queue length. The proposed RS-ATSC algorithm was also tested under various MPRs of CVs and found to be effective and feasible under low MPR values. Specifically, the results showed that 90% and 50% of the algorithm’s safety benefits can be achieved at MPR values of 50% and 30%, respectively.

In conclusion, the proposed RS-ATSC is a promising and feasible algorithm that can adapt traffic signals to optimize real-time safety in the CVs environment. The algorithm outperforms the traditional actuated traffic signal control in terms of the produced number of rear-end traffic conflicts. The proposed RS-ATSC algorithm can be very effective when the MPR of CVs is equal to or higher than 30%. The higher the MPR value, the more the safety effectiveness of the algorithm. More importantly, when implemented to a specific intersection, the RS-ATSC algorithm can be designed to continue learning itself using real-world traffic and geometric data of this intersection. Considering these site-specific data can potentially lead to better safety and mobility performances.

8.2 Study Limitations and Future Research

Several future areas of research are suggested to extend the work presented in this thesis and to address its limitations. Firstly, study limitations and recommended future research areas related to the developed real-time safety models can be summarized as follow:

a) The sample size of the trajectory data was relatively limited. Only six signalized intersections were considered. Future research may consider more intersections and larger datasets to validate the developed models.
b) Only rear-end conflicts at the intersection’s approaches were considered. Other types of traffic conflict at signalized intersections such as left-turn opposing, right-angle, crossing, merging, and lane-change conflicts may be considered in future studies.

c) Future research may consider developing real-time safety models that consider other road facilities, such as other types of intersections and freeways.

d) Safety of active road-users (e.g., pedestrians and cyclists) were not included.

e) The developed models predict the number of conflicts using a specific conflict indicator (e.g., TTC, MTTC, DRAC). Developing new safety models based on a safety index that combines several conflict indicators to better reflect the conflict severity is a potential area of future research.

f) The developed models are conflict-based. More work is needed to investigate the relationship between conflicts and collisions. Moreover, safety measures other than traffic conflicts, such as the risk of collision or the predicted number of crashes [219] [220], can be used to represent real-time traffic safety.

g) The developed real-time safety models apply only to under-saturated signal cycles. Over-saturated cycles, where a vehicle can stay in the same approach for more than one cycle, were not considered in this research and should be considered in future work.

h) The effect of the signal coordination on the results was not considered and may be considered in future studies.

i) In the Full Bayesian (FB) analysis, non-informative prior distribution was assumed for each unknown parameter. The informative priors were recommended in the literature to improve the FB model’s goodness of fit [221] [222]. Using informative priors to develop SPF's at the cycle level is recommended as a future area of research.
j) The sample size of the trajectory data for the two destination jurisdictions in the transferability analysis was relatively limited. Investigating the models’ transferability using larger datasets is recommended.

k) The friction between through lanes and left/right turn lanes was not considered in the safety analysis. The effect of this friction becomes more apparent when left/right turn lanes are oversaturated. Considering this friction in the real-time SPFs is suggested as a future area of research.

Secondly, study limitations and recommended future research areas related to the proposed procedure to evaluate safety from traffic simulation can be summarized as follow:

a) The procedure is restricted to rear-end conflicts identified by TTC. Considering different types of conflicts and other conflict indicators is recommended as a future area of research.

b) The procedure does not address the discrepancy in the spatial distributions of both simulated and field-measured traffic conflicts illustrated in previous studies ([47] [48] [49]). Future research may consider new calibration procedures for simulation models to alleviate this discrepancy.

Thirdly, study limitations and recommended future research areas related to the proposed RS-ATSC algorithm can be summarized as follow:

a) Although the RS-ATSC algorithm reduces delay times, its mobility performance cannot be considered as optimum. The reason is that the RS-ATSC is a safety-oriented algorithm whose optimized policy is based on minimizing the number of traffic conflicts to optimize safety. Other ATSC algorithms that consider minimizing delay times as a primary objective can lead to better mobility performance. In fact, traffic delays are an essential issue since congestion occurs more frequently and leads to significant economic and environmental
costs. Meanwhile, traffic safety is also a fundamental issue due to high collision frequencies and severities at signalized intersections and their associated enormous social and economic costs. Therefore, both mobility and safety should be considered as fundamental optimization objectives in ATSC algorithms. Since previous research has been focused on optimizing delays, the main contribution of this research is to present a new algorithm that optimizes safety without deteriorating mobility (without increasing delays). Based on the results of this research, safety and mobility of signalized intersections seem to be non-conflicting objectives, although their optimum designs may not be the same. The developed RS-ATSC algorithm can further be modified to incorporate both safety and mobility in a multi-objective optimization problem. In such a problem, a weight can be assigned to each objective based on its associated cost (e.g., savings resulted from decreasing delays or collisions). These weights can vary among different locations and jurisdictions.

b) The algorithm’s performance needs to be tested under non-ideal V2X communication systems. The results’ sensitivity to several sources of error in connected systems (e.g., position error, packet delay, and packet loss) should be investigated.

c) The algorithm can be extended to model multiple intersections (e.g., a corridor or a network) instead of one isolated intersection. In this case, the signal coordination must be considered.

d) The algorithm’s performance should be investigated under extremely oversaturated conditions where the queue length exceeds the V2I DSRC domain.

e) The state space in the algorithm can be expanded to be a continuous state space by converting the Q-matrix to a neural network (i.e., deep reinforcement learning).
f) It is suggested to investigate the results’ sensitivity to various parameters, such as the discount factor, the update time-interval, and the V2I DSRC domain.

g) Developing an uncertainty-aware RL-based ATSC algorithm is recommended. Two types of uncertainty should be considered: (1) the imprecise knowledge of the environment and (2) the intrinsic stochasticity of the environment.

h) Incorporating other conflict types, such as crossing and merging conflicts, is recommended.

i) Safety measures other than traffic conflicts, such as the risk of collision or the predicted number of crashes [219] [220], can be used to represent real-time traffic safety and define the reward function in the RS-ATSC.
Bibliography


[34] C. Hupfer, "Computer aided image processing to modify traffic conflicts technique," Transportation Department, University of Kaiserslautern, Germany, 1997.


[97] R. van der Horst and J. Hogema, "Time-to-collision and collision avoidance systems," in


[100] N. Saunier and T. Sayed, "Automated Analysis of Road Safety with Video Data,"
Transportation Research Record: Journal of the Transportation Research Board, no.

[101] Saunier, Nicolas and Tarek Sayed, "A feature-based tracking algorithm for vehicles in
intersections," In The 3rd Canadian Conference on Computer and Robot Vision (CRV’06)

Evaluations: Case Study of a Signalized Right-Turn Safety Treatment," Journal of the
Transportation Research Board”, Transportation Research Record, no. 2280, 2012.

Conflicts Context for Before-and-After Studies," Transportation Research Record:
Journal of the Transportation Research Board, no. 2198, pp. 52-64, 2010.

analysis for behavioural studies: concept and experience," IET Intelligent Transport


[114] Huang, Fei, Pan Liu, Hao Yu and Wei Wang, "Identifying if VISSIM simulation model and SSAM provide reasonable estimates for field measured traffic conflicts at signalized intersections," *Accident Analysis & Prevention*, no. 50, pp. 1014-1024, 2013.


[125] Y. Ren, Y. Wang, X. Wu, G. Yu and C. Ding, "Influential factors of red-light running at signalized intersection and prediction using a rare events logistic regression model," Accident Analysis & Prevention, no. 95, pp. 266-273, 2016.


[195] K. Pearson, "X. On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling," *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, vol. 302, no. 50, pp. 157-175, 1900.


