Modelling and simulation of vehicle movements at signalised junctions

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MODELLING AND SIMULATION OF VEHICLE MOVEMENTS AT SIGNALISED JUNCTIONS

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School of Civil and Environmental Engineering

2014

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(Time = 12s)

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LIST OF ABBREVIATIONS

ACI	Artificial Computation Intelligence
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BML	Biham-Middleton-Levine
CA	Cellular Automata
CI	Criticality Index
DOC	Deceleration Occurrence caused by Conflict
EE	Elementary Effect
FCA	Fuzzy Cellular Automata
FHWA	Federal Highway Administration
GA	Genetic Algorithms
GLIDE	Green Link Determine
HCM	Highway Capacity Manual
HDB	Housing and Development Board
ITS	Intelligent Transport Systems
Lowess	Locally Weighted Smoothing linear regression
LOS	Level of Service
LTA	Land Transport Authority
LTOR	Left Turn On Red
MAPE	Mean Average Percentage Error
MPE	Mean Percentage Error
MSE	Mean Square Error
NaSch	Nagel-Schreckenberg
NB	Negative Binomial
NCA	Neural Cellular Automata
NN	Neural Networks
PCE	Passenger Car Equivalent
PCU	Passenger Car Unit
PET	Post-encroachment Time
QO	Quasi-Optimised

RAG	Red-Amber-Green
RLC	Red-Light Camera
RMSE	Root Mean Square Error
RTM	Regression to the Mean
SCATS	Sydney Coordinate Traffic Adaptive System
SCOOT	Split Cycle and Offset Optimisation Technique
SFR	Saturated Flow Rate
SOM	Self-Organising-Map
SSAM	Surrogate Safety Assessment Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TRANSYT	Traffic Network Study Tool
TRRL	Transport and Road Research Laboratory
TSI	Total Sensitivity Index
TTC	Time to Collision
V2P	Vehicle to Pedestrian
V2V	Vehicle to Vehicle

LIST OF NOTATIONS

acc, dec	Maximum acceleration and deceleration rates
b	Number of cells occupied by front vehicle in x direction
β_n	Linear combination of the three input factors to compute stopping probability
C	The winner neuron in SOM clustering method
c	Duration of signal cycle
c_1	Duration of straight-through green phase of studied approach
c_2	Duration of right-turn green phase of studied approach
C_1^{car}	Front gap threshold in subject lane for cars
C_1^{hv}	Front gap threshold in subject lane for heavy vehicles
C_2^{car}	Front gap threshold in target lane for cars
C_2^{hv}	Front gap threshold in target lane for heavy vehicles
C_3^{car}	Rear gap threshold in target lane for cars
C_3^{hv}	Rear gap threshold in target lane for heavy vehicles
CI	Criticality Index
D	Total distance travelled for tracked vehicle
d_{ij}	Distance between two vehicles' centriods
d_j	Euclidean distance in clustering analysis
d_n	Spacing of the n^{th} vehicle
DS	Distance to stop-line

D_{sh}	Difference between average travel time in a shared lane and in an exclusive lane
e_i, o_i	Theoretical and observed frequency
F_1	1 st Fuzzy set for forwarding movement affected by front vehicle
F_2	2 nd Fuzzy set for forwarding movement affected by signal timing
F_3	Lane-changing fuzzy set
F_4	Right-turn filtering fuzzy set
$\bar{f}_c^1, \bar{f}_c^2$	Frequency of lane-changing per vehicle at each lane
$\bar{f}_c^g, \bar{f}_c^{ar}$	Frequency of lane-changing per vehicle during green and amber-red phase
fps	Frame rate of input video
$\bar{g}_o$	Average available gap in the opposing vehicle stream before filtering
$g_a(i)$	The i^{th} front gap alongside
$g_l(i)$	Front gap in the i^{th} neighbouring lane
g_n	Front gap of the n^{th} vehicle
g_n^l, g_n^r	Lateral gaps for left and right sides
g_n^o	Gap provided by opposing straight flow of the n^{th} vehicle
g_n^t	Front gap in target lane of the n^{th} vehicle
$g_n^{t, rear}$	Rear gap in target lane of the n^{th} vehicle
g_p	Front gap of pedestrian
g_t	Minimum clearance between vehicles

$h_{j,c}(m)$	Neighbourhood function of winner neuron C
k, p	NB parameters
L	Length of cell space (finite lattices)
l	Minimum gap for vehicle driving in current lane
l_0	Minimum gap for vehicle driving in a slow platoon in current lane
$l_{t,rear}$	Minimum rear gap in target lane for lane-changing vehicle
m	No. of combinations in EE method
O	Driver response before stop-line ($O = \min(O_1, O_2)$)
O_1	Output of F ₁
O_2	Output of F ₂
P_1	Set of input parameters
p	Simulated pedestrian
pa	Vehicle arrival distribution at junction approach
p_c	Position of the 1 st actual lane-changing
p_{lc}	Probability of lane-changing
p_{lc}^1	Probability of first type lane-changing
p_{lc}^2	Probability of second type lane-changing
PH	Whether it is peak hour (0,1)
pos_c	Position of the 1 st actual lane-changing
p_r	Probability of random deceleration
p_s	Probability of vehicle to stop at onset of amber

RLC	Whether RLC is installed (0,1)
SP	Signal phases
T	Vehicle type
T_{sh}	Average travel time of vehicles in a shared lane
T_{ex}	Average travel time of vehicles in an exclusive lane
t	Number of time step
t_1	Time step when right-turn vehicle comes and waits to enter conflict zone with opposite straight-through vehicles
t_2	Time step when the same right-turn vehicle passes through the conflict zone
t_c	Time of the 1 st actual lane-changing
t_{PET}	Post-encroachment time
t_{TTC}	Time to collision
t^r	Time to the onset of red phase
$\bar{t}_{rt}$	Average travel time of right-turn vehicles
t^s	Signal timing
t^t	Travel time
μ	Membership degree with different values of input and output factors
V	Moving velocity of subject vehicle
vol_s	Traffic volume in the subject lane
vol_n	Traffic volume along neighbouring lane
vol_{os}	Traffic volume in opposing straight-through lane

vol_r	Traffic volume in right-turn
v_1	Moving velocity estimated from tracked velocity
v_2	Moving velocity estimated from tracked position
v_{int}	Initial velocity of vehicle
$\bar{v}_o$	Average velocity of the opposite straight-through vehicle before filtering
v_p	Front velocity of pedestrian
v_p^l	Lateral velocity of pedestrian
v_{max}	Maximum velocity of vehicle
v_n	Velocity of the n^{th} vehicle
v_n^o	Velocity of the opposing straight-through vehicle of the n^{th} right-turn vehicle
$v_n^{t, rear}$	Rear velocity in target lane of the n^{th} vehicle
v_r	Random deceleration rate (1cell/s^2)
$\bar{v}_{rt}$	Average velocity of the right-turn vehicle before filtering
W	Weight vector in clustering analysis
$\bar{w}_c, \bar{w}_f$	Average willingness of lane-changing or filtering
$X = [x_1, x_2, x_3]^T$	x_1, x_2 and x_3 are the three indicators (TTC, PET and CI) recorded automatically for each conflict
(x_i, y_i)	Position of a vehicle in global coordinates
X_i	The i^{th} input in EE method
x_n	Forwarding position of the n^{th} vehicle

$Y(P_1)$	Simulation output when input is P_1
x_p, y_p	Position of simulated pedestrian in x and y directions
φ_a, φ_d	Acceleration/ deceleration rates
φ_r	Random deceleration rates
Δt	Time interval in proposed CA models (1s)
η	Learning velocity

SUMMARY

As an urban environment, Singapore has more than 1,400 signalised junctions. Much attention is paid to maintaining a high service level of the signalised junctions to make sure all road users are travelling efficiently and safely. This research study focuses on microscopic modelling and simulation of vehicle movements at signalised junctions. The study is conducted through four stages.

First, traffic data are collected and analysed through field observations and automatic data acquisition. An automatic vehicle classification and tracking method is developed through image and video processing techniques. As vehicle moves in multiple directions at signalised junctions, conventional vehicle tracking algorithms are modified by incorporating a projective transformation to each video frame. Traffic flow characteristics, including traffic volume, arrival distribution, headway, vehicle velocity, and acceleration rates are computed for modelling and simulation purposes. Microscopic movement characteristics, such as moving velocity and acceleration rates are found to be affected by many factors, such as current velocity, front gap, signal phases, and distance to stop line.

Cellular Automata (CA) models for vehicle movements at signalised junctions are developed. Compared to existing CA models, the models developed in this study are more flexible for simulating complex vehicle movements at various geometric layouts. To ensure computation efficiency, homogenous and heterogeneous vehicle movements are modelled with two CA models with different cell sizes and transition rules. The proposed models are calibrated and validated both in macroscopic (travel time) and microscopic (velocity profile, acceleration rates and vehicle conflicts) levels. Simulation experiments are conducted to estimate traffic performance in various geometric and traffic conditions. It is found that the performance of geometric design is affected by traffic conditions, including traffic volume and vehicle movements. Apart from relying on quantitative models, microscopic simulation based on CA

models can help engineers to assess the traffic performance of their design in various traffic conditions and signal timings.

While current CA models are mostly applied on capacity assessment, in this study, proxy indicators, such as “Deceleration Occurrence caused by Conflict” (DOC), are computed in each simulation run to estimate occurrences and severity of vehicle conflicts. Simulated vehicle conflicts shows very good corroborative agreement with accident counts. The proposed safety assessment model is compared to an existing safety assessment method, namely the Surrogate Safety Assessment Model (SSAM). The proposed model is applied in several aspects, including risk degree assessment of different conflict types and estimating safety impact of traffic management strategies, such as permissive right-turn and Red-Light Cameras (RLCs). Compared to existing safety assessment methods based on crash occurrences, CA models are able to replicate realistic vehicle-vehicle and vehicle-pedestrian conflicts and provide safety assessment conditions with user-defined characteristics.

Moreover, to simulate driver behaviour, such as perception and decision-making procedures, conventional CA models are incorporated with decision-making techniques. A Fuzzy Cellular Automata (FCA) model and a Neural Cellular Automata (NCA) model are developed with embedded fuzzy sets or Artificial Neural Networks (ANNs). The proposed FCA and NCA models are validated and applied to simulate risky driving behaviour and erratic lateral movements of motorcycles. Compared to conventional CA models, the FCA and NCA models allow users to simulate decision-making procedures of each individual vehicle. It is found that traffic performance (in both capacity and safety aspects) is affected by driver’s behaviour, such as lane-changing, right-turn filtering and risky driving. The perception and attitude of drivers are also found to affect overall traffic performance at the signalised junctions.

This study extends current applications of CA models and provides valuable tools and findings for transport professionals in designing and managing signalised junctions.

With the addition of new technologies, such as video processing and CA modelling, the relationship between vehicle movements and traffic management strategies are better understood, which is of great value both for academic research as well as practical applications.

CHAPTER 1 INTRODUCTION

1.1 Chapter introduction

This chapter introduces the background and significance of this study. As design and operation of signalised junctions is a very complex issue that combines various factors including traffic composition, signal setting, as well as driver behaviour that involves human factors, a microscopic simulation tool is a very useful design tool. In this study, Cellular Automata (CA) is therefore selected to assess traffic performance at signalised junctions in both capacity and safety aspects. The following parts address research objectives, and scope of work for the research project, followed by the last section being the organisation of this thesis.

1.2 Background

Cities around the world are looking for new answers to deal with perennial road traffic problems, such as traffic congestion and safety. In recent years, much attention has been paid to road junctions controlled by signal lights, as signalised junctions form one of the most common bottlenecks in the urban traffic system. It is because junctions are places where different traffic movements come into conflict. As an urban environment, Singapore has more than 1,400 signalised junctions. Motorists drive on the left side of the road, similar to the United Kingdom driving convention.

Signalised junctions are critical components of the road network in terms of both capacity and safety. It is very important to study vehicle movements at signalised junctions to improve the level of junction design and control, and to enhance capacity as well as remediation of accidents at signalised junctions.

Several traffic flow theories, such as car-following models (Hoogendoorn and Bovy, 2001), hydro-dynamical theories (Batchelor, 2000), and different means of microscopic simulation have been developed to describe the behaviour of vehicles as

well as the traffic flow at signalised junctions. After the 90s, with the increasing computation capability, Cellular Automata (CA) models become rather popular. Based on flexible transition rules, it is becoming easier to use CA models to simulate microscopic traffic behaviour realistically while leveraging on parallel CA computation. The development and usage of CA models have greatly increased the efficiency in modelling road traffic movements (Tian and Wu, 2006; Tang et al., 2005). Compared to commercial simulation packages, CA models are found to be more flexible to model microscopic vehicle movements and interactions (Chai and Wong, 2014b; Kerner et al., 2013).

The volume, position, velocity and other microscopic attributes of vehicles and non-vehicles, as well as time, are discrete in CA models (Wolfram, 1984). To simulate a straight-through traffic lane, it is represented as a series of lattices. Each lattice is called a cell in the system and it can be either empty or occupied by vehicle at a given time. During each discrete time step, all the lattices in the system are updated based on the transition rules. The state of each vehicle at the current time step is determined by its velocity and the state of its neighbourhood cells in the previous time step.

This research study is based on an improved CA model to simulate complex vehicle movements at signalised junctions. Traffic performance in both capacity and safety aspects are estimated in various traffic conditions.

1.3 Research objectives

The principal objective of this research programme is to develop a more flexible model to simulate complex traffic movements and driver behaviour at signalised junctions based on the CA model. The specific aims are to:

1. Analyse common capacity and safety issues of signalised junctions under Singapore's local conditions;

2. Improve the current CA model and use it to simulate complex vehicle movements and driver behaviour at signalised junctions. The improved model shall be able to simulate movement characteristics and interactions in heterogeneous traffic flow. By performing numerical simulations, traffic performance in both capacity and safety aspects, including traffic delay, density-flow relations, behaviour of various types of road users including motorcycles and non-motorised vehicles and occurrences and severity of vehicle conflicts, shall be estimated. Model calibration and validation shall be conducted in both microscopic and macroscopic levels using observed data.

3. Apply the improved CA model to evaluate traffic performance of several specific design issues and operating conditions at signalised junctions, including erratic movements of motorcycles, shared-lane usage, risky driving, safety impacts of permissive right-turn and operation of a Red-Light Camera (RLC). Each design feature shall be examined to assess the impact on general capacity and safety level.

1.4 Scope of work

The foundation of this study is to apply normative CA models and traffic flow theory on junction design. The project is undertaken by conducting a series of field surveys and observations to collect various data to develop the simulation model.

Data collection focuses on junctions with fairly common types of layout or involving specific design issues such as lane merging area and shared lanes. Data extraction work is handled by video and image processing packages, such as MATLAB Image Processing Toolbox. An automatic vehicle detection and tracking algorithm is developed using MATLAB Computer Vision System Toolbox to collect sufficient data from video records.

The current simulation model based on CA is improved to simulate vehicle movements and driver behaviour at signalised junctions. Observed data such as junction configuration, signal settings, maximum velocity and total volume of

vehicles are defined for the simulation model. Lane merging and shared lanes are also assigned. By computing the position of each simulated vehicle, the model is operationalised.

Various simulation experiments shall be conducted to study design and operation issues at signalised junctions. Through such experiments, the capabilities of the proposed models to simulate vehicle movements and provide reasonable analysis of traffic performance are tested. Through analysis of simulation results, characteristics of mixed traffic flow at signalised junctions as well as impacts of various control strategies are assessed.

Figure 1.1 summarises the general research methodology for this study.

1.5 Organisation of the report

The report is divided into 8 chapters including this introductory chapter which introduces background, objectives, research scope, methodology, and framework of research.

Chapter 2 deals with literature review of critical issues about the research topic. The literature review highlights basic concepts about CA models including their applications in road traffic modelling. Several typical CA models and some latest applications are also presented in this chapter.

Chapter 3 focuses on methodology of research, especially on data assembly. Video and image processing techniques for traffic data acquisition are also described in this chapter. Computer-aided manual and automatic vehicle tracking methods are used in this study. The data analysis method and results of traffic flow characteristics are also covered in this chapter. Observed traffic flow characteristics at signalised junctions, for vehicles and pedestrians, include traffic volume, arrival distribution, velocity and

position profile, spacing, maximum velocity, maximum acceleration rate and deceleration rate.

Chapter 4 is a detailed description of improving current CA models to simulate vehicle movements at signalised junctions. First, a composite CA model with multiple cell sizes is developed for homogenous vehicle movements. The model is applied to estimating traffic performance at shared lanes. Furthermore, by using a smaller cell size, another CA model is developed to simulate mixed traffic flow and pedestrians at signalised crosswalks.

Chapter 5 introduces the application of a CA model to safety assessment through computation of safety indicators. The proposed method is compared with existing methods based on crash records and microscopic simulations, and applied to several aspects. Safety impacts of control strategies, such as permissive right-turn and Red-Light Camera (RLC) are estimated. Risk degree and occurrences of various conflict types (including vehicle-vehicle and vehicle-pedestrian conflicts) are compared and discussed in various traffic conditions.

Chapter 6 focuses on incorporating a current CA model with decision-making techniques such as Fuzzy Logic and Artificial Neural Network (ANN). First, a Fuzzy Cellular Automata (FCA) model is developed by applying fuzzy sets and functions to describe drivers' response under various traffic conditions. The FCA model is tested through various simulation scenarios to replicate driver responses, such as lane-changing behaviours and risky driving. Furthermore, a Neural Cellular Automata (NCA) model is introduced by embedding pre-trained ANN into CA models. The ANN helps to replicate dynamic decision-making of road users. A simulation study of erratic motorcycle movements indicates the proposed NCA model is able to provide reasonable simulation and analysis of dynamic decision-making.

Chapter 7 covers a summary of current studies and recommendations for further work.

Figure 1.1 Flow-chart showing key components of research methodology

CHAPTER 2 LITERATURE REVIEW

2.1 Chapter introduction

This chapter reviews critical issues related to the research topic. The first part of this chapter introduces design and operational issues of signalised junctions in Singapore, which include design objectives, geometric design and signalised control systems. Several specific design issues, such as shared lane, permissive right-turn and Red Light Camera are discussed in Section 2.3. Next, current studies on estimation of capacity and safety of signalised junctions are discussed. In Section 2.4, a CA model is introduced for simulation of microscopic movements at signalised junctions. Typical CA models featuring one and two-dimensional traffic simulations are presented. Gaps in current research are identified in Section 2.5. Current studies and their limitations are summarised in the chapter summary.

2.2 Signalised junctions in Singapore

2.2.1 Objectives of signalised junction design

Junctions are bottlenecks of road capacity and hot spots of safety. There are more than 1,400 signalised junctions in Singapore. Intelligent Transport Systems (ITS), such as Green Link Determining (GLIDE) and Junction Electronic Eyes (J-Eyes), are applied to manage and improve capacity and safety of signalised junctions (Land Transport Authority, 2013).

Safety at signalised junctions is also a very important issue. In 2009, about one in five (21%) road traffic accidents (injury and fatal) occurred at signalised junctions (Hau and Ho, 2010). The number increased to 23.4% in 2011 (Singapore Police Force, 2012). Over the three years from 2009 to 2011, 112 fatal accidents occurred at signalised junctions. For pedestrian safety, from 2007 to 2012, there has been an average of 82 accidents (injury and fatal) each year involving pedestrian, cyclists or vehicles at signalised pedestrian crosswalks. On average, 3 pedestrians are killed and 55 pedestrians are injured in these accidents per year (Iswaran, 2013).

The objective of signalised junction design is to facilitate an efficient and safe environment that caters to a combination of movement directions for all road users. A proper junction design should be able to match closely with road users' characteristics. Basic design considerations should include factors as summarised in Table 2.1.

Table 2.1 Design considerations of signalised junctions

Human factors	Design components
Driver, pedestrian and cyclist habits	Geometric design
Decision making of road users	Traffic control strategies
Traffic characteristics	Safety
Design capacity	Frequency and severity of conflicts
Mixed traffic flow of different vehicle types	Economics
Vehicle velocities	Cost of construction and improvements
Headway and gaps	Delay cost of road users
Movements of pedestrians and cyclists	Air quality cost

2.2.2. Geometric design

Geometric design of signalised junctions involves functional layout of travel lanes and pedestrian crosswalks in all the movement directions. A proper geometric design can improve both junction capacity and safety. Table 2.2 summarises geometric and operational variables for a typical signalised cross junction, as shown in Figure 2.1.

Figure 2.1 A signalised junction with signalised pedestrian crosswalks

Table 2.2 Geometric and operational variables of site configuration

No.	Geometric and operational variables
1	Number of Lanes
	Number of Exclusive Right-Turn Lanes
	Number of Exclusive Right-Turn Lanes with Storage
	Number of Exclusive Right-Turn Lanes without Storage
2	Number of Slip Roads ¹
	Number of Slip Roads with Storage Lane
	Number of Slip Roads without Storage Lane
3	Number of Shared-lanes
	Number of Shared (Left-Thru) Lanes
	Number of Shared (Right-Thru) Lanes
	Number of Shared (Left-Right) Lanes
	Number of Shared (Left-Right-Thru) Lanes
4	Downstream Merging Area
5	Median
6	Traffic Island
7	U-Turns
8	Pedestrian Crossings
9	Signal timings
10	Red Light Camera
11	Velocity Limit
12	Yellow Box ²

¹: Slip road: between two connecting roads that bypass the direct junction of the roads;

²: Yellow-box: vehicles may not enter the area so marked unless their exit from the junction is clear

2.2.3 Signal control systems

Traffic signals, which may be known as stop lights, are electrically operated control devices which alternatively direct traffic to stop and to proceed. When more than one vehicle movements are in conflict at road junctions, signal control may be used to direct vehicles from several movements to take turns in stopping and giving way to other movements. Unlike road signs (e.g. stop signs), traffic signals at junctions change according to certain signal timing plans. With traffic signals, vehicles moving in different directions are assigned an order to go through the junction-box area with time separation. Traffic signals direct vehicles to wait at the stop-line or right-turn waiting area thus increasing the travel time of going through the junctions.

However, a properly designed timing plan of traffic signals will optimise the overall junction capacity by “organising” traffic flow of different movements, as well as enhance junction safety.

There are two kinds of signal control, pre-timed and actuated. Pre-timed signal control is using signal timing plans which have been already decided and the plans are selected based on expected traffic volumes (often by period of day). Actuated control is to detect dynamic traffic volumes and accordingly calculate the best signal plan. This kind of signal control is more capable of responding to traffic volume changes.

Nowadays, traffic signal control systems are applied all over the world to coordinate individual traffic signals of a network level so as to increase the capacity and safety of the overall road network. Such wide-area systems include a central computer or several computers to manage a series of traffic signals, typically using a communication network to link the many traffic signals at the junctions.

The strategy of a signal control system is based on determining the phase times at individual junctions, which are affected by numerous parameters such as general traffic volumes, interruption of continuous traffic, pedestrian volumes, and accidents. Most signal control systems interconnect signals across a series of signalised junctions.

With ever increasing complexity of computing technology, several signal control systems have been developed to handle complex situations and to provide optimised time plans for large networks. Some of these well-known signal control systems are introduced as described below.

Traffic Network Study Tool (TRANSYT) – is a macroscopic deterministic simulation and optimisation system which was originally developed by Transport and Road Research Laboratory (TRRL) in the U.K. (Hale and Courage, 2002). The system assesses and optimises the performance of signalised junctions by estimating vehicle stops and delays. As one of the oldest signal control systems first introduced in 1960s, TRANSYT is the foundation of many other widely-used systems.

Split Cycle and Offset Optimisation Technique (SCOOT) – is a traffic adaptive control system that was also developed by TRRL in the U.K. (Chen, 2010). This system is based on the TRANSYT system with two major differences (Robertson and Bretherton, 1991):

- 1) The SCOOT system is using real-time traffic flows and it is an adaptive control system, which means the system is able to respond according to changes of the environment;
- 2) The system focuses on global optimisation to the signal settings of the whole network rather than individual junction,.

Sydney Coordinate Adaptive Traffic System (SCATS) – it is developed by the former Department of Main Roads (now the Roads and Maritime Services) of New South Wales, Australia. The system uses a set of pre-programmed timing plans but can be adjusted in response to real-time traffic conditions (Nicholson et al., 2010; Hu et al., 2011). The system is now used in 27 countries including Australia and New Zealand. The GLIDE system used in Singapore is also based on SCATS (Lum and Halim, 2006).

The Singapore GLIDE system, which is based on SCATS, was first applied in 1982 to over 197 junctions (Chin, 1993) and later expanded to cover more than 1,400 junctions all over the island. The system is able to change the green time in response to changes in traffic flow. The system links signals at adjacent junctions together, coordinating the start point of the green phase. A “green wave” is therefore created to allow vehicles to travel from one junction to another with less stopping. In this system, vehicles as well as pedestrians are detected by detector loops installed just before the stop-line or buttons at pedestrian crossings, respectively. The system treats safety of pedestrians as the most important consideration. To make sure pedestrians have enough green time to cross the junction, vehicles travelling in the same direction are also given longer green time.

2.2.4 Performance measurements and criteria

The performance of signalised junctions is estimated by several parameters such as traffic delay and Level of Service (LOS). Traffic delay is the extra travel time of a vehicle, passenger or pedestrian due to conditions that slow down the desired movement of traffic. Traffic delays are measured as the difference relative to travel times between real and free-flow condition (AASHTO, 2009). To measure the effectiveness of the operation of junctions, the concept of delay is generally used. Stopped delay, approach delay and control delay are the three types of delay that are generally used. Stopped delay is measured as the time that a vehicle is stopped at a junction. Due to the ease with which it can be measured, stopped delay is usually used to determine the level of service at signalised junctions (Gokdag et al., 2007). Approach delay includes stopped time, and time lost for acceleration and deceleration from/to a stop. Control delay is the delay that occurs due to the type of control at junctions. It is the difference between the travel time that would have occurred in the absence of junction control, and the travel time that results because of the presence of junction control. Control delay includes deceleration, stopped and acceleration delays (Gokdag et al., 2007). Detailed delay computation procedures are described in Appendix A.

LOS at a junction is the delay experienced by a motor vehicle travelling through a junction during the busiest (peak) 15 minutes of traffic of the day (Transportation Research Board, 2000). The level of service at signalised junctions can be determined based on the average stopped delay per vehicle, as shown in Table 2.3.

Table 2.3 Level of Service at signalised junctions

Stopped delay (s)	LOS
< 10	A
10-20	B
20-35	C
35-55	D
55-80	E
>80	F

For evaluations of traffic performance at signalised junctions, some applicable criteria are as summarised in Table 2.4 (FHWA, 2009).

Table 2.4 Criteria of traffic performance at signalised junctions

Performance criteria	Major concerns
Volume-to-Capacity Ratio	Motorist capacity
Traffic delay	Motorist capacity
Queue Length	Motorist capacity
Crash occurrences	Motorist safety
Crash severity	Motorist safety
Pedestrian delay	Pedestrian capacity
Pedestrian accessibility	Pedestrian usability
Transit delay	Transit capacity

As shown in Table 2.4, several performance measures are readily quantifiable, such as volume-to-capacity ratio, vehicle delay, and queue length, while others have a higher level of uncertainty for prediction (crash occurrences, pedestrian accessibility). Even though some measures are not very quantifiable, it is important to recognise and consider them in the selection and evaluation of signalised junction design.

2.3 Design and operation strategies at signalised junctions

2.3.1 Shared lane of straight-through and right-turn vehicles

In the context of Singapore's junction design, a shared lane consists of lane markings that inform vehicles that they can go in one of the indicated directions at a signalised junction. There are typically two kinds of shared lane. One is straight-through and left-turn shared lane, which is used at small junctions without slip road. The other type is a straight-through and right-turn shared lane, which usually appears at large junctions and is considered much more critical, as it handles both straight-through and right-turn vehicles that are entering junction-box area. The introduction of a straight-through and right-turn shared lane is determined by the right-turn volume. Mostly, when right-turn traffic volume is not very high, only one

exclusive right-turn lane is used (sometimes as a storage lane) as shown in Figure 2.2. In this scenario, signal phase is typically designed as shown in Figure 2.3.

Figure 2.2 Typical three-lane approach

Figure 2.3 Typical four-phase signal setting

At many junctions, right-turn volumes on a pair of opposite approaches are not evenly-matched. The layout design shown in Figure 2.3 will require more green time for the more heavy approach in the pair of opposite approaches. In this situation, the signal phase at the opposite approach can remain unchanged; an additional shared lane or two exclusive right-turn lanes can be introduced at the heavier approach (see Figure 2.4).

Figure 2.4 Three-lane approach with shared lane or an additional exclusive right-turn lane

A shared lane is preferred by designers because it can cater to the traffic volume those changes between peak and off-peak periods. For example, more straight-through vehicles will enter a shared lane of straight-through and right-turn movements when there are more straight-through vehicles. By increasing the

capacity for right-turn vehicles, the addition of a shared lane will help to increase junction capacity, and it also allows more straight-through vehicles to pass per cycle.

However, the lane capacity of a shared lane is not as high as the average lane capacity of lanes for exclusive individual movements. A major drawback of shared lanes is that queuing right-turn vehicles may block the straight-through vehicles on the shared lanes during the full-green phase. A shared lane can then cause severe reduction of junction capacity and vehicle blockage, thus leading to an increase in traffic delay (Wu, 2011) as shown in Figure 2.5.

(T: Straight-through vehicle, R: Right-turn vehicle)

Figure 2.5 Blockage caused by right-turn vehicle during full-green phase

A straight-through vehicle may on the other hand block a right-turn vehicle during the right-turn (green arrow) phase. When a blockage occurs, blocked vehicles will queue behind the blocker and wait for the next signal phase, unless there is available gap to move to adjacent lane. When blockage at a shared lane occurs, some queuing vehicles will attempt to change to exclusive lanes. This ad hoc lane-changing near to the stop-line (which is permitted in Singapore and elsewhere) may cause safety problems for vehicles in the vicinity. In order to introduce a shared lane to individual junction, the performance of the shared lane, in terms of junction capacity and safety of all road users, are key concerns. Therefore, one should be very careful whenever deciding whether to install a shared lane at signalised junctions.

In order to determine the feasibility of adding a shared lane to a signalised junction, a number of factors should be considered, such as, the geometry of the junction, capacity of a given lane group or approach, designation of lane groups and lane blockage probability. Over the past 40 years, several studies have been undertaken to investigate shared-lane usage. The most commonly-used evaluation technique is

that given in the Highway Capacity Manual (HCM) (Transportation Research Board, 2000). In the HCM2000, the blockage effect is estimated using a simple regression model and is not based on direct analysis of vehicle movements.

Some quantitative models have been developed to calculate the capacity of shared lane. A lane group based macroscopic model was established by Liu et al. (2008) to estimate traffic performance for shared lane and blockages. The model considers queue accumulation and the effect of approach design (lane arrangements). The model also calculates blockage probabilities due to signal settings and geometrical layout of junctions. However, as the model only calculates the capacity of a shared lane, the impact of adding a shared lane to the whole approach is not analysed.

An ‘empirical Saturated Flow Rate (SFR) estimation model’ was presented by Chen (2011) who applied the models for signalised junctions with or without shared lanes. The study focused on shared lanes of straight-through and left-turn movements in Japan, which has the same left-hand driving as Singapore. It is emphasised that SFR estimation for a lane group with a shared lane is essential in the operation stage of a signalised junction. SFR estimation becomes a difficult task as there will be larger fluctuations in the SFR with the shared lane compared to without. In Chen et al.’s (2012) study, real-time traffic data were collected on workdays at 9 shared left-turn lanes of 6 representative signalised junctions, located in the urban area of Aichi Prefecture, Japan. It was found that the HCM2000 method appears to overestimate the shared left-turn SFR in Japan. Moreover, a regression at the significance level of 95% showed that the number of through lanes, pedestrian and bicycle volumes, left-turn proportion, green time, left-turning radius and number of receiving lanes are correlated to the occurrence probability of lane blockage in shared straight-through and left-turn lanes at a signalised junction.

Even though several studies provide methodologies with improved efficiency of estimating traffic delay of a junction with shared lanes, a model based on microscopic simulation has not been developed. By developing realistic simulation models, various scenarios can be simulated. The impact of introducing shared lanes at signalised junctions can be estimated directly based on the simulation model.

Arising from the work of this study, a series of findings on this topic has been established that are reported in a research paper (Chai and Wong, 2014b).

2.3.2 Permissive right-turn

In Singapore, the most common right-turn signal phases are straight-through green phase with permissive right-turn, followed by a protected right-turn green phase, or straight-through green phase followed by a protected right-turn phase, the so called Red-Amber-Green (RAG) Arrow control, as shown in Figure 2.6. Under a permissive right-turn arrangement, right-turn vehicles are permitted to make a turn during the straight-through green phase when sufficient gaps exists (Qi et al., 2010).

Figure 2.6 Permissive right-turn (top) and RAG Arrow control (below)

Vehicles making permissive right-turn movements experience shorter delay, but are in conflicts with other vehicle movements and hence collision risks are higher (Chen et al., 2012). On the other hand, under RAG Arrow control, right-turn vehicles only have an exclusive right-turn green phase and are not allowed to filter through during the straight-through green phase. Such signal settings will be able to reduce vehicle conflicts but result in a higher overall delay (Al-Kaisy and Stewart, 2001). Therefore, whether to allow permissive right-turns is a trade-off between junction capacity and safety (Chen et al., 2012).

Many approaches at junctions in Singapore contain shared straight-through and right-turn lanes. The use of shared lanes is usually based on the traffic volumes of the two movement streams, especially the right-turn traffic volume. Having a shared lane can help to increase right-turn capacity and to balance vehicle flows of

diverging movements at an approach (Liu et al., 2008). However, at approaches with a shared lane, blockage may occur which in turn can result in rear-end conflicts at junction approaches. Some large junctions with permissive right-turns also include a turning pocket beyond the stop-line to give right-turn vehicles a guided waiting area and a better sight line when making a right-turn.

2.3.3 Red Light Cameras (RLCs)

Since 1986, Red Light Cameras (RLCs) have been installed at many junctions in Singapore to reduce red light violations and improve junction safety. However, accurate estimation of the effect of RLCs is a very challenging issue.

Numerous studies have been conducted to estimate the safety impact of RLCs (Erke, 2009; Retting et al., 2008). These studies are based on analysis of red running violations and vehicular crashes. In a before-after study conducted by Retting et al. (2008) the number of red-light violations at 6 studied junction approaches reduced from 57.5 to 1.6 counts per 10,000 vehicles per approach several months after RLC surveillance started. It was found that high red running violations are related to many factors such as fast approach velocity, high traffic volumes and high historical accident counts (Al-Omari and Al-Masaeid, 2003). A regression analysis conducted by Shin and Washington (2007) found that wider cross roads and lower traffic volumes can reduce red running violations. Lum and Wong (2003) have conducted a before-after study of driver stopping propensity from RLC installation in Singapore's context. It was found that vehicles are more likely to stop at an approach with RLC, and the effect varies with site characteristics. Several studies estimated the effect of RLCs on occurrences of vehicular crashes and the results varied considerably (Council et al., 2005). Vanlaar et al. (2014) conducted an Autoregressive Integrated Moving Average (ARIMA) time series analysis of accident occurrences as related to RLCs. It was found that RLC enforcement has an overall favourable net effect on traffic safety but the effect varies with traffic conditions.

Some studies found the installation of RLCs reduces incidences of rear-end collisions (South et al., 1988), while several other studies indicated that the effects

on rear-end collisions are small or even unfavourable (Huang et al., 2008; Obeng and Burkey, 2008; Retting et al., 2003). For right-angle collisions, it is generally agreed that RLCs have favourable effects (Aeron-Thomas and Hess, 2005; McCart and Eichelberger, 2012; Retting and Kyrychenko, 2002).

It is very challenging to estimate accurately the effect of RLCs. First, there is the “spillover” effect, which is due to drivers at adjoining non-RLC approaches, or non-RLC junctions located in the vicinity of RLC junctions, having some reactions to RLCs which makes comparison difficult and biased (Shin and Washington, 2007). Moreover, as RLCs are usually installed at junctions with high accident counts, analysis based on crash occurrences at high-risk sites alone would not be representative of network-wide junctions due to the “Regression to the Mean (RTM)” effect (Erke, 2009). Many studies did consider RTM and spillover effects and successfully estimated the safety effect of RLCs, such as by controlling RTM effects through empirical Bayesian analysis that gives a good indication of safety effects of RLCs (Retting and Kyrychenko, 2002; Shin and Washington, 2007). Council et al. (2005) investigated possible spillover effects by including a separate analysis for untreated signalised junctions. Before-after studies entail demarcating each site on the year of the first RLC installation. However, as most RLCs were installed in Singapore before 1990s, such before-after study is not feasible. A different approach to estimate the safety impacts of RLCs is needed, and a microscopic simulation approach is adopted in this research study.

2.4 Microscopic simulation based on Cellular Automata (CA)

2.4.1 Introduction of CA models

In conventional traffic models, description of a vehicle’s microscopic behaviour is considered a very time consuming and complex process. However, as the power of computation increases, a number of models based on CA systems have been developed. These models are dynamical systems that put space, time, vehicle’s velocity and position into discrete numbers that are useful and flexible.

The first well recognised CA model was developed in 1980s by Wolfram (1984). He produced a book called “A New Kind of Science” and introduced the most

popular “184 model” which uses one-dimensional lattices to simulate road traffic. In 1992, one of the most popular CA models was developed by Nagel and Schreckenberg and later was called NaSch model (Schreckenberg et al., 1995). The model can represent the most basic phenomenon of real traffic such as acceleration and deceleration of vehicles. This model has been widely used and studied. At the same time, as multi-lane traffic becomes more popular, a number of lane-changing rules were developed and this formed the multi-lane NaSch model.

The application of CA models for urban traffic flow simulation has been successful. However, current CA models should be improved for more complex traffic situations such as mixed traffic flow and shared-lane usage. Meanwhile, simulation of traffic interactions at junctions is of great value towards improving the level of service and safety of urban traffic network.

2.4.2 Typical CA models

i) Nagel-Schreckenberg (NaSch) model for highway traffic

In the NaSch model, a lane (highway) is represented by a series of one-dimensional cells. Each cell can be occupied or not occupied by one vehicle at each discrete time step. The state of the traffic system is updated according to pre-defined movement rules (transition rules).

In the classic NaSch model, the velocity of each vehicle v is able to take one of the $v_{\max} + 1$ integers $v = 0, 1, \dots, v_{\max}$ (cell/s). The position and velocity of the n^{th} vehicle are represented by x_n and v_n . Therefore, the spacing in between the n^{th} vehicle and the front vehicle at time t is calculated as $d_n = x_{n+1} - x_n$. For the next time step, $t \rightarrow t + \Delta t$ ($\Delta t = 1\text{s}$ in this study), vehicles' position and velocity will be updated according to the following transition rules:

Rule 1: Acceleration

If $v_n < v_{\max}$, the velocity of the n^{th} vehicle is increased by 1 cell/s, but v_n remains unaltered if $v_n = v_{\max}$.

$$v_n \rightarrow \min(v_n + 1, v_{\max})$$

Rule 2: Deceleration (due to other vehicles)

If $d_n/\Delta t \leq v_n$, which means if the current vehicle continues moving, it will collide with the front vehicle at next time step. Therefore, velocity of the n^{th} vehicle is reduced by 1 cell/s.

$$v_n \rightarrow \min \left(v_n, \left(\frac{d_n}{\Delta t} - 1 \right) \right)$$

Rule 3: Randomisation

If $v_n > 0$, velocity of the n^{th} vehicle will be decreased randomly by 1 cell/s with a pre-determined probability p_r , in which such random decelerations may arise due to interactions of neighbourhood vehicles or safety considerations of drivers, i.e.,

$$v_n \rightarrow \max (v_n - 1, 0), \text{ with probability } p_r.$$

Rule 4: Update vehicle movement

Each vehicle is moved forward according to its new velocity determined in Steps 1-3, and the next time step's position shall be equal to the current position plus the additional distance covered in Δt , i.e.,

$$x_n \rightarrow x_n + v_n \times \Delta t$$

ii) NaSch model with lane-changing rules

Lane-changing rules are added to develop a multi-lane NaSch model. For example, vehicle movements of a two-lane CA model can be divided into two sub-steps. In the first sub-time step, vehicles are able to change lane according to lane-changing rules, as described in the following; at the second sub-step, vehicles move forward according to traditional NaSch models. There are two major reasons for a driver to change lane: (1) the situation in the neighbouring lane is more convenient (with larger gaps) for driving, and (2) to move to the appropriate turning or straight-through lane at a junction approach. Two general requirements shall be fulfilled for a driver to change lane: there must be an incentive and second, there must be enough gaps to allow lane changing. The most well-known lane-changing rules are introduced by Rickert et al. (1996). In their lane-changing rules, vehicles can change lane only if the following four criteria are satisfied:

$$(C1) g_n < l$$

$$(C2) g_n^t < l_0$$

$$(C3) g_n^{t, rear} < l_{t, rear}$$

$$(C4) rand() < p_{lc}$$

where g_n and g_n^t are gaps in front of the n^{th} vehicle along the subject lane and the target lane. Gaps in front of the n^{th} vehicle along the subject lane and the target lane are represented as g_n and g_n^t . $g_n^{t, rear}$ is the rear gap along target lane. l , l_0 , $l_{t, rear}$, and p_{lc} are the input parameters to specify lane-changing rules. l is the minimum gap for vehicle driving in current lane, l_0 is the minimum gap for vehicle driving in a slow platoon in current lane, $l_{t, rear}$ is the minimum rear gap in target lane, and p_{lc} is the probability of lane-changing. $rand()$ is a random operator within $[0, 1]$.

Rule C1 represents the willingness of lane-changing. For example, if the front gap g_n is not sufficiently large, driver will want to change to another lane. Minimum front gap l is computed as $l = \min(v + 1, v_{max}) \times \Delta t$. Rule C2 is to check if the traffic condition in the target lane is more convenient. The driver will decide to change lane as long as $g_n^t < l_0$, where l_0 is the minimum gap for vehicle driving in a slow platoon in the current lane. Rule C3 is to check rear gap along the target lane as $l_{t, rear} = v_{max} \times \Delta t$. Moreover, according to realistic traffic movement, random lane-changing decisions are also modelled. Even though willingness as well as gap criteria are both fulfilled, the driver will decide to change lane with a probability p_c (C4).

iii) Biham-Middleton-Levine (BML) model for two-dimensional vehicle movements

The BML model is regarded as the first two-dimensional CA model (Biham et al., 1992). In the BML model, cell space is defined as a matrix. Each cell represents the crossing of an east-west road and a north-south road. Each road is parallel to the x-direction or y-direction of a Cartesian coordinate system. It is also assumed traffic flow in the x-direction comes from east-bound while traffic flow in the y-direction comes from the north-bound direction of the cell space. At the initial time step,

vehicles are randomly distributed in the cell space. Vehicles coming from the two directions update their states at alternate time steps. The states of x-direction vehicles are updated at every odd time step, and y-direction vehicles are updated at every even time. For each vehicle, it will move forward only when the target cell is empty, otherwise it will stay in the current position at the next time step. Moreover, in the BML model, each cell can have three possible states: empty or occupied by an arrow $\uparrow$ or $\rightarrow$ (as occupied by vehicle moving in the x or y direction). In view of the deterministic rules, the BML model is regarded as a deterministic model (Fukui and Ishibashi, 1996).

2.4.3 CA's applications for simulation of signalised junctions

According to previous researches, two approaches are mostly widely used when modelling a road network with signalised junctions. The first one is to consider a road network as a two-dimensional lattice (i.e., a grid). Some studies model each road in a network as a single longitudinal lattice (single or multi-lane) with junctions. However, to model vehicle movements at signalised junctions, more realistic transition rules need to be developed.

Comparing with other theories and models, CA models are flexible to model complex vehicle movements. Vasic and Ruskin (2012) developed a CA model to simulate traffic flow at an isolated junction. In this study, more flexible transition rules are added to model vehicle interactions. However, as vehicle velocity is fixed in this CA model, the model is not realistic enough to simulate complex movements at signalised junctions. Other studies which apply CA to model signalised junctions are summarised in Table 2.5.

For highway simulation based on CA, Dong (2002) as well as Zamith et al. (2010) used CA for traffic flow simulation experiments. Some studies focused on highway traffic with junctions, based on two-dimensional CA models, in which traffic flow characteristics for the junction were studied. The details are shown in Table 2.6.

Table 2.5 CA's applications for single signalised junction

	Most important improvement	Related points to this study
Jin et al. (2001)	Lane changing behaviour at approach and departure lanes are modelled	It is found that traffic performance is affected by both traffic conditions and signal control
Wu et al. (2005)	Vehicle interactions at a T-junction with signal control are analysed	Mixed vehicle type simulation based on BML model. Vehicle compositions will affect junction capacity
Deo and Ruskin (2006)	Two different vehicle types, namely cars and buses, (or similar length vehicles), are simulated	Mixed vehicle type simulation; analyse the effect of vehicle type distribution
Spyropoulou (2007)	Discusses the feasibility of using CA models to simulate signalised junction. Relationships between randomisation inputs and simulation outputs are studied	Building different scenarios for different link length and cycle time into simulation
Zhang and Duan (2007)	Focuses on crosswalk modelling. Analyses behaviour of pedestrians and influence of pedestrians' behaviour on vehicle flow, pedestrian flow, and vehicle waiting time.	Influence of pedestrian behaviour on vehicle flow, vehicle waiting time
Lan et al. (2010)	Erratic behaviour, such as lateral drift and 'swing' of motorcycles are modelled	Lane-changing and lateral movements of different types of vehicles

Table 2.6 CA's applications for highway traffic with junctions

	Most important improvement	Related points to this study
Jiang and Wu (2006)	A realistic two-lane cellular aggressive lane-changing behaviour of fast vehicle that considers velocity flow relationship	Lane-changing behaviour and mixed vehicles with different velocity modelling
Clarridge and Salomaa (2010)	Analysis of highway traffic with a slow-to-stop rule	Shows the influence of operation velocities, different deceleration lane lengths
Han and Ko (2012)	A highway with junction is simulated, especially lane merging at entrance	Two types of transition rules of lane merging

2.4.4 Comparison of CA and commercial simulation packages

Compared to other microscopic simulation models and software, such as SIDRA and PTV VISSIM, CA models are more flexible in simulating complex scenarios and creating user-defined variables, as indicated in Table 2.7 (Akçelik et al., 1999; PTV, 2006).

Table 2.7 Comparison of CA model and microscopic simulation packages

	SIDRA	PTV VISSIM	CA
Allow users to define new moving parameters	N	Y	Y
Different moving strategy for motorcycles and heavy vehicles	N	N	Y
Lateral drift of vehicles	N	N	Y
Swing of motorcycles (Weave and drive between vehicles)	N	N	Y
Situational driver decision model	N	N	Y

2.5 Limitations of existing studies

2.5.1 Limitations of current junction assessment approaches

Most current junction assessment approaches are based on analytical models or statistical analysis. However, traffic performance at signalised junctions, in both capacity and safety aspects, are affected by many factors, such as signal settings, lane-markings, traffic conditions and driver behaviour that involves human factors (Wong et al., 2007). A more flexible and systematic approach is needed.

2.5.2 Limitation of current CA models

As discussed in Section 2.4.3, several applications have been developed for simulation of signalised junctions. Each of them focused on particular scenarios and developed enhanced models by adding and adjusting transition rules. Even though some researchers have shown great interest in CA to model traffic movements, most existing junction models are not realistic enough. Several aspects have not been covered in their research:

1. Traffic flow characteristics in existing models, such as vehicle trajectory, velocity profile, spacing, acceleration and deceleration rates, are from highway CA models and have not been calibrated to reflect actual behaviour within the signalised junction area.
2. The impact of complex lane arrangements has not been considered, especially for specific design issues such as shared lane and downstream lane merging.
3. Few existing models have involved dynamic decision-making of road users, such as deceleration due to vehicle conflicts, lane usage or amber running. Human factors have not been well considered in current CA models.
4. Most current CA models for signalised junctions are validated at the macroscopic level. However, vehicle movements are quite complicated, and validation at the microscopic level (microscopic movement or trajectories) has not been well covered in CA models at signalised junctions yet.
5. Last but not least, most current CA models are applied in estimating traffic capacity. Due to the strict deceleration rule in current CA models, vehicle conflicts and crashes cannot be simulated in current CA models. A new CA model for safety assessment at signalised junctions has not yet been developed.

2.6 Chapter summary

This chapter covers a review of various studies that have been undertaken for simulation of various operational issues related to signalised junction design, specifically in the CA modelling of traffic interactions at signalised junctions.

First, design and operation of signalised junctions as well as studies on several specific design issues, including shared-lane usage, permissive right-turn and installation of Red-Light-Camera (RLC), are discussed. Current approaches have been developed to assess traffic performance on both capacity and safety aspects. However, current researches focus more on the macroscopic level without consideration of the behaviour of individual vehicles and the interactions among them. As driver behaviour is highly related to junction design issues, lane markings and signal settings, a macroscopic model may not be able to produce accurate

results. Therefore, microscopic simulation would be able to fill current gaps and thus analyse design problems in a more realistic way.

The second part of the review is a detailed introduction of CA models. To make CA models more suitable for urban traffic simulation, some modifications such as irregular cell spaces and extended neighbourhood, have been made to standard CA models. Classic and widely used urban traffic CA models have been described in this chapter. Various previous studies have shown that the CA model is very suitable for simulating road traffic. Compared to other microscopic simulation software, a CA model has flexible transition rules that allow an analyst to define new parameters and simulate vehicle movements more accurately.

Although the application of CA in modelling traffic flow is quite successful, several gaps have been identified in simulating signalised junctions. These gaps are mainly due to the lack of calibration and validation from observed vehicle movements, as well as lack of consideration of driver behaviour and human factors. Moreover, most current CA models are limited to capacity assessment. Hence, this study shall focus on building a more realistic CA model to simulate various junction design problems and evaluate traffic performance in both capacity and safety aspects at the signalised junctions.

CHAPTER 3 TRAFFIC DATA ACQUISITION AND ANALYSIS

3.1 Chapter introduction

To build a more realistic CA model, sufficient traffic data are necessary. Required data include vehicle trajectory, velocity profile, and acceleration and deceleration rates. This chapter describes how traffic data are collected through video and image processing technologies. Through using computer vision techniques, vehicles are tracked and classified automatically. Moreover, to collect observation data for safety assessment, conflicts between vehicles and conflicts between vehicle and pedestrian are detected and recorded.

The second part of this chapter describes data analysis procedure and results. Movement characteristics of vehicles and pedestrians, including maximum velocity, front gap, acceleration and decelerations rates, are calibrated to create the micro-simulation model.

3.2 Data requirements

3.2.1 Site configuration

Data are used as the input of simulation as well as calibration and verification of the simulation model. Several cross junctions were observed to obtain data as the sample input of simulation, where the junction geometric and operational data were used to build simulation scenarios. In addition, signal settings were measured for simulation, including cycle length, start of green, duration of green, order of signal displays and clearance time. Detailed geometric data for survey sites are shown in Appendix B.

3.2.2 Traffic flow variables

In this study, traffic flow data of different types of vehicles, as well as pedestrians/cyclists, are collected for simulation and model validation. The required traffic flow data are shown in Table 3.1.

Table 3.1 Traffic flow factors

	Variables	Collection method
Vehicle	Length occupied by one vehicle	Literature
	Width occupied by one vehicle	Literature
	Volume of each lane and turning rate	Extract from video
	Velocity of different types of vehicle (mean, standard deviation, percentile values)	Extract from video
	Acceleration and deceleration rates	Extract from video
	Spacing of vehicles in various conditions	Extract from video
	Lane changing rate of different vehicle density	Extract from video
Motorcycle/ Bicycle	Length occupied by one motorcycle/bicycle	Literature
	Average swing width of each side	Literature
	Turning rate of motorcycle/bicycle	Extract from video
	Average velocity of different types of motorcycle/bicycle	Extract from video
Pedestrian	Average walking velocity	Extract from video

3.3 On-site observational study

The data collection focused on specific zones of junctions, such as shared lane at the approach and downstream lane merging at the departure end of the junction. Video cameras were positioned on a pedestrian footbridge that is located at a certain distance before the stop-line or in a high building near the junction. By using digital recording format, traffic flow data at a discrete format of 0.04s interval can be collected (Koh, 2005).

3.3.1 Methodology

In this project, several signalised junctions were chosen for video recording. The junctions observed were selected based on geometric and operational features as described below. Video recordings were made during the evening peak periods to take into account of high traffic volume.

For video recording, two or more video cameras were used for on-site recording of each junction. One video camera was placed to record the overall traffic flow from common corridors of Housing and Development Board (HDB) housing blocks

located near the junction. Additional cameras were placed to record signal timing or other directions of traffic flow obscured from the first camera as a result of obstacles. Synchronising of video records captured by different cameras was undertaken by matching a reference vehicle. In essence, a timeline was calibrated by taking note of the recorded video frame numbers among multiple scenes when the reference vehicle first crossed the stop-line (at 0.04s resolution per frame).

3.3.2 Site selection

A specific junction including its approach and departure lanes for on-site data collection must be identified in the first place. In terms of choice of sites, the selected junction is of a design that is commonly found in Singapore. To get an uninterrupted and complete view of video recording, a junction with footbridges or tall buildings nearby is desired. The followings should also be kept in mind before carrying out field work at the study site (Utter, 2001):

- 1) The selected site should have standard lane markings;
- 2) Location should preferably be horizontal (flat);
- 3) Traffic flow at the selected location should not be interrupted by incidents or on-road construction;
- 4) Safe place for observer should exist at the selected location.

Selected survey sites (detailed site configuration is included in Appendix B) for vehicle movements are:

- 1) Sengkang East Road - Sengkang East Way;
- 2) Jurong Town Hall Road- Jurong East Ave 1;
- 3) Woodlands Ave 2 – Woodlands Ave 5 – Woodlands Ave 9;
- 4) Woodlands Ave 2 - Woodlands Ave 5;
- 5) Woodlands Ave 6 – Woodlands Ave 7;
- 6) Choa Chu Kang Ave 3 – Choa Chu Kang Way;
- 7) Woodlands Ave 4 – Woodlands Ave 7.

In addition, to study vehicle movements at downstream merging areas, 4 additional survey sites were chosen:

- i) Bishan Street 22 – Bishan Road;
- ii) Bukit Panjang Road – Pending Road;
- iii) Bukit Batok East Ave 3 – Bukit Batok East Ave 6;
- iv) Jurong West St 91 (Near Blk 933).

3.4 Traffic data acquisition from video and image processing

3.4.1 Video pre-processing

To get road and traffic data from video records, co-ordinates of image (pixels) have to be changed into global coordinates (metres). Camera location needs to be estimated at first. Camera calibration was conducted to map geometric elements, primarily road user positions, from image space to the world space. A toolbox developed using MATLAB was used to annotate the calibration data, find initial estimates, conduct the camera calibration and estimate camera location from recorded video (Bouguet, 2010). The video records of traffic flows were taken on top of a HDB building in the vicinity of a signalised junction. The estimated camera perspective and position are shown in Figures 3.1 and 3.2.

Corresponding control points are annotated in image and global space. The global coordinates are calculated from their positions on the global map (Ismail et al., 2010). An original video frame and a transformed video frame are shown in Figures 3.3 and 3.4. The length of line segments is measured in video frames (Figure 3.5). The global length is measured using a road distance meter on-site. Several control points are selected on-site for measuring distance between each pair of points. By projective transformation of control points (Figure 3.6), the recorded video images can be transformed as orthographic frames.

Figure 3.1 Estimated grid of rectangular target (Site No.1)

Figure 3.2 Estimated position of camera

Figure 3.3 Recorded video frame

Figure 3.4 Transformed video frame

After the transformation, a global coordinate system can be created to transfer pixel values from the picture into global position.

Validation of calibrated data is based on comparison between real distance from on-site measurement and estimated distance from pixel values of calibrated video (Angel et al., 2002). Crosswalk width (3m) is selected as the reference distance. As shown in Figure 3.6, the difference in pixels is 34, then 1m equals to 11.33 pixels.

Figure 3.5 Reference distance

To transfer pixel values to global distances, several test cases (length of lane markings) are selected within approach and departure lanes. As taller objects will lead to larger parallax errors, hence all the samples are selected on ground level.

Locations of sampled lane markings are shown in Figures 3.6a and 3.6b, as well as the location of control points and camera locations. Two transformations are made by using different control points.

Figure 3.6a-b Location of sampled lanes (blue labels) and control points (red points) for two transformations

A linear regression analysis is made to test the relationship between estimated and true distances (Wu et al., 2004). As indicated in Figure 3.7, the regression line used is $y = x$, which stands for estimated distance being equal to true distance. The results show a relatively small Mean Square Error (MSE) at 0.032. The coefficient of determination (R^2) is 0.9856 which is significant at 0.1% (Wang et al., 2004). On the other hand, the calibration results also show a slightly larger error when true distance is larger, and this may be caused by an accumulation of small errors.

For approach 1 as shown in Figure 3.6, the mean error is much smaller than other areas. The difference between estimated distance and true distance is relatively small even though the true distance is only 1m. Therefore, it can be inferred that Transformation-1 is more suitable for data extraction for approach 1 than for other approaches. This suggests when using this camera calibration technology, one should choose control area closer to target regions for data collection. From the validation results, parallax errors are not negligible for all the approaches and departures. Additional calibration is needed to deal with such errors in future research.

Figure 3.7 Error test of Transformation-1

To test whether calibration accuracy is related to distance from calibration points, another camera calibration (Transformation-2 in Figure 3.6b) is made. The chosen calibration points are closer to the camera position. Same samples are selected to test accuracy of this transformation. The results are shown in Table 3.2.

Table 3.2 Comparison of average error

Area	Average Error	
	Transform-1	Transform-2
Approach 1	2.03%	3.13%
Departure 1	4.28%	8.17%
Approach 2	4.39%	2.03%
Departure 2	7.09%	1.56%

Table 3.2 shows clearly that in Transformation-2, accuracy loss is greater for areas far away from calibration points. The results also show that locations closer to control points are more accurate, which is the same as the results from Transformation-1. Moreover, it is also found that locations closer to the camera point are more accurate than others.

3.4.2 Automatic vehicle classification and tracking

In this study, the algorithm involves three stages, as shown in Figure 3.8. The first step is to estimate the position of the video camera and transform the co-ordinates of video frames into global co-ordinates. By using the transformed video, the size of vehicles in the video frame will not be related to the distance from the camera's

position. Next, the optical flow method is applied to detect vehicles and record each vehicle's position and size in each video frame. The algorithm is modified by removing shadows and automatically calculates moving direction and size of each detected vehicle. Vehicle type is identified based on defined ranges of vehicle sizes. Finally, traffic parameters, such as trajectory, velocity profile and gaps between vehicles are calculated according to the recorded data.

In this study, existing toolboxes (Computer Vision System Toolbox and Image Processing Toolbox) have been modified to improve detection ability. First, changing of light condition is removed by automatically detecting the colour of road pavement. Shadow elimination is conducted according to the algorithm suggested by Hsieh et al. (2006). A trajectory filter based on Kalman's method is used to link vehicle positions at neighbouring video frames to form a continuous trajectory (Faragher, 2012). Moreover, to detect small objects, including motorcycles and pedestrians, sensitivity of the original detection algorithm has been modified. With the add-on modules, accuracy of vehicle detection is much increased and the model is able to produce continuous trajectories automatically.

The optical flow method is used to detect vehicles from video images by estimating the changes of colour in each pixel. Optical flow refers to two-dimensional movement in a plane of camera image (Aires et al., 2008). The optical flow can compute motion vectors of objects between the camera and the objects in the background environment. The detailed algorithm is shown in Appendix C. One of the main advantages of using optical flow is that the position and velocity profile can be easily computed. The tracking algorithm is built into MATLAB based on the Computer Vision System Toolbox. The tracking procedure is shown in Figure 3.9.

The model estimates motion vectors in each frame according to a video sequence. By thresholding and performing morphological closing on each motion vector, the model is able to produce binary feature images. After that, the model locates the vehicles in each binary feature image using the Blob Analysis block. Then it uses the Draw Shapes block to draw a green rectangle around the vehicles that pass beneath the white line; tracking results are shown in Figures 3.10 and 3.11.

Figure 3.8 Procedure of vehicle classification and classification method

(Vel.: vehicle, Th.Img: Thresholding image, B.Box: Blob box)

Figure 3.9 Procedure of vehicle detection and tracking

Figure 3.10 Motion vectors computed for each moving pixel

Figure 3.11 Tracking results

Vehicles are classified as Small Vehicles (private cars and taxis), Medium Vehicles (light goods vehicles and minibuses), Large Vehicles (heavy goods vehicles and buses), Motorcycles and Bicycles, and Pedestrians, as shown Table 3.3. Movement parameters of various types of vehicles are not considered in this algorithm because of vehicles' average velocity being much lower at junction area than usual. Detection results of mixed traffic flow at signalised junction are shown in Figures 3.12 with threshold video shown in Figure 3.13.

Table 3.3 Range of geometry features to classify vehicles and non-motorised transport

Vehicle type	Length (m)	Width(m)
Small vehicles	3.0-4.5	1.2-2.0
Medium vehicles	4.5-8.0	1.7-3.0
Large vehicles	8.0-15.0	3.0-3.0
Motorcycles and bicycles	1.4-3.0	0.4-1.2
Pedestrians	0.4-1.0	0.4-1.0

Figure 3.12 Detection results of mixed traffic flow at junction approach

Figure 3.13 Threshold video (moving obstacles in white and background in black)

Using traditional data extraction methods, traffic parameters such as traffic density and vehicle velocity are measured manually. Instead, by using automatic vehicle detection and tracking method, automatic recording and computation of such parameters are possible.

1) Global trajectory and distance travelled

Vehicle global trajectory is computed as the position of the centroid of a vehicle recorded in time order. The three-dimensional trajectory of a typical tracked vehicle is shown in Figure 3.14. Distance travelled is estimated by a summation of distance between the vehicle centroid in every pair of neighbouring frames. Distance between two centroids in global coordinates $P(x_i, y_i)$ and $Q(x_j, y_j)$ is calculated as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (3-1)$$

For n = total frames captured, $i = 1$ to $n-1$ and $j = i+1$ to n , total distance travelled is given by:

$$D = \sum_{i=1, j=i+1}^{n-1, n} d_{ij} \quad (3-2)$$

2) Velocity profile estimation

The motion vector of every vehicle (v), which is the average velocity of each pixel within the vehicle as shown in Figure 3.15, is recorded in the vehicle detection and tracking system. Therefore, the estimated velocity of a vehicle is calculated as:

$$v_1 = v \quad (3-3)$$

On the other hand, the average velocity of a vehicle travelled can also be computed by changes of its position:

$$v_2 = d_{ij} \times fps \quad (3-4)$$

where fps is the frame rate of input video (number of frames in each second). A velocity profile of a typical tracked vehicle is shown in Figure 3.15.

3) Front or rear gap

The position, size and motion vector of each detected vehicle is recorded. Front and rear gap (G) is calculated as the distance between two centriods (D) minus the part inside the outline of detected vehicles (L_1+L_2), as shown in Figure 3.16.

Figure 3.14 Trajectory of a typical tracked vehicle

Figure 3.15 Velocity profile of a vehicle tracked

Figure 3.16 Front or rear gap between vehicles

In order to analyse the performance of the method, videos of 2 different junctions (Sites No. 1 and 4 as in Appendix B) were used. The duration of each video is 20min (30,000 frames). Comparison of manually extracted and automatically detected traffic volumes of different types of vehicles is summarised in Table 3.4. According to computed accuracies between detected and actual traffic volume, the proposed vehicle detection and classification method is accurate at signalised junctions. The errors are due to missed or over-segmented (two close vehicles are detected as one) vehicles. For example, one missed vehicle in a sample of 100 vehicles will lead to 1% error. Accuracy in classification of Small Vehicle, Medium Vehicle and Large Vehicle are acceptable. According to Table 3.4, larger errors are found between detected and actual Pedestrian in Video 1, as well as Motorcycle and Bicycle in Video 2. In both cases, the numbers of detected objects are much smaller than the actual numbers due to overlapping or merging of multiple objects. The accuracy could be improved through applying multiple cameras.

3.4.3 Automatic detection of vehicle conflicts

Traffic conflicts are defined as “observational situation(s) in which two or more road users approach each other in space and time to such an extent that a collision is imminent if their movements remain unchanged” (Amundsen and Hydén, 1977). For vehicle movements, a conflict occurs as a break-down in the interaction between road users, including vehicles and non-motorised traffic (bicyclists and pedestrians). In this study, traffic conflicts were extracted by identifying

microscopic movements of vehicles, such as braking or noticeable deceleration of vehicles.

Table 3.4 Accuracy comparisons of vehicle detection and classification

	Vehicle type	Actual	Detected	Accuracy
Video No.1 (1,400 pcu/h)	Small Vehicle	2,273	2,043	89.88%
	Medium Vehicle	1,111	893	80.38%
	Large Vehicle	321	294	91.59%
	Motorcycle and Bicycle	560	459	81.96%
	Pedestrian	1,847	1,149	62.21%
Video No.2 (800 pcu/h)	Small Vehicle	973	857	88.08%
	Medium Vehicle	387	336	86.82%
	Large Vehicle	306	290	94.77%
	Motorcycle and Bicycle	639	459	71.83%
	Pedestrian	1,035	849	82.03%

First, thresholds of safety indicators to detect conflicts affect surrogate safety assessment. In most previous studies, a conflict with TTC smaller than 1.5s or PET smaller than 1s is considered as critical (van der Horst, 1991; Wang and Stamatiadis, 2013; van Nes et al., 2013). The critical TTC for unintentionally dangerous situation is selected as 3s to 4s (van der Horst and Hogema, 1994; Hirst and Graham, 1997). According to field observations, when TTC is at 3s, over 90% conflicts have PET values lower than 3.5s and deceleration rates larger than 2.0m/s^2 (vehicles) and 1.0m/s^2 (pedestrians). Therefore, critical TTC and PET are selected at 3s and 3.5s, critical deceleration rates are selected as 2.0m/s^2 (vehicles) and 1.0m/s^2 (pedestrians).

The critical value for each vehicle type is selected from observed change of declaration for detected vehicles. For example, subject and conflicting vehicles are detected and tracked, and changes in deceleration are profiled as shown in Figures 3.17a and 3.17b. According to Figure 3.17a, the maximum deceleration is 2.0 m/s^2 at $t=9\text{s}$ and 2.5m/s^2 at $t= 20\text{s}$. Moreover, to remove random deceleration or normal deceleration in front of the stop-line, additional criteria, TTC and PET, are estimated at each time step based on moving velocities and relative distance between subject and conflicting vehicles, as plotted in Figures 3.17c and 3.17d. A conflict is recorded only if TTC between subject (decelerated) vehicle and

conflicting vehicle is smaller than 3s or PET is smaller than 3.5s. For each detected conflict, the position, speed, acceleration and deceleration rates of the two vehicles (pedestrians), as well as gap between the two vehicles (pedestrians), are recorded. A total of 1,002 conflicts between vehicles were observed at the studied junctions, including 401 rear-end conflicts, 119 lane-changing conflicts and 482 crossing conflicts. A total number of 318 conflicts between vehicles and pedestrians are also observed at the signalised crosswalks.

3.5 Computation of traffic movement characteristics

3.5.1 Motorised vehicles

i) Traffic volume and Passenger Car Unit (PCU) per lane

As mentioned in earlier sections, automatic vehicle detection and tracking may cause some errors because some vehicles may not be detected. Therefore, traffic volume for each observed junction was recorded manually (see Appendix D). The observed traffic volume at one approach during an evening peak period is shown in Figure 3.18.

Figure 3.17 Profiles of acceleration/ deceleration and TTC/PET

For simplified computation, to represent mixed traffic flow, vehicles are converted to cars according to the Passenger Car Equivalent (PCE) values shown in Table 3.5. The values for turning (Kok and How, 1992) and straight-through (Pang and Meng, 1990) vehicles have previously been estimated for Singapore junctions.

Table 3.5 PCE (calibrated for Singapore signalised junctions)

Vehicle type	PCE (turning)	PCE (straight-through)
Private cars (including taxis or pick-up)	1.00	1.00
Motorcycles	0.54	0.48
Heavy vehicles (trucks, buses)	1.44	1.20

Figure 3.18 Observed traffic volumes within every 1 minute (summation of 4 lanes) at evening peak period (13-Mar, 2012)

ii) Arrival distribution

Vehicle arrivals are independent of each other unless the flow is saturated. A discrete distribution is needed to generate arrivals of vehicles in the simulation. Commonly used arrival distributions include: Poisson distribution, Binomial distribution and Negative Binomial distribution (Gardner et al., 1995). The three distributions can be applied in the following situations:

- 1) Poisson distribution: Traffic density is small and interactions among vehicles can be neglected;
- 2) Binomial distribution: Congested flow or controlled by upstream junction; and

3) Negative Binomial (NB) distribution: Traffic volume remains unstable and the variance of arrivals is large (Turner and Nicholson, 1998).

In this study, the arrival time of each vehicle is observed and recorded in each 10 seconds. The trend component due to the increasing traffic volume over time is corrected before parameters for the NB distribution are estimated, giving a flow profile such as the one shown in Figure 3.18.

After removing the trend component, the traffic volume is found not to be stable and the variance of the vehicle volume in each minute is larger than its mean ($s^2/\bar{m} > 1$), hence the NB distribution is chosen to generate the arrivals for the vehicles in simulation. The distribution function is (Tripathi, 2006):

$$P(X = x) = C_{x+k-1}^{k-1} p^k (1-p)^k \quad x = 0, 1, 2, \dots \dots \quad (3-5)$$

where p and k are the NB parameters, $0 < p < 1$, k is a positive integer. The value of p and k can be estimated as:

$$\hat{p} = \bar{m}/s \quad (3-6)$$

$$\hat{k} = \bar{m}^2/(s^2 - \bar{m}) \quad (3-7)$$

Table 3.6 shows an example of estimation of parameters of one approach with 4 lanes (Site No. 2, weekday 6pm-7pm). One hour's traffic flow was recorded and broken into 360 10-second intervals. The interval of 10s was chosen based on the traffic volume observed, as the number of vehicles arriving in every 10s is basically within the range of 0-10. The number of vehicle arrivals (4 lanes) within each 10-second interval is recorded to produce average value and deviation.

Table 3.6 Arrival data and estimated parameters

Sample size	Average ($\bar{m}$)	Variance (s^2)	$\hat{k}$	$\hat{p}$
360	2.99	4.29	7.00	0.69

To validate the hypothesis of the arrival distribution following a NB distribution, a χ^2 test is applied, as shown in Table 3.7. The total degrees of freedom $DF = 9 - 1 - 2 = 6$ is used, and checking the χ^2 distribution table: $\chi_{0.05}^2 = 12.592 > 12.31$

(Montgomery et al., 2009). Therefore, the hypothesis of vehicle arrivals following a NB distribution is not rejected.

As the number of vehicle arrivals (n) within every 10s follows a NB distribution with $k = 7.00$, $p = 0.69$, and there are four lanes at the approach, the probability of generating one vehicle at each lane (f_1) per second can be calculated as:

$$f_1 = n/40 \quad (3-8)$$

where f_1 is the maximum possible number of vehicles that can arrive in 10s for a 4-lane approach. In simulation, a MATLAB function 'nbinrnd(k,p)' to generate random numbers following a NB distribution at each time step is used. Another random number f_2 from 0 to 1 is generated at each time step. If $f_1 > f_2$, a new vehicle will be generated at the entry of the approach with an equal probability in each lane.

Table 3.7 Chi-square statistics for vehicle arrival data

No. of vehicle arrivals, n	Observed frequency, o_i	Theoretical Probability	Theoretical frequency, e_i	$\frac{(e_i - o_i)^2}{e_i}$
0	20	0.074	26.8	1.81
1	54	0.162	58.2	0.28
2	88	0.200	72.1	3.49
3	68	0.186	67.1	0.01
4	59	0.144	52.0	0.95
5	37	0.098	35.5	0.07
6	19	0.061	22.0	0.41
7	6	0.035	12.7	3.50
>7	9	0.039	13.9	1.79
Total	360	1.000	360	$\sum(\frac{(e_i - o_i)^2}{e_i}) = 12.31$

iii) Two-dimensional movement of vehicles

At signalised junctions, right-turn and U-turn vehicles track curvilinear trajectories and have velocity in two-dimensions (both in X and Y directions) (See Appendix D). Therefore, to study the two-dimensional movements of right-turn and U-turn vehicles, observed trajectories of both movements at a field site (Site No. 2) are plotted, as shown in Figures 3.19 and 3.20.

Figure 3.19 Observed trajectories of and designated paths in CA model

In Figure 3.20, the junction-box is gridded by an 8×8 matrix. Each cell represents a $3.5\text{m} \times 3.5\text{m}$ area in real size. Most U-turn vehicles enter the junction-box from the median lane, and more than half of them continue to keep driving in the kerbside lane while others move to the centre lanes.

Figure 3.20 Trajectories of U-turn vehicles

iv) Velocity profile

From vehicle tracking, a time history of vehicle velocity is calculated. The following formula uses 2 neighbouring positions of one vehicle, 2 from X-coordinate and 2 from Y-coordinate, in order to find the difference between Position-1 and Position-2 so that the velocity can be obtained.

$$\frac{\sqrt{(x_1-x_2)^2+(y_1-y_2)^2}}{\Delta t} \times 3.6 \quad (3-9)$$

The formula serves to determine the velocity of the vehicle in km/h by multiplying a factor of 3.6. Vehicles are further classified into three groups based on the following situational movement behaviour (Daniel et al., 2011).

1) Non-stopping vehicle

Vehicles entering during green phase do not stop at the stop-line, and these vehicles are classified as non-stopping vehicles. As vehicles turning right always have a larger deceleration and lower velocity than those moving straight-through, vehicles moving straight-through always pass through the junction within a shorter time interval. It is found that a non-stopping vehicle's velocity is affected by the relative time with respect to the beginning of green phase. There are two possible velocity profiles for vehicles moving straight-through. For Case I, the subject vehicle arrived and entered the junction area shortly after the beginning of the green phase, and did not slow down (see Figure 3.21). On the contrary, a slight acceleration is detected. In Case II, the tracked vehicle entered the junction area in the middle of the green phase (11s of total 34s of green phase) and cleared the junction area before the green phase ended (Figure 3.22). From velocity-time history, the vehicle was moving at a relatively slower velocity than Case I and shows a small deceleration (1.5m/s^2) before it reached the stop-line (95s). After crossing the stop line, acceleration was detected.

Figure 3.21 Velocity profile of a typical non-stopping vehicle entering at the early part of green phase (Case I)

Figure 3.22 Velocity profile of a typical non-stopping vehicle entering in the middle of green phase (Case II)

2) Stopped vehicle

Vehicles, which are forced to stop for the red phase, are classified as stopped vehicles. The subject vehicle in Figure 3.23 was moving in a straight-through direction at the signalised junction. While moving closer to the stop-line during the red phase, it decelerated. Then, after stopping and waiting at the stop-line for a while, this vehicle accelerated and moved forward into the junction-box area after the start of green.

Figure 3.23 Velocity profile of a stopped vehicle

3) Slowed-down vehicle

Some vehicles that arrived towards the end of the red phase did not stop fully. Such vehicles slowed down before the stop-line and accelerated after the start of the green phase, as shown in Figure 3.24. This is similar to Case II of the non-stopping vehicles arriving in the middle of green phase.

Figure 3.24 Velocity profile of a slowed-down vehicle

v) Spacing

By definition, spacing is the difference in position between the front of a vehicle and the front of the next vehicle (in metres). An observational study of spacing was undertaken on cars queuing in platoons at 3 junction locations. Statistics of observed spacing are shown in Table 3.8 and Figure 3.25.

Table 3.8 Observed spacing of stopped cars at junction approaches

	Site No.1	Site No.2	Site No.3
Sample size	156	114	127
Mean (m)	7.11	7.05	7.11
Standard deviation (m)	0.46	0.52	0.56
Minimum value (m)	5.60	5.87	6.01
Maximum value (m)	9.09	8.80	10.25

Figure 3.25 Distribution of observed spacing of cars at Site No.1

vi) Maximum velocity of different types of vehicles

Statistics of observed 95th percentile vehicle velocity within approach and departure lanes (moving along observation length=150m) of different types of vehicles are shown in Table 3.9. Statistics of observed 95th percentile vehicle velocity within junction-box area of different types of vehicles are shown in Tables 3.10a and 3.10b.

Table 3.9 Observed maximum velocity within approach and departure lanes (all movements)

	Car			Motorcycle			Heavy vehicle		
Survey sites	No.1	No.2	No.3	No.1	No.2	No.3	No.1	No.2	No.3
Sample size (within 5 min)	114	125	118	35	30	30	102	117	121
95 th maximum value (km/h)	58.3	52.7	58.7	52.9	49.5	52.0	48.7	45.0	44.4

Table 3.10a Observed 95th percentile velocity in junction-box area (straight-through)

	Car			Motorcycle			Heavy vehicle		
Survey sites	No.1	No.2	No.3	No.1	No.2	No.3	No.1	No.2	No.3
Sample size (within 8 min)	44	49	80	13	3	26	67	66	70
95 th percentile value (km/h)	57.4	56.9	59.4	52.8	56.4	53.6	49.9	53.5	47.0

Table 3.10b Observed 95th percentile velocity in junction-box area (right-turn)

	Car			Motorcycle			Heavy vehicle		
Survey sites	No.1	No.2	No.3	No.1	No.2	No.3	No.1	No.2	No.3
Sample size (within 8 min)	58	64	79	12	13	26	48	66	72
95 th percentile value (km/h)	33.7	35.4	32.4	34.8	33.4	39.6	31.9	28.5	29.0

Cumulative probability is used to determine the 95th percentile velocity, as shown in Figure 3.26.

Figure 3.26 Cumulative distribution of observed 95th percentile vehicle velocity along approach and departure lanes (Site No.1)

vii) Maximum acceleration and deceleration rates

The maximum acceleration and deceleration rates of vehicles are limited by vehicle engine capacity and braking system. Most vehicles can decelerate at a much quicker rate than to accelerate. In addition, if the front vehicle decelerates, the following vehicle always has a smaller perception-response time. Momentum of different types of vehicles is not the same. For small vehicles and large vehicles, the capacity to accelerate and decelerate is different as well. Table 3.11 shows acceleration and deceleration characteristics extracted from acceleration and deceleration curves (Akcelik and Besley, 2002; Mehar et al., 2013).

However, in an urban traffic system, there are other factors that may have strong influence on acceleration and deceleration rates. At signalised junctions, two kinds of traffic behaviour will occur. One is free flow traffic, mostly for vehicles passing through the junction during the green signal phase. In such a situation, the acceleration and deceleration rates for vehicles are determined by their individual velocity, the velocity of the preceding vehicle, and the gap between the two vehicles. The other is queuing behaviour, when the signal is amber or red, and vehicles' acceleration and deceleration rates are very different to those in the first situation because the front vehicle is either stopped or moving relatively slowly when queuing.

Table 3.11 Acceleration and deceleration characteristics of different vehicle types

	Car	Bus/truck
Acceleration time from 0 to 30km/h (s)	2.5-4.7	5.3-8.0
Acceleration time from 30 to 80km/h (s)	3.9-6.0	7.9-18.3
Deceleration time from 80 to 30km/h (s)	8.0-19.2	14.1-21.7
Deceleration time from 30 to 0 km/h (s)	3.6- 5.2	5.1-9.4

Apart from vehicle's acceleration and deceleration capabilities, under Singapore's local conditions, an 85th percentile deceleration rate of -4.5m/s^2 was observed (Koh and Wong, 2007). In the present study, according to velocity profiles observed at 3 locations, the 95th percentile acceleration rate is 6.8m/s^2 for cars and 4.6 m/s^2 for heavy vehicles and the 95th percentile deceleration rate is -6.3m/s^2 for cars and -6.4 m/s^2 for heavy vehicles.

3.5.2 Pedestrians and bicycles

To study the movement characteristics of pedestrians, 3 signalised pedestrian crosswalks at Sites No. 2, 5 and 6 in Appendix B have been observed during the peak hour (6-7pm). Based on automatic pedestrian and bicycle tracking, several statistics are estimated. Table 3.12 summarises observed pedestrian volumes at different survey sites.

Average pedestrian travel times are observed for each crosswalk for both directions. Average pedestrian moving velocity is calculated as shown in Table 3.13.

Table 3.12 Observed pedestrian and bicycle volumes (6-7pm/peak hour)

	Direction 1		Direction 2	
	Pedestrians	Bicycles	Pedestrians	Bicycles
Crosswalk 1	291	43	234	64
Crosswalk 2	23	4	58	8
Crosswalk 3	151	23	199	37

Table 3.13 Average travel time and moving velocity of pedestrians

	Crosswalk 1		Crosswalk 2		Crosswalk 3	
Direction	1	2	1	2	1	2
Crosswalk width (m)	24.5	24.5	16.3	16.3	31.2	31.2
Average travel time (s)	18.8	18.5	13.1	12.9	23.6	22.8
Average velocity (m/s)	1.30	1.33	1.24	1.26	1.32	1.36

From Table 3.13, the average velocity of pedestrians is found to be around 1.2-1.3 m/s. For longer crosswalk width, the average velocity also tends to be higher. According to automatic pedestrian tracking, the observed 95th percentile walking velocity is 2.1 m/s for all the survey sites.

3.6 Chapter summary

In this chapter, the traffic data acquisition and analysis procedure were described. First, video processing techniques were developed for vehicle detection and tracking. Through projective transformation of video footages, detected vehicles were classified automatically.

The second part of this chapter described the procedure of data analysis of traffic characteristics. Traffic volumes were recorded and converted to PCE values. Arrival distributions of vehicles were found to follow an NB distribution.

Moreover, to build realistic simulation models, trajectory and velocity profiles of vehicles were observed. It was found that the average spacing between queuing vehicles is around 7.1m. According to vehicles' velocity profiles, the 95th percentile velocity, acceleration and deceleration rates were also observed. Average walking velocity was also computed at several signalised crosswalks.

CHAPTER 4 CA MODEL FOR VEHICLE MOVEMENTS AT SIGNALISED JUNCTIONS

4.1 Chapter introduction

This chapter contains two major parts. First, a composite Cellular Automata (CA) model with multiple cell sizes is developed to replicate homogenous vehicle movements at the signalised junctions. Compared to existing mathematical approaches, a CA model is more flexible in accommodating variable traffic and road conditions and produces realistic results at both macroscopic and microscopic levels. To represent geometric configuration of junctions, the CA model is constituted of cells of two different sizes. A smaller cell size is chosen to model the junction-box area while larger cells are used for approach and departure lanes. Apart from usage of composite cell sizes, several improvements of conventional CA models are involved, such as multiple cell states, minimum clearance between vehicles, amber running, right-turn waiting area and start-up lost time. The proposed CA model is calibrated and validated on both macroscopic and microscopic levels. The traffic performance of shared lanes at junction approaches is estimated through simulation experiments.

Second, an improved CA model is developed to simulate heterogeneous traffic flow at the signalised junctions. Three vehicle types (cars, heavy vehicles and motorcycles) are simulated with different movement characteristics, such as front gaps, acceleration and deceleration. Three types of lateral movement strategies of motorcycles, including lane-changing and lateral drift within the same lane, are simulated. Through validation by comparison with field data on both macroscopic and microscopic levels, the proposed model is found to be able to replicate vehicle movements of mixed traffic flow at the signalised junctions. Furthermore, a signalised crosswalk is modelled by using a smaller cell size. Pedestrian movements and interactions between neighbouring pedestrians are simulated.

4.2 CA model for homogenous-vehicle movements

4.2.1 Cell space

As an example, Survey Site No.2, which is a typical cross-junction in Singapore, is selected in this study. The studied approach is the east-bound approach along which contains one short exclusive left-turn lane adjoining a slip road, one exclusive straight-through lane, one shared straight-through and right-turn lane, and one short exclusive right-turn lane, as shown in Figure 4.1.

Through observations of approach and departure lanes as introduced in Chapter 3, the average spacing of 397 queuing cars (velocity =0) at 3 selected signalised junctions is 7.09m (minimum 5.60m), with an average gap of 2.24m (minimum 1.94m). This suggests the minimum practical spacing of two adjacent vehicles within one lane is around 7.0m. When a traffic stream is moving, the spacing will not be smaller than the stand-still situation. Therefore, cell length is selected as 7.0m for approach and departure lanes to reduce the complexity of computation, as shown in Figure 4.2. In this simulation, each car occupies one cell and the minimum gap between two consecutively occupied cells will be 0.

Figure 4.1 Geometric layout of the studied junction

At the junction-box area, a square cell size of 3.5m×3.5m is chosen to connect the approach and departure lanes, while representing site configuration at the same time. From observations of vehicle paths within the junction-box area, vehicles are assumed to stay within designated lanes, as shown in Figure 4.3. The slip road is

modelled as a normal left-turn lane but is not controlled by the traffic signal group. However, due to priority rules at the downstream area, vehicles travelling through slip roads have to give way to straight-through vehicles from the cross approach. Therefore, a virtual red signal phase is applied to slip road movements during straight-through green phase at the cross approach along Jurong Town Hall Road. Furthermore, while lane-changing behaviour is allowed and may be found along the approach and departure lanes, it is rarely observed within the junction-box area (Tang et al., 2005).

Figure 4.2 Cell size along approach and departure lanes

Figure 4.3 Observed trajectory of right-turn vehicle and designated path in CA model

For tracked path trajectory within the junction-box area, a minimum clearance between vehicles of 1 cell is set to ensure the minimum spacing of 7.0m. Smaller cells are always occupied pair-wise. This means when a particular cell is occupied, rear and alongside cells cannot be occupied. Specific scenarios for simplified lanes within junction-box area are illustrated in Figures 4.4a-4.4c. As smaller cell size

(3.5m×3.5m) is defined in junction-box area, four alongside cells (as shown in Figure 4.4b) of a right-turn vehicle cannot be occupied.

Figure 4.4a Simplified lane for straight-through or left-turn

Figure 4.4b Simplified lane for right-turn Figure 4.4c Cell states

4.2.2 Model parameters and variables

In this study, a series of parameters are defined in the CA model. Some parameters are calibrated according to collected traffic characteristics as reported in Chapter 3, with others from the literature. The details are listed in Table 4.1.

L is the travel length of one vehicle. In this case, n is set as 48, including 20 cells of approach, 8 cells of junction-box along movement direction and 20 cells of departure;

p_r is the probability of randomisation deceleration. In this model, p is calibrated as 0.2 to yield the most realistic average time headway per vehicle, as shown in Appendix E.

t is the number of time step. One time step represents 1s in this simulation for computational efficiency. According to the observed signal setting, signal cycle of case junction is 132s, straight-through green phase of selected approach is 30s, and

right-turn green phase is 20s. The simulation procedure covers 3,600 time steps (1h), as set by analyst.

Table 4.1 Model parameters

Notation	Description	Range of value	Source
L	Road length modelled	48 (cells)	Site measurement
L_x, L_y	Size of cell space	48, 48 (cells)	Site measurement
t	Number of time step	0~3,600 (s)	Set by analyst
v_{int}	Initial velocity of vehicle	1 (cell/s)	Video extraction
v_{max}	Maximum velocity of vehicle	3 (cells/s)	Video extraction
pa	Arrival distribution	0~100%	Video extraction
acc, dec	Maximum acceleration and deceleration rates	1 (cell/s ²); (2 cell/s ² inside junction-box)	Video extraction
c	Duration of signal cycle at evening peak	132 (s)	Site measurement (6pm, 13-Mar, 2012)
c_1	Duration of straight-through green phase of studied approach at evening peak	30 (s)	Site measurement (6pm, 13-Mar, 2012)
c_2	Duration of right-turn green phase of studied approach at evening peak	21 (s)	Site measurement (6pm, 13-Mar, 2012)

v_{int} is the initial velocity of vehicle at the instant it enters the cell space. According to sensitivity analysis, as shown in Figure 4.5, initial velocity from 1cell/s to 3cells/s will not significantly affect simulation results. Therefore, the initial velocity is set as 1cell/s which is approximately 25.2 km/h.

Figure 4.5 Sensitivity analysis of initial vehicle velocity
(each point represents the result of one simulation)

v_{max} is the upper bound of velocity in simulation. At approach and departure lanes, with cell length of 7.0m, the maximum velocity of vehicles is set as 60km/h (16.7m/s), which translates to 2.4 cells/s. In CA models, velocity is represented as an integer, and to represent 2.4 cells/s, 40% of vehicles will move at a velocity of 3 cells/s and the complementary 60% of vehicles will move at a velocity of 2 cells/s.

When the cars/buses are turning within the junction-box, their 95th velocity reduces to about 30km/h according to field observations, which is approximately 2.4 cells/s for the reduced cell size of 3.5m within junction-box. The velocities are represented in percentage equivalent integers in the same way as for approach and departure lanes.

acc, dec are maximum acceleration and deceleration rates of vehicles. The maximum acceleration and deceleration of cars are 7m/s^2 and -9m/s^2 (Bae et al., 2001). An 85th percentile deceleration rate of -4.5m/s^2 was observed in Singapore local conditions (Koh and Wong, 2007). Vehicles' velocity profiles extracted from on-site observations of 3 sites shows the 95th percentile acceleration rate of cars at 6.8m/s^2 and the 95th percentile deceleration rate at -6.3m/s^2 . As vehicle's velocity must be integers, acc and dec are both set as 1 cell/s² (7.0m/s^2) along approach and departure lanes and 2 cells/s² (7.0m/s^2) within junction-box area.

A sensitivity analysis of the effect of acceleration rate on simulation results is shown in Figure 4.6. It is shown that for acceleration rates within 1-2 cells/s², simulation results are not greatly affected. This is due to traffic delay at signalised junctions being mainly caused by signal control and vehicle blockage, and not acceleration and deceleration capability.

pa is vehicle arrival distribution of each lane. In this study, vehicles are generated at each time step according to a calibrated NB distribution at each 10-second interval based on observed traffic volume. For simplified computation, to represent mixed traffic flow, vehicles are converted to cars according to PCE shown in Table 3.5. For the studied site, the traffic volume of motorcycles is relatively low (around 7%). Motorcycles are found to move in-between other vehicles and the small proportion of motorcycles can be neglected.

Figure 4.6 Sensitivity analysis of acceleration rate

4.2.3 Transition rules

In the composite CA model with two cell sizes, forwarding rules of vehicle are built based on an improved single lane NaSch model. The way vehicles progress is by “seeing” the gap that is in front of them (Nagel and Schreckenberg, 1992). They slow down when the gap is reducing which means the vehicle in front is slowing too. Several changes have been made in this study to improve on the conventional NaSch model.

(i) Multiple cell states

In this model, three types of vehicles are generated to represent straight-through, left-turn and right-turn vehicles. Therefore, in this simulation, each cell (excluding the boundary cells) could be in 5 possible states, as shown in Table 4.2.

Table 4.2 Possible cell states

State No.	Description
1	Not occupied
2	Cannot be occupied (minimum clearance between vehicles)
3	Occupied by a right-turn vehicle
4	Occupied by a left-turn vehicle
5	Occupied by a straight-through vehicle

(ii) Minimum clearance between vehicles

In certain conditions, when the vehicle is crossing into the junction-box area, the target cell cannot be occupied due to minimum clearance between vehicles. In such situations, the vehicle will occupy the next available cell which could be its present cell, as shown in Figure 4.7 (v stands for current velocity of vehicle, d stands for current front gap).

Figure 4.7 Minimum clearance between vehicles

(iii) Multiple acceleration and deceleration rates

In the composite CA model, maximum acceleration or deceleration is higher than 1 cell/s² within the junction-box area. If the front gap is longer than 4 cells, the acceleration rate will be 2 cells/s², otherwise it will be 1 cell/s². When the front gap is 1 long cell or 2 short cells (with minimum clearance between vehicles of 1 cell), the deceleration rate is -2 cells/s². Otherwise it will be -1 cell/s².

(iv) Signal control and amber running

At signalised junctions, vehicles need to decelerate as well as to stop when approaching the stop-line if the signal is red. To deal with this situation, this model introduces a new rule whereby the subject vehicle detects the gap between the front vehicle as well as the distance to the stop-line when the signal is red.

However, drivers approaching a signalised junction at the onset of amber have to decide whether to stop or cross the stop-line. According to the maximum deceleration rate calibrated in earlier sections, some vehicles will not be able to fully stop before the stop-line. A regression model of stopping probabilities of vehicles at amber onset has been calibrated under Singapore's local condition (Koh, 2005). The variables include distance to stop-line, velocity, vehicle type, traffic light condition and red light camera.

In the improved CA model, the stopping probability of the first vehicle at the onset of amber is calculated according to the regression model. A decision is made according to the stopping probability and whether there is enough distance to stop. If there is not enough distance to stop fully, the vehicle will proceed to cross the stop-line. If the decision is to stop, the following vehicle(s) will also stop. If not, same procedure will apply to the following vehicle until one vehicle stops.

v) Start-up lost time

Start-up lost time occurs at the beginning of each green phase. Some amount of time elapses between the start of a green phase and the first queued vehicle moving through the stop-line. There is then an additional amount of time for the next vehicle to begin moving and pass through, and so on. The total time taken for all waiting drivers to react and accelerate is the start-up lost time. In this study, the response time of the first three queuing vehicles was observed at Sites No.1-3 (see Appendix B). With a sample of 50 groups of vehicles, the average start-up lost times of the first three vehicles are 0.70s, 0.58s, 0.55s. In the improved CA model, start-up lost time is added by postponing the start of the first 2 vehicles each for 1 time step.

vi) Right-turn waiting area

Right-turn waiting areas are widely used in Singapore and are also used at studied approach. Right-turn vehicles can move forward and wait in the waiting area until the right-turn green arrow phase. Vehicles moving to the waiting area have to stay clear of opposite straight-through vehicles. In the improved CA model, the same

strategy is used, as illustrated by the black cells in simplified lane No.3 and No.4 shown in Figure 4.8.

Figure 4.8 Waiting area within simplified right-turn lanes (black cells)

vii) Forwarding rules

The applicable forwarding transition rules are then as follows:

The velocity v of each vehicle can take one of the $v_{max} + 1$ allowed integer values $= 0, 1, \dots, v_{max}$. Suppose, x_n and v_n denote the position and velocity, respectively, of the n^{th} vehicle. Then, $d_n = x_{n+1} - x_n$ is the spacing between the n^{th} vehicle and the $(n+1)^{\text{th}}$ vehicle in front of it at time t . At each time step $\rightarrow t + \Delta t$ (set as 1s in this study), the arrangement of the N vehicles on a finite lattice of length L is updated according to the following rules:

Rule 1: Acceleration.

If $v_n < v_{max}$, the velocity of the n^{th} vehicle is increased by $\varphi_a = 1$ cell/s (2 cells/s within junction-box area), but v_n remains unaltered if $v_n = v_{max}$, i.e.

$$v_n \rightarrow \min(v_n + \varphi_a, v_{max})$$

Rule 2: Deceleration (due to other vehicle).

At green or amber phase:

If $d_n/\Delta t \leq v_n$, then if the subject vehicle continues moving, it will collide with the front car at next time step. Therefore, the velocity will be reduced by $\varphi_d = 1$ cell/s (2 cells/s within junction – box area) to $\frac{d_n}{\Delta t} - \varphi_d$;

At red phase: Assume DS is the distance between a vehicle and the stop-line.

If $\min(d_n, DS)/\Delta t \leq v_n$, then if the subject vehicle continues moving, it will exceed the front car or exceed the stop-line at the next time step, and the velocity of the n^{th} vehicle is reduced to

$$\min(d_n, DS)/\Delta t - \varphi_d$$

$$v_n \rightarrow \min(v_n, (d_n/\Delta t - \varphi_d), (DS/\Delta t - \varphi_d))$$

Rule 3: Randomisation.

In NaSch model, the first two rules (acceleration and deceleration) make sure the following vehicle will travel at the maximum possible velocity without surpassing the front vehicle. However, in reality, not all the vehicles will travel at the maximum possible velocity. Therefore, a random deceleration rule is built to reduce simulated velocity to be more close to the reality.

If $v_n > 0$, the velocity of the n^{th} vehicle is decreased randomly by $\varphi_r = 1$ cell/s with probability p_r but v_n does not change if $v_n = 0$, i.e.,

$v_n \rightarrow \max((v_n - \varphi_r), 0)$ with probability p_r . According to Appendix E, when vehicle decelerates with probability $(p_r) = 0.2$, simulated average travel time per vehicle is closed to observed values with errors within $\pm 3\%$.

Rule 4: Vehicle movement.

Each vehicle is moved forward according to its new velocity determined in Steps 1-3, i.e.,

$$x_n \rightarrow x_n + v_n \times \Delta t$$

viii) Lane-changing rules

Along approach and departure lanes, vehicles change their lane very often. The vehicles change lane in two main types. One is to move to the corresponding straight-through or turning lane of the junction; the other is to move to a less congested convenient lane. According to field observations, the first type of lane-changing occurs for all vehicle types while the second type of lane-changing occurs mainly for cars and heavy vehicles. In the proposed CA model, one time step is divided into two sub-steps: in the first sub-step, the vehicles may change lane following the lane-changing rules, and in the second sub-step each vehicle may move forward electively as in the single-lane model.

If the following three requirements are satisfied, vehicles will make a lane change in one time step (1 lateral cell) with a probability of p_{lc}^1 (first type) and p_{lc}^2 (second type).

- (1) front gap is smaller than C_1^{car} cells (cars) or C_1^{hv} cells (heavy vehicles);
- (2) front gap in target lane is larger than C_2^{car} cells (cars) or C_2^{hv} cells (heavy vehicles); and
- (3) rear gap in target lane is larger than C_3^{car} cells (cars) or C_3^{hv} cells (heavy vehicle).

4.2.4 Model validation

The performance of the CA model is evaluated by a comparison of vehicle trajectories against field data. Another real-world junction (Site No.2 as described in Appendix B) is selected. Vehicles' position and velocity at each time step are collected by video image processing technologies. In order to generate the same initial headway, the observed arrival distribution and initial vehicle density are used to generate vehicles in the simulation.

i) Macroscopic validation

To investigate the model validity, a simulation is performed using observed vehicle characteristics including traffic density, arrival distribution, moving velocity and relative proportion of vehicle volumes in shared and exclusive lanes. After 30 signal cycles (about 1 hour), the simulation results of traffic delay (difference of estimated

travel time at signalised control and free flow) of each lane or each movement direction converge with error of 0.01s. A comparison of observations and simulation results is shown in Table 4.3. The results of traffic delay show very good agreement. The error at Lane 1 (left-turn lane) is caused by the non-inclusion of a zebra pedestrian crossing for modelling and relatively small traffic delay. The CA model developed for a shared lane is found to be able to replicate realistic signalised junction traffic at the macroscopic level.

Table 4.3 Comparison of traffic delay per vehicle (s/veh) from CA simulation and field data

	Lane 1	Lane 2	Lane 3			Lane 4
	Left-turn	Through	Through	Right-turn	All	Right-turn
Field data	7.48	91.87	133.85	142.37	132.53	45.23
CA simulation	6.92	92.68	134.25	140.25	133.55	44.98
Error	– 7.49%	0.88%	0.30%	– 1.49%	0.77%	– 0.55%

ii) Microscopic validation

In microscopic validation, vehicle's trajectory is compared between on-site observations and simulation. After one signal cycle, a total of 93 vehicles are captured within four approach lanes from observation. These vehicles are generated in the simulation with observed arrival time and velocity at the instant the vehicle enters the cell space. An error assessment is also done for the sample of 93 vehicles. The summarised results, including distribution of velocities, Root Mean Square Error (RMSE) and Mean Percentage Error (MPE), are shown in Tables 4.4 and 4.5. These relatively small and acceptable errors (within 5%) between the simulation and field data present evidence that the CA model could well describe traffic dynamics at the microscopic level.

4.3 Model application: Traffic performance of shared lane

By definition, a shared lane can be used by vehicles making different turning movements. For example, if it is a shared straight-through/ right-turn lane, the lane can be used by all straight-through and right-turn vehicles. Vehicles typically choose the exclusive or shared lane with the shortest queue length (Liu et al. 2008). A straight-through vehicle may block a right-turn vehicle during the right-turn

phase, and a right-turn vehicle may block a straight-through vehicle during the straight-through phase as well. When such a blockage occurs, the blocked vehicle will queue after the blocker and wait for the next signal phase unless there is available gap to move to the adjacent lane.

Table 4.4 Comparison of observations and simulation results of velocity of 93 vehicles over the cell space

	Observations	Simulation
Average velocity	0.82 cell/s	0.86 cell/s
Standard deviation	0.85 cell/s	0.79 cell/s

Table 4.5 Deviations of observed and simulated velocity profiles of 93 vehicles

	Group 1 (18 vehicles)		Group 2 (38 vehicles)		Group 3 (37 vehicles)	
	RMSE (km/h)	MPE (%)	RMSE (km/h)	MPE (%)	RMSE (km/h)	MPE (%)
Lane 1	4.92	0.99	5.20	5.65	5.67	4.53
Lane 2	1.06	-2.10	1.42	-2.85	3.96	-3.49
Lane 3	3.25	4.18	3.96	4.04	3.51	2.28
Lane 4	2.53	-1.52	3.78	2.36	1.95	-0.64

The proposed model is applied to estimate traffic performance at signalised junctions with complex geometric layouts. Several simulation experiments are conducted for a whole junction approach that contains a shared lane. Through various scenarios, the issue of whether a shared lane will increase overall junction performance is analysed under various traffic conditions. A shared straight-through and right-turn lane, which is the most common type in Singapore, is studied. Traffic delay for both types of vehicle movements is used as an indicator of traffic capacity aspect (Ross et al., 1989). Shared lane delay, D_{sh} , is computed as the travel time difference for a vehicle in shared lane, T_{sh} , and an exclusive lane, T_{ex} , under the same traffic density, as shown in equation 4.1.

$$D_{sh} = T_{sh} - T_{ex} \quad (4.1)$$

In this study, a lane group that contains one shared lane is modelled. The lane group consists of an exclusive slip road for left-turn movements, two exclusive lanes (one

for straight-through and one for right-turn), and a shared lane. Four scenarios with different overall traffic volumes for each vehicle movement are created and simulated to test traffic performance under various traffic compositions.

4.3.1 Simulation set up

A lane group, as shown in Figure 4.1, with four lanes is established according to geometric layouts of the selected junction approach at Site No. 2 (see Figure B-4 in Appendix B). Simulation runs are completed for 30 observed signal cycles during the evening peak hour on weekdays (approximately 1 hour). Four simulation scenarios, as shown in Table 4.6, are created. For each simulation scenario, 36 combinations of vehicle proportions using the shared lane are simulated. In each combination, the proportion choosing to use the shared lane varies from 0 to 0.5, while the traffic volume is fixed. It is noted that the maximum relative proportion of either movement shall not exceed 0.5 on the rationale that given a choice of 2 lanes (exclusive and shared), the split is at most 50% along the shared lane. Four scenarios are created under different traffic conditions, as shown in Table 4.6 (Brooks, 2010). Simulation results show the change of traffic delay due to shared lane usage under a certain traffic condition. According to the observed signal timing, capacity of an exclusive straight-through lane is 381pcu/h. Therefore, in this study, as there are two exclusive lanes and one shared lane, the low traffic volume is chosen as 300pcu/h, and the high traffic volume is chosen as 600pcu/h.

Table 4.6 Simulation scenarios with different traffic volumes

Scenario	Straight-through traffic volume ¹	Right-turn traffic volume ²
1	low (300pcu/h)	low (300pcu/h)
2 (observed)	low (300pcu/h)	high (600pcu/h)
3	high (600pcu/h)	low (300pcu/h)
4	high (600pcu/h)	high (600pcu/h)

Straight-through traffic volume¹: Traffic volume on exclusive straight-through lane and on shared lane with straight-through route decision;

Right-turn traffic volume²: Traffic volume on exclusive right-turn lane and on shared lane with right-turn route decision;

4.3.2 Scenario 1: Low straight-through traffic volume, low right-turn traffic volume

In this scenario, the simulation is conducted under observed signal timing (30s each for both straight-through and right-turn). Figures 4.9a and 4.9b show the estimated traffic delay for all straight-through and right-turn vehicles in the system. The bottom X and Y axes are proportions of straight-through and right-turn vehicles choosing the shared lane. A series of data points (shown as dots in Figures 4.9a and 4.9b), were generated for various combinations of vehicle proportions, and the Lowess method (locally weighted smoothing linear regression) was used to generate the surface. Detailed simulation results are shown in Appendix F.

Figure 4.9a Estimated traffic delay of right-turn vehicles (Scenario 1, R-square: 0.8933), Figure 4.9b Estimated traffic delay of straight-through vehicles (Scenario 1, R-square: 0.8891)

According to simulation results, higher traffic delay occurs when there is 1:1 split of right-turn and through-vehicles in the shared lane (shown as the semi-transparent plane). This is consistent with the simulation results of an individual shared lane,

indicating that the maximum average traffic delay, as well as the maximum blockage effect, occurs when the two vehicle movements along the shared lane are evenly-matched. The results suggest that when either of the relative proportions for straight-through and right-turn vehicles is below 20%, average delay per movement remains low and relatively insensitive. In reality, one can expect that as a self-organised system, traffic proportions along shared lane will be interchangeable when either (but not both) movement predominates. Therefore, when there is enough capacity along exclusive lanes, the traffic performance of a lane group is mostly affected by blockage effect along shared lane. In addition, the higher traffic delay for right-turn vehicles is a result of the lower velocity during the turning movement.

4.3.3 Scenario 2: Low straight-through traffic volume, high right-turn traffic volume (as observed)

Figure 4.10 shows the average traffic delay for all vehicles for varying relative proportions of the two vehicle movements using the shared lane. The lowest average traffic delay occurs at two vehicle proportions. The first one is when 50% of right-turn and 0% of straight-through vehicles are using the shared lane. This situation is very extreme. In reality, as competition between the two vehicle movements exists, this situation cannot be achieved, as straight-through vehicles will also enter the shared lane. The second one is when 27% of right-turn vehicles and 30% of straight-through vehicles are using the shared lane, which is close to the observed proportion (0.33, 0.28). This indicates, as a self-organised system, traffic on the whole approach tends to the minimum overall traffic delay itself.

Figure 4.10 Estimated traffic delay of all vehicles (Scenario 2, R-square= 0.9296)

As adaptive signal timing is applied in Singapore, when traffic volume of a certain vehicle movement is higher, extra green time will be given to that movement. To study the impact of signal timing on shared lane performance, simulation is conducted for two sets of signal settings, one for same signal timing as Scenario 1 and the other for adjusted signal timing, based on Webster's method, for the traffic volumes in Scenario 2. In the adjusted signal timing, the green time for straight-through and right-turn is 23s and 46s, respectively.

Figures 4.11a to 4.11d (plotted to different delay scale) show the estimated traffic delay for all straight-through and right-turn vehicles in the system with two signal timings. In this case, as shown by the plane surface in Figures 4.11a and 4.11b, when the traffic volumes of the two vehicle movements within the shared lane are evenly matched, the average traffic delay for all vehicles in the approach is not maximised. It indicates, for the whole approach under the higher traffic volume, larger traffic delay caused by the usage of the shared lane is due not only to the blockage effect, but also to the different traffic volume and the proportion of different vehicle movements using the shared lane.

According to Figure 4.11a, the lowest average traffic delay per right-turn vehicle occurs when more right-turn vehicles and no straight-through vehicles choose the shared lane. One possible reason is that observed traffic volume of right-turn vehicles is much higher than straight-through vehicles. When straight-through vehicles in the shared lane block more right-turn vehicles, the queue length as well as vehicles' travel time, will increase rapidly. Therefore, if the blockers (straight-through vehicles) are removed, the average delay for all vehicles will decrease.

On the other hand, the lowest traffic delay of straight-through vehicles occurs when no straight-through vehicles or right-turn vehicles choose the shared lane (see Figure 4.11b). The simulation results indicate that under certain conditions, such as when the right-turn volume is much higher than the straight-through volume, even though the shared lane increases the overall capacity for right-turn vehicles, usage for the shared lane is not beneficial to straight-through vehicles.

Figure 4.11a Estimated traffic delay of right-turn vehicles (Scenario 2, Observed signal timing, R-square: 0.9083), Figure 4.11b Estimated traffic delay of straight-through vehicles (Scenario 2, Observed signal timing, R-square: 0.9621) Figure 4.11c Estimated traffic delay of right-turn vehicles (Scenario 2, Adjusted signal timing, R-square: 0.9083), Figure 4.11d Estimated traffic delay of straight-through vehicles (Scenario 2, Adjusted signal timing, R-square: 0.9052)

Reduction of traffic delay per straight-through and right-turn vehicle in two signal settings (relative to observed signal timing) are calculated and summarised in Tables 4.7 and 4.8. In both Tables 4.7 and 4.8, a positive value represents a reduction of traffic delay while a negative value represents an increase of traffic delay. It is noted that the random nature of some variables in the CA model may generate outcomes with the odd inconsistent values. For example, arrival distribution of vehicles of the two movements affects the occurrences and severity of blockage along shared lane.

Table 4.7 Delay per right-turn vehicle in adjusted signal timing

RT¹ ST²	0	0.1	0.2	0.3	0.4	0.5
0	36.79%	28.12%	35.21%	-12.84%	13.38%	22.83%
0.1	16.64%	15.50%	7.99%	-36.97%	17.90%	3.41%
0.2	17.46%	17.89%	3.51%	-7.52%	7.58%	6.57%
0.3	6.55%	-1.24%	3.91%	-5.19%	-26.49%	11.90%
0.4	5.75%	3.22%	8.05%	-9.16%	-16.06%	-26.26%
0.5	7.63%	4.60%	4.87%	-2.04%	-26.76%	-15.83%

RT¹: Relative proportion of right-turn vehicles using shared lane;

ST²: Relative proportion of straight-through vehicles using shared lane

Table 4.8 Delay per straight-through vehicles in adjusted signal timing

RT¹ ST²	0	0.1	0.2	0.3	0.4	0.5
0	-4.81%	-17.40%	-19.06%	-15.22%	-12.93%	-21.86%
0.1	-8.85%	-23.62%	-0.18%	-7.80%	-22.38%	-19.13%
0.2	-16.33%	-16.16%	-21.30%	-18.86%	-29.49%	-35.95%
0.3	-15.81%	-17.69%	-16.37%	-8.46%	-31.90%	-35.25%
0.4	-23.17%	-21.33%	-13.99%	-19.22%	-19.39%	-29.43%
0.5	-29.28%	-18.52%	-39.54%	-42.08%	-25.99%	-28.31%

RT¹: Relative proportion of right-turn vehicles using shared lane;

ST²: Relative proportion of straight-through vehicles using shared lane

According to Figure 4.11c and Table 4.7, the adjusted signal timing has reduced traffic delay for right-turn vehicles in several simulation scenarios as more green time is given for right-turn vehicles. The reduction is larger in scenarios where more vehicles in both movements are using the exclusive lanes instead of the shared lane. This is due to right-turn capacity of the studied approach being increased as more green time is given for right-turn vehicles. However, when the relative proportion of the two movement streams using the shared lane is increased, the blockage effect along the shared lane will lead to larger traffic delay. Moreover, with the adjusted signal timing, the green time for straight-through vehicles is reduced, and right-turn vehicles are more likely to be blocked along the shared lane during right-turn green phase. In simulation scenarios with higher relative proportions of the two movement streams, delays to right-turn vehicle are larger with adjusted signal timing.

In Figure 4.11d and Table 4.8, delay per straight-through vehicle is increased in all scenarios. This is due to straight-through capacity being reduced due to the shorter straight-through green phase. Therefore, even though the signal timing is adjusted to meet the heavy right-turn traffic volume, the blockage effect along the shared lane will still reduce the capacity of the lane-group significantly, especially when more vehicles are using the shared lane.

The simulation results of the two signal timings indicate that larger traffic delay will occur when a higher proportion of right-turn vehicles are using the shared lane. Therefore, apart from adjusting the signal timing, one of the possible upgrade options for the studied approach is to change the shared lane into an exclusive right-turn lane to avoid the blockage effect.

4.3.4 Scenario 3: High straight-through traffic volume, low right-turn traffic volume

Figures 4.12a and 4.12b show the results with the observed signal timing, and Figures 4.12c and 4.12d are the results with signal timing adjusted according to the traffic volume (46s for straight-through, 23s for right-turn). According to Figure 4.12a, the lowest average traffic delay of the right-turn vehicles occurs when none of right-turn vehicles or none of the straight-through vehicles choose the shared lane. The lowest traffic delay for straight-through vehicles occurs when 50% of straight-through vehicles and none of the right-turn vehicles choose the shared lane (see Figure 4.12b). The results for straight-through vehicles, which is the majority of vehicles, are similar to those for right-turn vehicles in Scenario 2. The results for right-turn vehicles, which are the minority, are similar to those for straight-through vehicles in Scenario 2.

Figures 4.12c and 4.12d show the same trends as the results for Scenario 2 with adjusted signal timing. The delays for straight-through vehicles, which are the majority of the traffic flow, are significantly reduced when fewer right-turn vehicles are using the shared lane. The lack of significant reductions indicates that adjusting timings will not help increase capacity much when more vehicles are using the shared lane.

Figure 4.12a Estimated traffic delay of right-turn vehicles (Scenario 3, Observed signal timing, R-square: 0.9804), Figure 4.12b Estimated traffic delay of straight-through vehicles (Scenario 3, Observed signal timing, R-square: 0.9736) Figure 4.12c Estimated traffic delay of right-turn vehicles (Scenario 3, Adjusted signal timing, R-square: 0.9492), Figure 4.12d Estimated traffic delay of straight-through vehicles (Scenario 3, Adjusted signal timing, R-square: 0.9674)

4.3.5 Scenario 4: High straight-through traffic volume, high right-turn traffic volume

In this scenario, traffic volumes of both streams are very high (600pcu/h for each vehicle movement), with observed signal timing (30s for both straight-through and right-turn). In this scenario, signal timing is not adjusted due to the balanced traffic volume for both movements. The simulation result shows that the traffic delay of the two types of vehicles is not significantly influenced by the proportion of vehicles using the shared lane (Figures 4.13a and 4.13b). This is because adding a shared lane gives both streams some extra space as well as causing blockages.

Figure 4.13a Estimated traffic delay of right-turn vehicles (Scenario 4, R-square: 0.8937), Figure 4.13b Estimated traffic delay of straight-through vehicles (Scenario 4, R-square: 0.9207)

Compared to Scenario 1, the simulation results in the other 3 scenarios do not reveal higher traffic delay with evenly-matched split along shared lane. When at least one traffic movement volume is heavy, the two exclusive lanes will not be able to provide enough capacity. Therefore, in Scenarios 2-4, vehicles in the exclusive lane will suffer from a longer queue due to heavy traffic volume and thus results in a higher overall delay.

The simulation results and conclusions are summarised in Table 4.9. The differences between the simulation results under the four scenarios show clearly that the performance of a shared lane in the approach is affected by the traffic volume of both the straight-through and right-turn movements. Therefore, when making decisions on shared lane usage, the traffic volume of both streams should be

considered instead of the traffic volume of right-turn vehicles only. Apart from the four simulated scenarios, the simulation model also allows road designers to input the observed traffic volume in the two movement directions and test the performance of a shared lane. If the results are similar to Scenarios 2 or 3, upgrading by creating an additional lane will be necessary because the shared lane is not beneficial for either one of the vehicle movements.

Table 4.9 Summary of simulation results

	Traffic condition	Conclusions
Scenario 1	Low straight-through traffic volume; Low right-turn traffic volume	Under light traffic condition, performance of shared lane is mainly affected by blockage effect. The maximum blockage happens when traffic volume of two movements are evenly matched.
Scenario 2	Low straight-through traffic volume; High right-turn traffic volume	The shared lane is not beneficial for straight-through vehicles. Changing the shared lane to an exclusive right-turn lane is suggested.
Scenario 3	High straight-through traffic volume; Low right-turn traffic volume	The shared lane is not beneficial for right-turn vehicles. Changing the shared lane to an exclusive straight-through lane is suggested.
Scenario 4	High straight-through traffic volume; High right-turn traffic volume	The shared lane similarly affects two movements. Under heavy traffic condition, performance of shared lane is mainly affected by insufficient capacity instead of blockage effect.

The CA model would be able to help authorities to make decisions on whether to use shared lane. Land Transport Authority (LTA) of Singapore is also generally cautious in arranging shared lanes. Most shared lanes in Singapore are arranged to save land usage while accommodating vehicles for both movements. Among the

junction improvement projects from 2010 to 2011, over 90% of newly-added lanes are exclusive and two shared lanes have been changed to exclusive lanes. Apart from calculating the capacity of a shared lane according to quantitative models (Xu et al., 2008), microscopic simulation can be used by engineers to assess the traffic performance of their design in various traffic conditions and signal timings.

4.4 CA model for heterogeneous-vehicle movements

4.4.1 Cell space

Traffic flow in Singapore consists mostly of three vehicle types, namely cars, heavy vehicles (bus and good vehicles) and motorcycles. In the proposed CA model, the three vehicle types are simulated with different physical sizes as well as movement characteristics.

As an improvement from current CA models, a smaller cell size is chosen to simulate multiple vehicle types in this study. Each cell is a 0.9 m by 0.9 m square. Lane width is taken to be 3.6 m and therefore four rows of cells constitute one lane. According to physical sizes of the three vehicle types as listed in Table 4.10, a car takes 5×2 cells, a heavy vehicle occupies 13×3 cells, while a motorcycle takes 3×1 cells. Moreover, for each vehicle, a leading cell (shown as a black cell in Figure 4.14) is defined to represent the reference position. The leading cell is also ‘aligned’ to driver’s position in Singapore’s driving convention.

Figure 4.14 CA model for mixed traffic flow at junction approach

Table 4.10 Sizes and occupied cells of vehicles

Vehicle type	Actual size (m)	Physical representation (m)	No. of cells
Car	4.2×1.7	4.5×1.8	5×2
Heavy vehicle	12.0×2.5	11.7×2.7	13×3
Motorcycle	2.5×0.8	2.7×0.9	3×1

According to field observations of mixed traffic flow, there is little difference in the turning path trajectory among different vehicle types (Chai and Wong, 2013). Therefore, a fixed turning path for all vehicle types for each lane is designed at junction-box areas. For each turning vehicle, the leading cell can only occupy cells of the designed path. Other cells occupied by the same vehicle will be behind and alongside the leading cell as according to respective vehicle sizes, as shown in Figure 4.15.

Figure 4.15 Cells occupied by turning cars (a), motorcycles (a) and buses (b)

The cell space is set up as shown in Figure 4.16 for the typical geometric layout of a cross-junction. Along each approach, there is one exclusive left-turn storage lane, one exclusive straight-through lane, one shared lane for straight-through and right-turn, and an exclusive right-turn storage lane.

Figure 4.16 Designed cell space for a typical cross-junction

4.4.2 Forwarding rules

In the proposed CA model, forwarding rules of the mixed traffic flow are improved from a NaSch model (Nagel and Schreckenberg, 1992; Tang et al., 2005). A new parameter, front gap (g_n), is defined in the proposed model. If x_n and x_{n+1} are the positions of the n^{th} and its preceding vehicle (leading cells), then the spacing is calculated as $d_n = x_{n+1} - x_n$. Front gap of the vehicle is therefore defined as $g_n = d_n - b - g_t$, where b is number of cells occupied by front vehicle in x direction and g_t is the applied minimum clearance between vehicles. An improved deceleration rule is defined as:

Amended deceleration rule (due to other vehicle):

At green or amber phase: If $g_n/\Delta t \leq v_n$, it means that if the subject vehicle continues moving at velocity v_n , it will collide with the front car at the next time step. Therefore, the velocity will be reduced by φ_d to $\frac{g_n}{\Delta t} - \varphi_d$;

At red phase: Assume DS is the distance between vehicle and stop-line.

If $\min(g_n, DS) / \Delta t \leq v_n$, it means that if the subject vehicle continues moving at velocity v_n , it will collide with the front car or exceed the stop-line at next time step, so the velocity of the n^{th} vehicle is reduced to

$$\min\left(\left(\frac{g_n}{\Delta t}\right), \left(\frac{DS}{\Delta t}\right)\right) - \varphi_d$$

$$v_n \rightarrow \min((g_n/\Delta t), (DS/\Delta t)) - \varphi_d$$

4.4.3 Lane-changing rules

Along the approach and departure lanes, vehicles can change their lane very often. The vehicles change lane in two main ways. One is to move to the marked straight-through or turning lane of the junction; the other is to move to a more convenient lane with larger front gap. According to field observations, the first type of lane-changing occurs for all vehicle types while the second type of lane-changing occurs mainly for cars and heavy vehicles. In the proposed CA model, one time step is divided into two sub-steps: in the first sub-step, the vehicles may change lanes following the lane-changing rules, and in the second sub-step each vehicle may move forward electively as in the single-lane model.

If the following three requirements are satisfied, all vehicles (first type) and 60% (calibrated from field observations) of vehicles (second type) will make a lane change in two time steps (2 cells per time step):

- (1) front gap is smaller than 5 cells (cars) or 10 cells (heavy vehicle);
- (2) front gap in target lane is larger than 10 cells (cars) or 20 cells (heavy vehicle);
- and
- (3) rear gap in target lane is larger than 15 cells (cars) or 25 cells (heavy vehicle).

4.4.4 Lateral drift within the same lane

Lateral movement may be caused by two reasons. First, before lane-changing, the subject vehicle needs to move to a position nearer to the target lane. Accordingly, it may take a longer time for a car to make the lane-changing manoeuvre. Especially

for junctions, when a car intends to make a turn but is located away from the target lane, this kind of lateral drift would become more common.

The second reason is to avoid conflict with motorcycles. When a car remains moving in the same lane but wants to overtake a motorcycle in front of it, or for the opposite situation in which a motorcycle wants to overtake a front car, lateral drift may also occur. There are also some special cases at the signalised junctions when motorcycles usually stop along-side the cars at the stop-line.

In consideration of the above, this study defines the lateral drift of a car by adding the following rules:

Rule 1: When a car is moving along-side the lane markings (the lateral boundary of a lane), both lane-changing and lateral drift are possible to take place depending on the traffic situation in the neighbourhood.

Rule 2: When a car is moving towards the lane markings, only lateral drift is considered to happen. This is because lane-changing can occur only after a lateral drift is made towards the lane markings.

Unlike most of the cars and heavy vehicles which are moving within the lane, motorcycles tend not to rigorously maintain lane discipline in following the lane markings. Sometimes the motorcycles will follow the leading car, but more often, motorcycles tend to filter into the lateral gap between two moving streams of cars. When approaching the stop-line, motorcycles are allowed to move into the gap alongside queuing cars whenever there is a wide lateral gap, and continue to move forward to the stop-line.

In the proposed CA model, if the front gap is smaller than 5 cells and there exists an alongside passage ahead with a gap longer than 5 cells, 75% of motorcycles will make lateral drift (1 cell per time step) to enter the gap as shown in Figure 4.17.

Figure 4.17 Lateral drift of motorcycles

4.4.5 Model calibration

A sensitivity analysis based on the Elementary Effect (EE) method was conducted to test which modelling parameters will affect simulation outputs significantly (Morris, 1991). The EE method has been successfully applied in sensitivity analysis of simulation models with a large number of inputs (Ge and Menendez, 2012). Traffic characteristics that are tested include average stand-still (queuing) front gap, maximum velocity of different vehicle types, initial velocity, average acceleration/deceleration rates, maximum acceleration/deceleration rates, and other parameters in the CA model, such as random deceleration rates.

First, different ranges for tested parameters are selected according to previous studies and common sense, as shown in Table 4.11. For each simulation run, one input parameter (X_i) is changed by a certain interval (Δ , pegged at $\pm 10\%$ in this study) while the other input parameters are kept the same. A sufficiently large number of combinations (m) of input parameters are generated to achieve an unbiased sampling. Trajectories (moving directions) of input parameters are generated according to the Quasi-Optimised (OT) approach developed by Ge and Menendez (2012). For each trajectory, two combinations of input parameters P_1 and P_2 are simulated to compute simulation results for the average travel time of vehicles, i.e. $Y(P_1)$ and $Y(P_2)$. According to the definition of EE, the elementary effect of each parameter along a trajectory is computed as $EE(X_i) = [Y(P_2) - Y(P_1)]/\Delta$. For each input parameter, the Total Sensitivity Index (TSI) is computed ($TSI(X_i) = \overline{EE(X_i)} / \bar{X}_i$) and is shown in Table 4.11. The TSI value represents the percent change of simulation results related to change (at $\pm 10\%$ in this study) of the

input parameters; a TSI value of 0.1 (or higher) is equivalent to 1% (or larger) change in the simulation results. In Table 4.11, most of the parameters are sensitive (TSI >0.1), except for initial velocity. The most sensitive parameters are found to be maximum velocity and the maximum acceleration and deceleration rates. The random deceleration probability in the NaSch model is found to be 0.2 through comparing simulation results with field observations, as shown in Appendix E. Other sensitive parameters are calibrated according to field observations as described below.

Table 4.11 Results of sensitivity analysis

Parameter	Range	TSI
Average stand-still front gap	1-10m	0.28
Maximum velocity (Car)	20-60km/h	1.45
Maximum velocity (Heavy vehicle)	20-60km/h	1.02
Maximum velocity (Motorcycle)	20-60km/h	0.91
Initial velocity	20-60km/h	0.02
Average acceleration rate (Car)	0.1-6.0m/s ²	0.46
Average acceleration rate (Heavy vehicle)	0.1-6.0m/s ²	0.55
Average acceleration rate (Motorcycle)	0.1-6.0m/s ²	0.21
Average deceleration rate (Car)	0.1-6.0m/s ²	0.32
Average deceleration rate (Heavy vehicle)	0.1-6.0m/s ²	0.15
Average deceleration rates (Motorcycle)	0.1-6.0m/s ²	0.16
Maximum acceleration rate (Car)	0.1-6.0m/s ²	0.64
Maximum acceleration rate (Heavy vehicle)	0.1-6.0m/s ²	0.58
Maximum acceleration rate (Motorcycle)	0.1-6.0m/s ²	0.34
Maximum deceleration rate (Car)	0.1-6.0m/s ²	0.72
Maximum deceleration rate (Heavy vehicle)	0.1-6.0m/s ²	1.10
Maximum deceleration rate (Motorcycle)	0.1-6.0m/s ²	0.58
Random deceleration ratio	0.05-0.30	0.86

1) Front minimum clearance between vehicles (g_t) for different types of vehicle are defined according to field observations as summarised in Table 4.12. A total of 450 standstill (queuing) vehicles from three different junction approaches are observed and the applied minimum clearance between vehicles is set to the minimum front gap observed (5th percentile). Moreover, if the motorcycle is moving alongside cars

or heavy vehicles, the front gap is calculated as between the subject motorcycle and the front vehicle that occupies exactly the same row of cells.

2) According to the observed 95th percentile vehicle velocity along junction approach and departure lanes (within 150m to the stop-line) at three different locations, the maximum velocity of cars is set as 56.7 km/h (15.7 m/s), which translates to 17 cells/s. Maximum velocities for motorcycles and heavy vehicles are set as 16 cells/s and 14 cells/s, respectively. When the cars/heavy vehicles are turning within the junction-box, their maximum velocity reduces to 30 km/h (4.4 m/s) according to field observations, which is approximately 9 cells/s.

Table 4.12 Observed and applied front minimum clearance between vehicles

	Front vehicle	Subject vehicle	Observed minimum gap	Applied g_t
1	Car	Car	1.6m	2cells
2	Car	Heavy vehicle	1.8m	2cells
3	Car	Motorcycle	1.0m	1cell
4	Heavy vehicle	Car	2.3m	3cells
5	Heavy vehicle	Heavy vehicle	2.5m	3cells
6	Heavy vehicle	Motorcycle	1.8m	2cells
7	Motorcycle	Car	1.6m	2cells
8	Motorcycle	Heavy vehicle	1.6m	2cells
9	Motorcycle	Motorcycle	0.8m	1cell

3) Multiple acceleration and deceleration rates are applied for different vehicle types. According to previous researches, maximum acceleration and deceleration rates for different vehicle types are limited by vehicles' capability (Bae et al., 2001; Limebeer et al., 2001; Woodrow and Poplin, 2002). Therefore, in the proposed CA model, acceleration and deceleration (φ_a and φ_d) applied at each time step are determined based on observed traffic flow at signalised junctions. A regression analysis has been conducted to get the relationship between current velocity, front gap and acceleration and deceleration rates. Table 4.13 summarises the applied acceleration and deceleration rates where v is the moving velocity and g is the front gap. Results are rounded and bounded ($0 \leq \text{acceleration} \leq \text{acc}$) and ($\text{dec} \leq \text{deceleration} \leq 0$).

Table 4.13 Maximum values and equations of acceleration and deceleration rates

Parameters	Car	Heavy vehicle	Motorcycle
Max. acceleration rate	4cells/s ² (3.6m/s ²)	3cells/s ² (2.7m/s ²)	4cells/s ² (3.6m/s ²)
Acceleration rate (cells/s ²)	$\varphi_a = -0.03v + 0.26g - 0.92$	$\varphi_a = -0.02v + 0.33g - 0.61$	$\varphi_a = -0.03v + 0.42g - 0.91$
Max. deceleration rate	-5cells/s ² (-4.5m/s ²)	-3cells/s ² (-2.7m/s ²)	-5cells/s ² (-4.5m/s ²)
Deceleration rate (cells/s ²)	$\varphi_d = -0.32v + 0.15g + 1.29$	$\varphi_d = -0.21v + 0.25g + 0.35$	$\varphi_d = -0.39v + 0.17g - 0.61$

4) Stopping propensity (p_s) of drivers of different vehicle types is simulated in the extended CA model. Drivers approaching a signalised junction at the onset of amber have to decide whether to stop or cross the stop-line. A regression model of stopping propensity of first stopping vehicles at the onset of amber signal has been calibrated from field observations. The variables include whether there is surveillance using a red light camera (RLC), distance to stop-line (DS) in metres, moving velocity (V) in km/h, and whether it is peak hour (PH). Stopping probabilities for different vehicle types are modelled by the following three equations:

$$p_s (\text{car}) = [1 + \exp\{-(-1.02 - 1.32\text{RLC} + 0.129\text{DS} - 0.54\text{V} - 0.03\text{PH})\}]^{-1} \quad (4-2)$$

$$p_s (\text{Heavy vehicle}) = [1 + \exp\{-(-2.61 - 0.85\text{RLC} + 0.17\text{DS} - 0.31\text{V} - 0.01\text{PH})\}]^{-1} \quad (4-3)$$

$$p_s (\text{motorcycle}) = [1 + \exp\{-(2.59 - 0.52\text{RLC} + 0.08\text{DS} - 0.72\text{V} - 0.01\text{PH})\}]^{-1} \quad (4-4)$$

where, RLC=1 if there is RLC surveillance; PH=1 if in peak hour.

4.4.6 Model validation

i) Simulation outputs

Each vehicle's position, velocity, and acceleration rates are recorded automatically in each time step. Therefore, the trajectories of vehicles can be plotted as shown in Figure 4.18.

(C:H:M applied to each movement at junction=3:1:2; Cars (C): black; Heavy vehicles (H): blue; Motorcycles (M): red)

Figure 4.18 “Space-time” plot of mixed traffic flow with cars, heavy vehicles and motorcycles

ii) Macroscopic validation

To investigate the model validity, a simulation using observed vehicle characteristics including traffic density, arrival distribution, moving velocity, signal phasing, and vehicle composition is performed for Sites No.5 and 6. After 20 signal cycles, average travel time of each type for vehicles from observations and simulation are shown in Table 4.14. The results of traffic delay show very good agreement. Therefore, the CA model for mixed traffic flow is demonstrated to be able to replicate realistic signalised junction traffic at the macroscopic level.

Table 4.14 Comparison of traffic delay (s) from CA simulation and field data

	Site No. 5			Site No. 6		
	Cars	Heavy vehicles	Motor-cycles	Cars	Heavy vehicles	Motor-cycles
Field data	97.48	101.87	74.39	109.85	122.37	92.53
CA simulation	94.30	103.98	76.63	115.61	118.63	95.38
Error	3.4%	-2.0%	-2.9%	-5.0%	3.2%	-3.0%

iii) Microscopic validation

The performance of the CA model is evaluated by a comparison of simulated vehicle trajectories against field data. A real-world junction (Jurong Town Hall Road and Jurong East Ave 1) is selected. Each vehicle’s position and velocity at

each time step are collected by video image processing technologies. In order to generate the same initial headway distribution, the observed arrival distribution and initial vehicle density are used to generate vehicles in the simulation.

After the one signal cycle, a total of 114 vehicles (73 cars, 20 heavy vehicles and 21 motorcycles) captured from field observations within the four approach lanes are generated in the simulation with arrival time and velocity at the instant the vehicle enters the cell space. Figures 4.19a and 4.19b show examples of comparison between trajectories (longitudinal distance) from the CA model and field data in Lanes 2 and 3.

(Lane 2; C: car; H: heavy vehicle; M: motorcycle)

Figure 4.19a Comparison of longitudinal distance of vehicles from CA model and field data

(Lane 3; C: car; H: heavy vehicle; M: motorcycle)

Figure 4.19b Comparison of longitudinal distance of vehicles from CA model and field data

4.5 CA model for pedestrian movements at signalised crosswalk

To determine the cell size at a crossing pedestrian, firstly, the average width of pedestrians is found to be 0.45m in Asian countries. According to the HCM, the average thickness of pedestrian is 0.3m and the dynamic space is 0.6-0.8m (Transportation Research Board, 2000). According to field observations conducted in Singapore, a pedestrian tends to follow the front person closely and the minimum gap is found as 0.29m. As a result, a cell size of 0.45m×0.45m is chosen for a crossing pedestrian. A minimum clearance between vehicles rule is also built-in, with the forward (moving direction) minimum gap being 1 cell and the lateral minimum gap being 0.

With the three different cell sizes applied in this study, the layout of the CA model is applied to a typical cross junction. For shared usage with vehicles, the pedestrian crosswalk will be represented by 4 rows of larger cells (0.9m×0.9m), as it is usually 3m wide. However, pedestrians are given priority during the pedestrian signal cycle. When at least one of the pedestrian cells (0.45m × 0.45m) at the pedestrian crosswalk is occupied, the cell (0.9m × 0.9m) covering that small cell will be regarded as being “occupied” and not available to the vehicles. On the other hand, when a larger cell (0.9m × 0.9m) on the crosswalk is occupied by a vehicle, pedestrians will not be allowed to occupy any of the pedestrian cells (0.45m×0.45m) within that area, as shown in Figure 4.20.

Figure 4.20 Layout of crosswalk mapped with small cells

Pedestrians are simulated only along pedestrian crosswalks, and basic movement characteristics are assumed according to an observation study conducted by Zhang et al. (2004), as summarised in Table 4.15. It is assumed that pedestrian arrivals follow a Poisson arrival distribution when the total volume of bi-direction flow is fewer than 1,000ped/h. One pedestrian can occupy only one pedestrian cell. According to proposed cell size, the average walking velocity is 3 cells/s in the direction of travel and 2 cells/s (maximum) in sideways direction. The three possible walking directions at each time step are shown in Figure 4.21.

Table 4.15 Movement characteristics of pedestrians

Average distribution of dense pedestrian flow	0.45m×0.45m (1ped/cell)
Average vertical velocity	Walk: 1.3m/s (3cells/s) Run: 2.6m/s (6cells/s)
Maximum horizontal velocity	0.9m/s (2cells/s)

Figure 4.21 Possible pedestrian walking directions

Transition rules for pedestrians are modified from a CA model for bi-directional walkways proposed by Blue and Adler (2001). Each time step is sub-divided as two sub-steps, as forwarding and lateral movement. At each time step, the following rules are applied in parallel updating the position and velocity of each pedestrian. Assume all pedestrians are moving along y direction. Positions of each pedestrian in forwarding and lateral directions are defined as y_p and x_p .

i) Forwarding rules:

Rule 1: Front gap (g_{p1}) is computed for each subject pedestrian (p_1) as:

$g_{p1} = v_{max}^p$ cells if front pedestrian (p_2) is moving in the same direction;

$g_{p1} = INT(0.5 * |y_{p1} - y_{p2}|)$ if front pedestrian is moving in opposite direction;

Rule 2: Update velocity: $v_{p1} = \min(g_{p1}/\Delta t, v_{max}^p)$

Rule 3: Overtaking: If $g_{p1}=0$ or 1, p_1 will pass p_2 in the next time step, therefore

$v_{p1} = \min(g_{p1}/\Delta t + 1, v_{max}^p)$

Rule 4: Update position $y_1 = y_1 + v_{p1} \times \Delta t$

ii) Lateral rules:

p_1 and p_2 (moving in opposing directions) in the same or neighboring lateral lanes are required to side step to avoid conflicting with each other. According to Blue and Adler (2001), pedestrian p_1 will side step if the front gap (g_{p1}) to an opposing pedestrian p_2 is within 4m (8 cells). Both p_1 and p_2 has a 0.5 possibility of side stepping with a lateral velocity, $v_{p1}^l=1$ cell/s. If additional conflict is detected after side stepping, pedestrian(s) will sidestep again to make sure no further conflict exists. If conflict with other pedestrian occurs after the subject pedestrian has already side stepped 2 cells within one time step, the subject vehicle will not side step and the opposing pedestrian will side step with 100% probability to avoid conflict.

4.6 Chapter summary

In this chapter, an improved CA model is first developed to simulate homogenous-vehicle movements at signalised junctions. By using multiple cell sizes, the proposed model is sufficiently flexible to simulate movements at signalised junctions with various geometric layouts. Simulation results are found to be useful for assessing traffic performance under various traffic and signal conditions.

The proposed CA model is used to estimate traffic performances for a shared lane. Simulations are conducted for an approach (lane-group) with one shared lane. It is found that when the traffic volumes of the two movement streams are quite different, the shared lane usage is not efficient in terms of reducing traffic delay. The simulation results are able to produce the threshold traffic volumes for which having a shared lane gives a reduction in traffic delay.

In the next part, a microscopic CA model is developed to simulate heterogeneous traffic flow at signalised junctions, including pedestrian movements at signalised crosswalks. Compared to existing CA models, the proposed model uses a smaller cell size to simulate mixed traffic flow. Vehicle types and transition rules are calibrated to represent real traffic flow at signalised junctions with a shared lane. Traffic flow characteristics, such as arrival distribution, spacing of queuing vehicles, maximum velocity, maximum acceleration and deceleration rates, are calibrated for Singapore's local traffic conditions and appropriate values are applied to each vehicle type.

Simulation results for various experiments show that traffic performance (capacity) at signalised junctions is affected by many factors, including traffic volume, geometric layouts and signal timing. The proportions of different vehicle movements along the same approach also affect the overall traffic performance. Moreover, since traffic conditions during peak periods and off-peak periods are very different, dynamic geometric layout can be considered to provide flexibility for dynamic traffic flow.

The CA model developed in this chapter is able to help authorities to estimate the capacity of junction before implementation. Apart from calculating the capacity of each lane according to quantitative models, microscopic simulation can help engineers to assess the traffic performance of their design in various traffic conditions and signal timings.

CHAPTER 5 CA MODEL FOR SAFETY ASSESSMENT AT SIGNALISED JUNCTIONS

5.1 Chapter introduction

At junctions, vehicles coming from different directions conflict with each other. Improper geometric design and signal timings at signalised junction will increase the occurrence of conflicts between road users and result in a reduction of the safety level. A series of studies have been developed to estimate road safety performance of signalised junctions for different junction types (Persaud et al., 2002; Oh et al., 2003; Oh et al., 2010). An ordered Probit model relating crashes at signalised junctions with road attributes was calibrated by Abdel-Aty and Keller (2005). Al-Ghamdi (2002) applied the binary logit model to examine the effect of crash characteristics and their causes, to study the injury levels of crashes involving right-turn vehicles. For Singapore's local context, an accident prediction model based on time series analysis has been developed by Kusumawati (2008). Instead of real collisions, some researchers have used vehicle conflicts involving right-turn movements, to assess the quantity of risk and safety level of specific junction designs (Zhang and Prevedouros, 2003; Kirk and Stamatiadis, 2012; El-Basyouny and Sayed, 2013).

In essence, there have been numerous studies analysing conflicts involving right-turn vehicles at signalised junction. However, most current studies are based on statistical analysis methods of crash occurrences or quantitative approaches to estimate the number of conflicts. This chapter reports on the development and application of a Cellular Automata (CA) model to simulate vehicular interactions at signalised junctions for assessing safety performance. A proxy indicator is defined as "Deceleration Occurrence caused by Conflict" (DOC) to estimate occurrences of vehicle conflicts. Three other indicators are applied to estimate the severity of each simulated conflict. Through various simulation experiments, the proposed method is found to be able to provide reasonable assessment of conflicts, and hence the detection of hazardous junctions, under a given set of geometric and operational conditions.

5.2 Model development

5.2.1 Classification of conflict types

In this study, conflicts are grouped as vehicle-vehicle conflicts and vehicle-pedestrian conflicts and further classified as different types according to movement directions.

(i) Vehicle-Vehicle conflicts

Assuming all vehicles are fully complying with signal control at signalised junctions, the vehicle-vehicle conflicts can be classified into seven types based on their positions and vehicle movements involved, as shown in Table 5.1.

Table 5.1 Types of vehicle-vehicle conflicts at signalised junctions

	Movement	Location	Description
1		Approach	Between two straight-through or two right-turn vehicles
2		Approach	Between straight-through and right-turn vehicles at shared lane
3		Approach	Between U-turn and right-turn vehicles at the same approach
4		Junction-box	Between right-turn and opposite straight-through vehicles
5		Departure	Between U-turn and straight-through vehicles
6		Departure	Between straight-through and left-in vehicles
7		Approach/ Departure	Overtaking and lane-changing vehicles

(ii) Vehicle-pedestrian conflicts at signalised junctions

The conflicts between pedestrians and vehicles at pedestrian crossings are classified as four types, as shown in Figure 5.1. If a junction is under Left-Turn-On-Red (LTOR) scheme (Land Transport Authority, 2011), during green-man phase, pedestrians also conflict with left-turn vehicles, as shown in (b). These conflicts occur at junctions without slip roads. For large junctions with slip roads, vehicle-pedestrian conflicts also occur along the slip road. During red-man phase, additional

conflicts occur between pedestrians and straight-through or right-turn vehicles, as shown in (c) and (d).

Figure 5.1 Conflict areas at pedestrian crossing

5.2.2 Safety indicators of conflict occurrences and severity

i) Deceleration Occurrences caused by Conflicts (DOC)

The Deceleration Occurrence caused by Conflict (DOC) is used to represent the occurrence of vehicle conflicts in the above-described CA model. In each run of the simulation, occurrence of vehicle deceleration is recorded. There are three possible causes of vehicle deceleration, as follows:

- 1) To avoid collision with the front vehicle (rear-end conflicts);
- 2) To avoid collision with neighbouring vehicles (lane-changing or crossing conflicts); and
- 3) To come to a stop before the stop-line.

Therefore, the frequency of DOC can be used to indicate potential occurrence of conflicts between vehicles or between vehicles and pedestrians. Higher frequency in the DOC implies more frequent vehicle conflicts and therefore higher crash risk in terms of frequency.

The DOC indicator is generated in accordance with simulated microscopic vehicle movements. The movement characteristics in CA model are calibrated from field observations, and quantitative assessments provide the deceleration rates. Such an approach provides an alternative safety assessment method from simulated vehicle movements under various traffic conditions

ii) Safety indicators of conflict severity

Three indicators of safety assessment of both occurrence and severity of vehicle conflicts are studied in this research: Time to Collision (TTC), Post-encroachment Time (PET) and Criticality Index (CI). The three models are incorporated into the microscopic simulation in the composite CA model.

Time to Collision (TTC)

Time to collision (TTC) is defined as the gap distance between a subject vehicle and another vehicle divided by their velocity difference (Lee, 1976). A lower TTC value means it has a very short time for vehicles to avoid collision. In this model, average TTC values are used to assess the hazard level of different kinds of conflicts. Suppose the relative velocity is $(v_n^t - v_{n+1}^t)$ at time t and gap is d_n^t , the time to catch up with front vehicle (or conflict vehicle) is t_{TTC} which can be calculated as:

$$t_{TTC} = d_n^t / (v_n^t - v_{n+1}^t) \quad (5.1)$$

Post-encroachment Time (PET)

Post-encroachment Time (PET) is defined as the time duration for a vehicle to reach, occupy, and leave the conflict zone if a conflict is observed (Cooper, 1984). For example, the conflict area between right-turn and opposite straight-through vehicles is defined as shown in Figure 5.2, where t_1 represents the time step when the right-turn vehicle starts to enter the conflict zone that is occupied by the opposite straight-through vehicle; t_2 represents the time step when the same right-turn vehicle exits the conflict zone (after passage of the straight-through vehicle). Therefore, PET is calculated as:

$$t_{PET} = t_2 - t_1 \quad (5.2)$$

Figure 5.2 Definition of conflict zone for Conflict type (4)

Criticality Index (CI)

Criticality Index (CI) is defined to measure the severity and likelihood of a probable conflict (Chan, 2006). Two assumptions have been made: 1) when collision velocity is higher, the collision will be more severe; 2) when TTC is longer, the collision is more likely to be avoided. Therefore, CI is calculated as:

$$CI = (v_n^t - v_{n+1}^t)^2 / t_{TTC} \quad (5.3)$$

5.2.3 Model validation

Simulated safety indicators in the form of average TTC, PET and CI based on 200 simulated conflicts, are compared against 200 observed vehicle conflicts from video extraction (Chai and Wong, 2013) at a case junction (Site No.7), as shown in Table 5.2. The CA model is confirmed to be able to replicate realistic signalised junction traffic at the macroscopic level for both capacity and safety assessment. For example, Conflict Type (4) is found to be more severe than other conflicts in both observed and simulated conflicts.

Table 5.2 Comparison of average safety indicators between CA simulation and field data

Conflict Type	TTC			PET			CI		
	Obs ¹	Sim ²	Error	Obs ¹	Sim ²	Error	Obs ¹	Sim ²	Error
1	0.95	0.97	-2.11%	1.45	1.48	-2.07%	9.50	9.10	4.21%
2	1.05	1.06	-0.95%	1.75	1.71	2.29%	7.55	7.28	3.58%
3	1.00	0.96	4.00%	1.05	1.06	-0.95%	9.56	9.73	-1.78%
4	0.52	0.50	3.85%	1.10	1.03	6.36%	19.34	17.82	7.86%
5	1.05	1.06	-0.95%	1.90	1.89	0.53%	8.59	8.49	1.16%
6	1.20	1.15	4.17%	2.45	2.41	1.63%	4.62	4.99	-8.01%
7	1.00	0.97	3.00%	1.50	1.56	-4.00%	7.80	8.23	-5.51%

Obs¹: Observed average safety indicator

Sim²: Simulated average safety indicator

5.3 Comparison between CA and SSAM

A software package called Surrogate Safety Assessment Model (SSAM) developed by Federal Highway Administration (FHWA) has been used to estimate conflicts. SSAM identifies critical safety indicators, such as Time-to-Collision (TTC) through trajectory files based on several algorithms (Gettman et al., 2008). In essence, SSAM relies on simulation packages (such as VISSIM), which require additional calibrations.

Several researchers have evaluated the feasibility of SSAM. Huang et al. (2013) developed a linear regression model to compare simulated and observed conflicts to evaluate the accuracy of SSAM and VISSIM simulation. They found that SSAM is able to provide acceptable results for rear-end conflicts. However, simulation results of lane-changing and crossing conflicts are only moderately acceptable, with higher Mean Average Percentage Error (MAPE) values.

5.3.1 Development and calibration of VISSIM and SSAM

PTV VISSIM is used to conduct microscopic simulation and produce trajectory files for safety assessment based on SSAM. A typical cross-junction, with the same geometric layout, signal timing and vehicle inputs as that used in the proposed CA model, was built in PTV VISSIM, as shown in Figure 5.3 and Appendix G. The physical size and desired velocity for different types of vehicles in VISSIM are also

the same as those modelled in CA. As motorcycles cannot be simulated in VISSIM, they are simulated as bicycles with motorcycles' movement characteristics. The Wiedemann74 model was selected to model car-following behaviour of vehicles (PTV, 2006). A reduced velocity area for turning vehicles at junction-boxes, and priority rules between right-turn vehicles and opposite straight-through vehicles, are defined according to field observations. Since SSAM is not able to analyse vehicle-pedestrian conflicts (FHWA, 2011), signalised pedestrian crosswalks are not simulated in PTV VISSIM.

Figure 5.3 Simulated junction layout in VISSIM

A two-stage calibration of VISSIM and SSAM was carried out based on a similar previous study (Huang et al., 2013). In the first-stage calibration, traffic volume, headway and velocity from field observations are used to calibrate the simulation model. A calibration procedure based on Genetic Algorithms (GA) and Chi-square tests are conducted to compare traffic flow rates and velocities from simulation and observations, based on calibrated values of the parameters (Liu et al., 2012).

The second-stage calibration is to improve the consistency between simulated and observed vehicle conflicts. For each conflict type (rear-end, lane-changing and crossing), sensitivity tests are conducted for each simulation parameter, to identify the effect of varying each parameter on conflict occurrence. Threshold TTC value is

chosen as 3s and threshold PET value is chosen as 3.5s as introduced in Section 3.4.3.

5.3.2 Comparison of simulated conflicts

Simulated vehicle conflicts from CA and SSAM are compared with observed vehicle conflicts with similar geometric layouts and signal timings. In CA, the simulation runs for 30 signal cycles, or approximately 1 hour. In VISSIM, the simulation runs also for one hour. Outputs are calculated using the results of five runs as suggested by Zheng et al. (2012) to reduce errors caused by random variables. Occurrences as well as severity of each simulated conflict based on computation of safety indicators are recorded automatically.

i) Conflict occurrences

Tables 5.3 and 5.4 summarise simulated conflicts from CA, SSAM and field observations. Observed conflict occurrences are averaged over the six survey sites. Conflict occurrences are classified into different severity levels based on TTC and PET. The CI is not applied given that SSAM uses only the TTC and PET indicators. A smaller TTC or PET value suggests more severe conflict. Table 5.3 summarises conflict occurrences based on TTC values while Table 5.4 is based on PET values. For each severity group, the proportions of conflicts are calculated.

From Tables 5.3 and 5.4, both CA and SSAM are found to generate realistic numbers of conflicts compared to field observations. Several conclusions can be observed on simulation results from CA and SSAM.

1) Compared to field observations, SSAM tends to generate more rear-end and lane-change conflicts. The main reason is that route-decision module in VISSIM, upon which SSAM relies in this study, may cause an overall over-estimation of rear-end and lane-changing conflicts at junction approaches. In VISSIM, route decisions are made at a certain user-defined point. However, in CA model, drivers can dynamically make route decision at any time step. This shows that the CA model is more flexible in simulating vehicle movements and interactions.

2) Even though VISSIM is calibrated to remove simulated crashes (with 0-value TTC and PET), around 50 crashes, mostly crossing conflicts, are detected in the SSAM approach. It indicates that the simulation has generated some unrealistic conflicts (Huang et al. 2008). Moreover, the proportion of severe crossing conflicts ($TTC \leq 0.5s$ or $PET \leq 1s$) in SSAM is much larger than field observations and CA.

3) On the contrary, compared to CA, the SSAM approach is found to underestimate the severity of rear-end and lane-changing conflicts. The most possible reason is, in the context of this study, all simulated drivers in VISSIM keep a relatively large lateral distance to vehicles on adjacent lane with cooperative lane-changing.

Table 5.3 Comparison of conflict occurrences based on TTC

	TTC$\leq 3s$			TTC$\leq 1.5s$			TTC$\leq 0.5s$		
	Obs[†]	CA	SSAM	Obs[†]	CA	SSAM	Obs[†]	CA	SSAM
Rear-end	134 (—)	136 (—)	292 (—)	58 (43%)	60 (44%)	29 (10%)	18 (13%)	10 (7%)	3(3)* (1%)
Lane-change	39 (—)	33 (—)	76 (—)	16 (41%)	13 (39%)	8 (11%)	4 (10%)	5 (15%)	2(2)* (3%)
Crossing	155 (—)	152 (—)	150 (—)	80 (52%)	76 (50%)	84 (56%)	52 (34%)	47 (31%)	73(49)* (49%)

Obs[†]: Observed vehicle conflicts

*: Number in the parenthesis indicate simulated crashes (TTC=0s)

Table 5.4 Comparison of conflict occurrences based on PET

	PET$\leq 3.5s$			PET$\leq 2s$			PET$\leq 1s$		
	Obs[†]	CA	SSAM	Obs[†]	CA	SSAM	Obs[†]	CA	SSAM
Rear-end	154 (—)	155 (—)	262 (—)	51 (33%)	47 (30%)	34 (13%)	30 (19%)	34 (22%)	10(3)* (4%)
Lane-change	39 (—)	33 (—)	70 (—)	16 (41%)	13 (39%)	42 (60%)	10 (26%)	5 (15%)	6(2)* (9%)
Crossing	175 (—)	178 (—)	165 (—)	75 (43%)	74 (42%)	95 (58%)	32 (18%)	35 (20%)	57(49)* (35%)

Obs[†]: Observed vehicle conflicts

*: Number in the parenthesis indicate simulated crashes (TTC=0s)

ii) Distribution of safety indicators

For each conflict type, Figure 5.4 summarises cumulative distributions of conflicts (observation, CA and SSAM) for a range of TTC or PET values. According to

Figure 5.4, distributions of safety indicators (both TTC and PET) from CA and field observations are very similar. However, a large number of 0 indicators are generated from SSAM and thus deviates from the other distributions of safety indicators.

From Figure 5.4, even though SSAM approach is calibrated to eliminate simulated crashes, the difference between SSAM and CA/observations is very obvious and vary among different conflict types. It is found that, for rear-end and lane-change conflicts, PET values from SSAM are much closer to CA and field observations than for TTC. Moreover, even though SSAM is found to over-estimate the occurrences of rear-end and lane-change conflicts, it is found to under-estimate the severity.

It is also found that although the conflicts simulated by CA and field observations show very good agreement, the severity of lane-change conflicts are slightly underestimated by the CA model according to Figure 5.4. This may be caused by discretisation or inadequate lane-changing rules in the proposed CA model.

Figure 5.4 Distribution of safety indicators from CA and SSAM

iii) Vehicle movements and conflict severity

In this study, Vehicle-to-vehicle (V2V) conflicts in Table 5.1 are classified as 3 different groups to compare with CA and SSAM. Types (1)-(3) Conflicts are classified as rear-end conflicts; Types (4) and (5) Conflicts are classified as lane-change conflicts, and Types (6)-(7) Conflicts are classified as crossing conflicts. However, distributions of safety indicators for different conflict types within the same group may not be the same. Comparisons between conflict types in each group are computed as shown in Figure 5.5.

According to Figure 5.5, distributions of safety indicators of conflicts within the same group are very different. Among rear-end conflicts, even though the three conflict types have similar distributions for varying TTC values, according to PET values, Type (3) Conflict (involving U-turn vehicles) is more severe. For lane-change conflicts, Type (7) Conflict (over-taking and lane-changing) is slightly less severe than the other conflict types (downstream merging). Moreover, Type (4) Conflict (right-turn against) is found to be more severe than Type (5) Conflict (involving U-turn vehicles). It is noted that conflicts are analysed as three major groups within SSAM hence SSAM cannot differentiate conflicts within each group. Higher conflicts reflect higher potential of actual crashes (Oh et al., 2010). To support surrogate safety assessment approaches, an empirical study was conducted which revealed a positive relationship between near-crash events and crashes (FHWA, 2010). As both CA and SSAM are built on vehicle trajectories, the two approaches simulate microscopic vehicle behaviour and conflicts, and estimate interactions between vehicles. Even though safety indicators, such as conflict occurrences, TTC and PET, are not directly comparable to conventional conflict techniques based on rating, more frequent and severe vehicle conflicts represent higher likelihood of collisions. Moreover, according to accident records in Singapore from 2009 to 2011, crossing crashes constitute around 50% of total occurrences and also being the highest fatality proportion (Singapore Police Force 2012). This corroborates with simulation results from both CA and SSAM that crossing conflicts, especially Conflict Type (4) has the highest severity (lower TTC and PET values) compared to other types. The accident occurrences also show that accident occurrences (especially severe injury and fatal) among all conflict types is

crossing> rear-end> lane-change. Over all, observed accident data validate the proposed surrogate safety assessment based on conflicts in being able to provide reasonable assessment of safety level.

iv) Conflicts between vehicles and pedestrians

Conflict occurrences simulated by the CA model with TTC smaller than 2.0s are summarised in Figure 5.6 while noting that Vehicle-to-pedestrian (V2P) conflicts cannot be analysed in SSAM (FHWA 2011). Based on relative movement directions, each conflict type is further divided into ipsilateral and opposite. From the simulation results, the proposed CA model allows users to estimate conflict occurrences between vehicles and pedestrians based on different severity levels.

Several conclusions can be observed in term of occurrence and severity of vehicle-pedestrian conflicts. First, conflicts during the green-man phase (Conflict types (a) and (b)) occur more often than conflicts during the red-man phase. As occurrence of vehicle-pedestrian conflicts is subject to the number of pedestrians using the cross-walk, the fewer occurrences of conflicts are due to fewer pedestrians crossing the junction during the red-man phase. Also, in terms of severity, opposite conflicts are found to be more severe than ipsilateral ones. Most conflicts with smaller TTC values are opposite conflicts. Similar results can be observed in all other scenarios. The same is found in several studies that are based on observation of road traffic (Ren et al., 2012). Opposite movement directions will result in higher relative speed and less time for reaction to avoid collision. Moreover, opposite conflicts occur with vehicles about to enter the departure lanes. Such vehicles have higher velocity compared to vehicles that have just left the stop-line.

Figure 5.5 Comparison of safety indicators within the same conflicts group

Figure 5.6 Conflict occurrences between vehicles and pedestrians

(Risk degree 1: $TTC \leq 0.84s$; Risk degree 2: $0.84s < TTC \leq 1.27s$; Risk degree 3: $1.27s < TTC \leq 1.98s$; Risk degree 4: $TTC > 1.98s$)

5.3.3 Discussions and conclusions

According to the simulation results, a large number of conflicts with indicators, both TTC and PET, being equal to 0 are estimated by SSAM. Those unrealistic conflicts lead to a larger error when analysing severity levels. Moreover, compared to CA and field observations, SSAM is found to over-estimate lane-change conflicts due to unrealistic lane-changing behaviour in VISSIM. Also, as there are only three groups of conflicts in SSAM, it is not feasible to study differences between different conflict types within the same group.

Compared to SSAM, the microscopic simulation approach by CA modelling has several advantages. First, CA models allow local calibration based on several aspects of vehicle movements and interaction between vehicles. Especially for signalised junctions, the behaviour and decisions of road users can also be simulated and adjusted based on observation. Based on local calibration, simulated conflicts from CA model are more close to observed conflicts. Furthermore, the CA model developed in this study is able to simulate and analyse conflicts between vehicles and pedestrians.

Compared to the CA approach, VISSIM-SSAM approach also has several advantages. Firstly, as first developed in 2008, the VISSIM-SSAM approach has been applied by many researchers and has been validated with crash records (Gettman et al., 2008; Huang et al., 2013). The present CA approach, on the other hand, being first published in 2014, and has not been validated as extensively as SSAM (Chai and Wong, 2014a). Moreover, even though both approaches allow users to adjust parameters such as maximum TTC, SSAM provides a well-developed user interface. SSAM also provides graphic details of angles and exact locations of each conflict. Last but not least, due to the discrete nature, CA provides less accurate resolution than continuous simulation models used in the VISSIM-SSAM approach. Therefore, when applying the CA approach in complex scenarios, special attention shall be paid to calibration and validation of the movement rules.

5.4 Application-1: Vehicle-vehicle conflicts involving right-turn vehicles

5.4.1 Experimental design

Four case junctions with different lane configuration and signal timings for right-turn vehicles along East-West approaches are created, as shown in Figure 5.7. The geometric layout with two lanes in each approach is very common in most minor signalised junctions in Singapore. Another reason for choosing two-lane approaches for simulation is that if no exclusive right-turn is given, conflicts along shared lane will be more frequent. For Junctions (1) and (2), a permissive right-turn phase followed by a protected right-turn phase is applied; for Junctions (3) and (4), a RAG Arrow: protected right-turn phase is applied. Junctions (1) and (3) have shared straight-through and right-turn lanes and Junctions (2) and (4) are using exclusive right-turn lanes.

To create various simulation scenarios, two variables, signal timings and traffic volume, are defined in each case junction. First, two signal timings (Set A and Set B, as shown in Figure 5.8) are applied with fixed cycle length and different green time for straight-through and right-turn green phases. The two applied signal timings have been observed in different locations with the same geometric layout as the Case Junctions. The studied approach is the major (or E-W) approach with larger traffic volume and longer green time. Two simulation experiments are conducted.

1) For each group of timings (Case Junction and Signal Timing), different traffic volume is applied in each scenario. Straight-through and right-turn vehicles in the approach are simulated at 200veh/h step intervals from 200veh/h to 1,000veh/h per approach for each vehicle movement independently (approximate saturation degree = 0.2 to 1.0 for each lane). The simulation runs for 30 signal cycles, or approximately 1 hour. Outputs are the average of results of 5 runs, as suggested by Zheng et al. (2012).

2) For each group of settings, the average DOC per vehicle for 25 runs in different traffic volumes is averaged. In this way, the average DOC for each combination of control strategies is estimated.

To determine the traffic volume of opposing straight-through flow in simulation, a sensitivity test is conducted over a range of opposing straight-through traffic volume from 100veh/h/lane to 600veh/h/lane (saturation degree=0.14 to 0.89). Two layouts with one or two opposing straight-through lanes are simulated. The right-turn traffic volume is fixed at 1,000veh/h per approach. The simulation results are summarised in Figure 5.9.

As shown in Figure 5.9, Type (4) Conflicts, as defined in Table 5.1, increase gradually with an increasing traffic volume of opposing straight-through vehicles. The frequency of DOC per vehicle for 2 opposing straight-through lanes is larger than for 1 lane. In both layouts, DOC per right-turn vehicle tends to a maximum value (0.6) when opposing straight-through flow exceeds 500veh/h/lane. In essence, when the opposing straight-through flow is saturated, there will not be sufficient gap for right-turn vehicles. In practice, a permissive right-turn signal phase will not be considered in such saturated situations. Therefore, in this study, the opposing straight-through traffic volume is fixed at 400veh/h/lane within two limiting regimes: at over 500veh/h/lane, the opposing straight-through flow will not be able to provide sufficient gaps for right-turn vehicles to filter through; at less than 300veh/h/lane, the opposing straight-through flow is basically too low to generate enough vehicle conflicts for analysis.

5.4.2 Simulation results

In all simulation scenarios, the average number of DOC per vehicle is calculated to indicate the degree of occurrence of vehicle conflicts. The simulation results show how input factors, including permissive right-turn or RAG Arrow, signal timing, shared lane and traffic volume, affect the occurrence of vehicle conflicts. The effect of a permissive right-turn, a shared right-turn lane and signal phasing on vehicle conflicts at junction approach was thus evaluated over a range of traffic volume for both traffic movements.

i) Severity of Types (2) & (4) Conflicts

Figures 5.10 shows the cumulative distributions of DOC for a range TTC values, for Types (2) & (4) Conflicts with 800veh/h for each vehicle movement in Junction (1) with Signal Timing (A). In the CA model, velocity and position of vehicles are discrete numbers, hence the simulated TTC values are also discrete.

Figure 5.7 Geometric configuration and signal phasing for case study junctions: Junctions (1)(2): Permissive right-turn phase followed by right-turn green arrow; Junctions (3)(4): RAG Arrow; Junctions (1)(3): Shared straight-through and right-turn lane; Junctions (2)(4): Exclusive right-turn lane.

	Set (A)	Set (B)
40s	30s	Green phase for straight-through vehicles
	3s	3s	Amber
	1s	1s	All-red
20s	30s	Green phase for right-turn vehicles
	2s	2s	All-red
20s	20s	Green phase for straight-Through vehicles
	3s	3s	Amber
	1s	1s	All-red
15s	15s	Green phase for right-turn vehicles
	2s	2s	All-red

Figure 5.8 Signal timings applied in simulation scenarios

Figure 5.9 DOC per right-turn vehicle for different opposing straight-through traffic volume

Figure 5.10 Cumulative distribution of DOC of Types (2) & (4) Conflicts

Suppose a TTC threshold of 1.5 s is selected so as to distinguish a relatively severe conflict. From Figure 5.10, around 15% of Type (2) (rear-end) conflicts and 99% of Type (4) conflicts will be selected. There are more conflicts simulated for Type (2) than Type (4) (crossing), but Type (4) conflicts are generally much more severe. This conclusion is consistent with traffic accident data, as in 2011 there were 593 rear-end, 63 lane-changing and over-taking collisions and 1,571 right-turn-against collisions that occurred at the signalised junctions (Singapore Police Force, 2012).

ii) Relationship between conflict occurrences (DOC) and traffic volumes

Traffic volume is found to have an obvious effect on Type (2) conflicts at the junction approach. Figure 5.11 shows the trend of DOC with varying input traffic volumes for Junction (1) and Signal Timing (A). For the other junctions and signal timings, the trends of DOC change with traffic volumes are much the same as in Figure 5.11. The X and Y axes represent traffic volumes of straight-through and right-turn vehicles in the approach, with a 200veh/h/lane step interval from 200veh/h to 1,000veh/h (approximately 20-100% of total capacity). Average DOC values are calculated for all straight-through and for right-turn vehicles. Larger DOC indicates more frequent occurrences of vehicle conflicts. The dots represent average simulation outputs of 5 runs in the same simulation scenario. Lowess method (locally weighted smoothing linear regression) was used to generate the surface (minimum R-square= 0.9532).

Figure 5.11 DOC per straight-through vehicle (R-square=0.9532)
(Type (2) Conflicts, Junction (1), Signal Timing (A))

From Figure 5.11, as higher DOC implies more frequent vehicle conflicts, conflicts for each straight-through vehicle decrease as the straight-through traffic volume increases, and increase when the right-turn traffic volume increases. Moreover, as conflicts for straight-through vehicles along junction approach are caused by right-turn vehicles, average conflicts per each straight-through vehicle will increase when the right-turn traffic volume is increasing.

Figure 5.12 shows the trend of DOC per right-turn vehicle with varying input traffic volumes. For the other junctions and signal timings, the trends of DOC change with traffic volumes are much the same as in Figure 5.12.

Figure 5.12 DOC per right-turn vehicle (R-square=0.8611)
(Type (2) Conflicts, Junction (1), Signal Timing (A))

Trends for right-turn vehicles are much the same in all the selected scenarios (both permitted and RAG Arrow, both long and short green times for the right-turn green phase), as DOC at its maximum value when there are high straight-through flow and low right-turn flow. The conflict frequency for each right-turn vehicle decreases as the right-turn traffic volume increases, and increases as the straight-through traffic volume increases, especially when the right-turn volume is low.

On the other hand, according to a linear regression analysis between simulated traffic volumes and DOC for Type (2) conflicts for all scenarios ($R^2 = 0.39$, $F = 7.05$), the influence of traffic volume is not found to be statistically significant ($p > 0.05$) for Type (2) conflicts.

iii) Relationship between conflict occurrences (DOC) and junction control

For all the junctions, the average DOC per vehicle for different traffic volumes and signal timings are calculated. Tables 5.5 and 5.6 respectively summarise the average DOC results for Types (2) & (4) conflicts. DOC per vehicle with TTC smaller than 1.5s indicates relatively severe conflicts. In Table 5.5, as Type (2) conflicts between right-turn vehicles and straight-through vehicles along the same approach occur mainly at shared lanes before the stop-line, Junctions (1) and (3) are selected for comparison. In Table 5.6, Junctions (1) and (2) are selected for comparison as they both have permissive right-turn signal phases, which are associated with Type (4) conflicts.

Table 5.5 Comparison of average DOC of Type (2) Conflicts

DOC per straight-through vehicle				DOC per right-turn vehicle		
Signal timings	Junction(3) RAG Arrow	Junction(1) Permissive	Difference	Junction(3) RAG Arrow	Junction(1) Permissive	Difference
Timing (A)	1.54 (0.23*)	1.31 (0.20*)	– 6.55%	1.23 (0.18*)	0.85 (0.13*)	– 30.89%
Timing (B)	1.62 (0.24*)	1.44 (0.22*)	– 12.69%	1.05 (0.16*)	0.75 (0.11*)	– 28.57%
Difference	4.80%	9.20%		– 17.10%	– 13.3%	

*: DOC per vehicle with TTC smaller than 1.5s

Table 5.6 Comparison of average DOC of Type (4) Conflicts

DOC per right-turn vehicle			
	Junction (1) shared lane	Junction (2) exclusive lane	Difference
Timing (A)	0.50 (0.49*)	0.35 (0.35*)	– 30.00%
Timing (B)	0.37 (0.37*)	0.29 (0.29*)	– 27.59%
Difference	– 35.14%	– 10.34%	

*: DOC per vehicle with TTC smaller than 1.5s

As shown in Table 5.5, permissive right-turns can reduce Type (2) conflicts at a junction approach in all simulated scenarios, because right-turn vehicles are less likely to block following straight-through vehicles during the full-green signal phase. The reduction for right-turn vehicles is more substantial because during the straight-through green phase, right-turn vehicles are allowed to queue beyond the stop line. However, during the right-turn green phase, straight-through vehicles cannot cross the stop line, resulting in more opportunities for Type (2) conflicts along approach. Signal timings are found to have an obvious effect on Type (2) conflicts along the approach. A longer right-turn green arrow phase and shorter straight-through green phase increases vehicle conflicts for straight-through vehicles and reduces conflicts for right-turn vehicles.

From Table 5.6, the use of a shared straight-through and right-turn lane is found to have an obvious negative effect on Type (4) conflicts. For signalised timings, a longer right-turn green arrow phase and shorter straight-through green phase (Timing (B)) will reduce Type (4) conflicts between straight-through vehicles and right-turn vehicles.

5.4.3 Discussion of simulation results

With a safety indicator of average DOC per vehicle that is obtained from microscopic simulation, the influence of a permissive right-turn, a shared straight-through and right-turn lane, signal timings and traffic volume are analysed. It is found that conflict occurrences involving right-turn vehicles (with both alongside and opposing straight-through vehicles) are affected by lane configuration and signal timings (as summarised in Table 5.7). DOC per vehicle with TTC smaller than 1.5 are selected for comparison. Through microscopic simulation, the impacts of several factors can be analysed quantitatively. In Table 5.7, an increase of

frequency of conflicts is represented by the symbol “+” and a reduction of conflicts by “-”. Effect of each input factor is estimated by averaging simulation results over a range of other factors.

i) Impact of permissive right-turn phase

According to the simulation results summarised in Table 5.7, the incidence of conflicts involving right-turn vehicles, both Types (2) & (4) conflicts, are very sensitive to the use of a permissive right-turn and shared-movement lane. A permissive right-turn significantly reduces the occurrence of Type (2) conflicts both for straight-through and right-turn vehicles along the junction approach (9.62% for straight-through vehicles, 29.73% for right-turn vehicles). However, the use of permissive right-turn results in additional Type (4) conflicts between right-turn vehicles and opposing straight-through vehicles. In conventional junction design guidelines, a permissive right-turn phase is considered to improve junction capacity by saving travel time for right-turn vehicles but tends to decrease junction safety due to more Type (4) conflicts. However, simulation results in this study show that a permissive right-turn is able to reduce vehicle conflicts along a shared lane at junction approaches, by reducing the risk of Type (2) conflicts.

It is also noted that in scenarios with a permissive right-turn, the reduction in DOC per right-turn vehicle along the approach is less than the increase in DOC per vehicle at the junction-box area in most simulation scenarios, that is, the negative effect outweighs the positive effect. Thus, for traffic engineers, when applying permissive right-turn control, management of Type (4) conflicts should be first taken into consideration. For example, there will be situations where the opposing straight-through traffic is not too heavy and there are enough gaps for right-turn vehicles to filter through and complete the turn. The geometric layout of junction approach should also be taken into consideration as a permissive right-turn can help to reduce vehicle conflicts along an approach with a shared lane.

Table 5.7 Summary of average DOC (TTC<1.5s) influenced by several factors

Factors	Type (2) Conflicts at junction approach		Type(4) Conflicts at junction-box
	Straight-through	Right-turn	Right-turn
Permissive right-turn	– 9.62%	– 29.73%	+ 58.80%
Straight-through and right-turn lane	+22.45%	+39.27%	+28.80%
Straight-through traffic volume along studied approach (200-1000 veh/h/lane)	Obvious (–)	Obvious (+)	Not obvious
Right-turn traffic volume along studied approach (200-1000 veh/h/lane)	Obvious (+)	Obvious (–)	Not obvious
Longer right-turn arrow phase (30s instead of 20s)	+ 7.01%	– 15.25%	– 22.74%

ii) Impact of shared straight-through/ right-turn lane

Usage of shared lanes can increase the flexibility of assigning lane grouping to accommodate variable traffic volumes by direction. However, a shared lane is not always beneficial as it can at time result in blockage, which leads to both capacity and safety constraints. Simulation results indicate the usage of shared lanes increases both Types (2) & (4) conflicts by a large amount. The increase of Type (2) conflicts within a shared lane is very obvious. However, according to the simulation results, the occurrence of Type (4) conflicts will also be increased with shared lane usage. This phenomenon can be explained by car following behaviour. When right-turn vehicles are queued at an exclusive lane, they pass the stop-line and move into the junction-box area in a platoon. Therefore, if a sufficient gap occurs in the opposing straight-through vehicles, it is likely that right-turn vehicles will tend to move in a platoon. However, for a right-turn vehicle coming from a shared lane, as they queue between straight-through vehicles, they enter the conflict zone separately, which could increase the frequency of conflicts with opposing straight-through vehicles.

On the other hand, according to the simulation results, both a shared lane and RAG Arrow will increase the occurrence of Type (2) conflicts. Therefore, if a RAG Arrow is selected to reduce Type (4) conflicts, an exclusive lane could be provided in lieu of shared lane to reduce Type (2) conflicts.

iii) Impact of traffic volumes

As the occurrence of conflicts is calculated as DOC per vehicle, the impact of total traffic volume is also analysed. The traffic volume at the studied approach is found to have a significant influence on Type (2) conflicts only. That is, a higher straight-through traffic volume will reduce conflicts per straight-through vehicle and increase conflicts per right-turn vehicle. On the contrary, a higher right-turn traffic volume will increase conflicts per straight-through vehicle and reduce conflicts per right-turn vehicle. These results have demonstrated that when one of the two traffic movements is dominant at a shared lane, vehicles in the other movement will have a higher conflict frequency.

On the other hand, for the case that the opposing straight-through volume is fixed, the right-turn volume is found not to have significant influence on Type (4) conflicts. This is the case even when total conflicts increase with traffic volume, as the average conflicts per vehicle remains unchanged.

iv) Impact of signal timing

In this study, two sets of signal timings are simulated. With the total green time fixed, 10s extra green arrow signal time is added in Signal Timing (B) at the expense of a 10s reduction in the straight-through green phase (see Figure 5.8). A longer right-turn green arrow time reduces the conflicts per right-turn vehicle (both Types (2) & (4) conflicts) and increases the conflicts per straight-through vehicle.

Therefore, in practice, the safety level for right-turn vehicles at junctions with a permissive right-turn phase and a shared straight-through and right-turn lane can be improved by giving a longer green time for the right-turn green arrow phase.

5.5 Application-2: Risk degree assessment of vehicle-vehicle conflicts

5.5.1 Conflict risk clustering based on SOM algorithm

i) Introduction of the algorithm

In this study, conflict risk is estimated by a clustering analysis based on the Self-Organising-Map (SOM) algorithm. Degrees of risk are classified according to the simulation results of the three safety indicators of TTC, PET and CI.

The SOM algorithm is a commonly used clustering method based on Neural Networks (NN). Compared to the k-means clustering algorithm, the SOM method is more efficient when the original clustering centre is not well defined (Ren et al., 2012). Like other NN models that use computation abstraction of biological neural models, SOM operates in two modes: training and mapping. In the training mode, a map is built using input examples. In the mapping mode, a new input is automatically classified. As inputs are classified by a simple geometry calculation, the learning algorithm is to cause different parts of the network to detect the similarity of certain input patterns and classify into groups. Through network training (iterations), similar inputs will be mapped to a same output node, and then followed by clustering (Zhang et al., 2010). As described in the following, there are several steps to apply the algorithm of multiple indices.

1) Initialisation

Define the input data (simulation results from CA) as $X = [x_1, x_2, x_3]^T$, where x_1 , x_2 and x_3 are the three indicators (TTC, PET and CI) recorded automatically for each conflict from micro-simulation based on CA. An initial weight vector $W = [w_1, w_2, w_3]^T$ is defined randomly.

2) Competition

At iteration number m , compute the Euclidean distances between all inputs and outputs to find the winner class for each input. The Euclidean distance is calculated as

$$d_j = \sqrt{\sum_{i=1}^L [x_i(m) - w_{ji}(m)]^2} \quad (5.4)$$

The winner class (C) is selected with the minimum distance, obtained by

$$C = \arg \min\{d_j, j = 1, 2, \dots, N\} \quad (5.5)$$

where j is the number of neuron outputs (degree of risk in this study), $w_{ji}(t)$ is the i^{th} component weight vector of the output node, $x_i(t)$ is the i^{th} input at time t .

3) Learning

For each output, update the weight of each index according to the following equation:

$$w_j(m+1) = w_j(m) + \eta(m)h_{j,c}(m)[X(m) - w_j(m)] \quad (5.6)$$

where $h_{j,c}(m)$ is the neighbourhood function of winner neuron C , and η is the learning velocity (pre-defined as 0.5 in the network training).

4) Repeating

The steps 2) and 3) are repeated until the outputs converge or the maximum iteration time is reached.

ii) Experimental design

A case junction (Site No.3 as described in Appendix B) has been developed by using CA model. Two simulation scenarios using the CA model are developed, one in congested flow (saturation degree= 0.9) and another in quiet flow (saturation degree= 0.5). Simulated signal timings are based on field observations over 6-7pm (congested) and 12am-1pm (quiet). In congested traffic, a total number of 1,391 conflicts, classified as seven conflict types shown in Table 5.1, are recorded from simulation. In quiet traffic, 548 conflicts are recorded. For the two scenarios, typical SOM clustering is conducted by using the Self-Organising-Map function of the Neural Network Toolbox in Matlab.

5.5.2 Clustering results

Clustering results for the two scenarios are shown in Tables 5.8 and 5.9, and Figures 5.13 and 5.14. From Tables 5.8 and 5.9, the strongest vehicle conflicts, with the lowest TTC, PET and highest CI, are represented as Risk Degree (1). Risk Degree (2) represents relatively strong conflicts. (3) represents relatively weak and (4) represents the weakest conflicts. In both simulation scenarios (congested and quiet traffic) the majority of total DOC recorded are classified as Risk Degrees (3) and (4). Only about 1% of DOC are classified as very strong conflicts. The simulation results indicate that weak conflicts have much more frequent occurrences than strong conflicts.

Compared to congested traffic, clustering centres of Risk Degrees (1), which is the most severe, in quiet traffic have smaller TTC value and larger CI value and about the same PET values. For Risk Degree (2), the cluster centre of quiet traffic also has smaller TTC value and larger CI value, even though the PET values are larger. It can be observed that vehicle conflicts in quiet traffic have a larger risk degree than in congested traffic. This conclusion is corroborated by a combined clustering analysis of DOC for both scenarios (Table 5.10), where quiet traffic has larger proportions of the first three classes.

Figures 5.13 and 5.14 show the clustering results from congested and quiet traffic. Each dot in the 3D space represents a DOC entry with three indicator values, TTC, PET and CI. As vehicle velocity and position are discrete values in the CA model, most of the dots coincide with each other. From the two figures, even though the number of conflict occurrences is much larger in congested traffic, the ranges of the indicators in observed conflicts are very similar for the two scenarios.

According to the seven conflict types as categorised in this study shown in Table 5.1, and combined with clustering results, a comparison of risk degrees of different conflict types for congested and quiet traffic are shown in Figures 5.15 to 18.

Table 5.8 Clustering results under congested traffic flow

Clustering results (Class No. = 4)	Conflict risk degree			
	1	2	3	4
	Very strong	Strong	Weak	Very weak
Clustering centre (TTC, PET, CI)	(0.18,0.33,51.6)	(0.36,0.86,24.4)	(0.78,1.09,10.2)	(1.36,2.45,1.93)
DOC no.	12 (0.86%)	192 (13.80%)	677 (48.67%)	510 (36.66%)

Table 5.9 Clustering results under quiet traffic flow

Clustering results (Class No. = 4)	Conflict risk degree			
	1	2	3	4
	Very strong	Strong	Weak	Very weak
Clustering centre (TTC, PET, CI)	(0.17,0.33,52.6)	(0.33,0.90,26.7)	(0.80,1.06,10.7)	(1.28,2.42,1.86)
DOC no.	7 (1.28%)	62 (11.31%)	294 (53.65%)	185 (33.76%)

Table 5.10 Clustering results of combined simulation scenarios

Clustering results (Class No. = 4)	Conflict risk degree			
	1	2	3	4
	Very strong	Strong	Weak	Very weak
Clustering centre (TTC, PET, CI)	(0.17,0.33,51.6)	(0.32,0.83,25.97)	(0.90,1.50,10.30)	(1.35,2.44,1.93)
DOC from congested traffic	30 (2.16%)	154 (11.07%)	714 (51.33%)	493 (35.44%)
DOC from quiet traffic	17 (3.10%)	79 (14.42%)	304 (55.47%)	148 (27.01%)

Figure 5.13 Clustering results of three indicators in congested traffic

Figure 5.14 Clustering results of three indicators in quiet traffic

Figure 5.15 Comparison of risk degree by conflict types (congested traffic)

According to Figures 5.15 and 5.16, under congested traffic, several conclusions can be made regarding the occurrence and risk degree of vehicle conflicts.

1) In terms of conflict occurrences, Conflict Types (1), (2) and (4) are more frequent than the others. Conflict Types (1) and (2) are rear-end conflicts along junction approach and Type (4) is between right-turn and opposing straight-through vehicles in the junction-box. Conflict Types (3) and (6) are relatively more frequent than the Conflict Types (5) and (7). However, as the proportions of U-turn vehicles are based on observation at the case junction, occurrences of Conflict Types (3) and (5) would include number of U-turn vehicles.

Figure 5.16 Summation of DOC by conflict types (congested traffic)

2) Vehicle conflicts at signalised junctions can be classified into three groups: rear-end (Conflict Types (1) (2) and (3)); crossing (Conflict Types (4) and (5)); and lane-change (Conflict Types (6) and (7)). According to the clustering results, the severity ranking is crossing > rear-end > lane-change. Conflict Type (4) is the most severe one with all of the Risk Degree (1) conflicts belonging to this type.

3) Among the two conflict types involving U-turn vehicles, Conflict Type (3) has a more frequent occurrence. However, Conflict Type (5) is more severe. Most of the conflicts in Conflict Type (3) are classified as Risk Degrees (3) and (4) while 10% of conflicts in Type (5) are classified as Risk Degree (2).

Figure 5.17 Comparison of risk degree by conflict types (quiet traffic)

Figure 5.18 Summation of DOC by conflict types (quiet traffic)

In quiet traffic, the occurrences of all conflict types are reduced significantly. However, it is found that the severity of lane-change and crossing conflicts is, in relative terms, increased in quiet traffic. For crossing conflicts, the occurrence of Conflict Type (4) in quiet traffic is the most reduced (by 78%) from that for congested traffic. Conflict Type (4) is still the most severe conflict type (11% of conflicts are in Risk Degree (1)). For lane-change conflicts, even though the occurrences have been reduced, the proportions of more severe conflicts (Degrees (2) and (3)) have been increased in quiet traffic, especially for Conflict Type (7).

5.5.3 Comparison of clustering results with crash occurrences

Simulation results are compared to crash records, as shown in Appendix H. Accident occurrences of different injury levels from 2009 to 2011 are shown in Tables 5.11 and 5.12. Table 5.11 summarises crash counts per congested hour (7-9am, 5-7pm) while Table 5.12 summarises crash occurrences per quiet hour (7pm-7am, 9am-5pm) over the three years.

Crash records show the same characteristics as the previous risk analysis. During quiet hours, crash counts per hour are almost the same as congested hours. However, as traffic volume at quiet hours is much smaller, the exposure is less in quiet hours. The less exposure is probably related to higher average velocity during quiet hours, as found in other research and also in the simulation outputs (Woo and Ho, 2013).

Table 5.11 Accident counts (2009-2011) per congested hour

Conflict type	Accident occurrences per hour		
	Light injury	Severe injury	Fatal
1	17.8	0.0	0.4
2	11.6	0.0	0.2
3	1.1	0.2	0.2
4	71.3	2.5	1.8
5	3.3	0.0	0.0
6	5.1	0.4	0.2
7	0.6	0.0	0.0
Total	110.8	3.1	2.8

Table 5.12 Accident counts (2009-2011) per quiet hour

Conflict type	Accident occurrences per hour		
	Light injury	Severe injury	Fatal
1	17.1	0.5	0.7
2	7.4	0.4	0.1
3	1.5	0.0	0.1
4	61.2	2.0	1.4
5	3.2	0.0	0.0
6	0.7	0.0	0.1
7	0.7	0.0	0.0
Total	91.8	2.9	2.4

Crashes due to Conflict Type (4) constitute around 50% of total occurrences and also the highest fatality proportion. This corroborates with simulation findings that Conflict Type (4) has the highest severity based on the much higher fatal and injury numbers compared to other types. The crash occurrences also reaffirm the simulation finding that risk degree among all conflict types is crossing> rear-end> lane-change. Over all, the observed accident data validate the consistency of the proposed method in being able to provide a reliable assessment of conflict risk.

5.6 Application-3: Safety impacts of Red-Light-Cameras (RLC)

5.6.1 Case junction

To achieve a generalised safety impact of RLCs, four cross-junctions are used in assessing the impact of RLCs. Each approach from the same junction has the same geometric layout, as shown in Figure 5.19. For each case junction four simulation

scenarios have been created, as summarised in Table 5.13. The traffic volume for each vehicle type and signal timing is based on average values from site observations of the six studied approaches. Cycle length for each case junction is 120s, with 35s for the straight-through green phase with permissive right-turn, and 20s of exclusive right-turn phase for each approach. As the overall capacity of each approach is calculated as 1,330pcu/h, the traffic volume in the peak hour is chosen as 1,300pcu/h/ approach (saturation degree= 0.9), and 580pcu/h/approach for the off-peak hour (saturation degree= 0.4). The simulation runs for 30 signal cycles, or approximately 1 hour. Outputs are the average results of five runs.

Figure 5.19 Geometric layouts and signal phases of case junctions

Table 5.13 Simulation scenarios

Scenario	Installation of RLC	Traffic condition
Scenario (1)	Yes	Peak (270pcu/h/lane)
Scenario (2)	Yes	Off-peak (90pcu/h/lane)
Scenario (3)	No	Peak (270pcu/h/lane)
Scenario (4)	No	Off-peak (90pcu/h/lane)

5.6.2 Simulation results

Two types of junctions are simulated. One junction type has RLC installed on one of the approaches (defined as the subject approach) and the other junction type does not have RLC installed. Simulation outputs for each simulation scenario are the DOC with different TTC values. Average DOC per vehicle is computed to assess conflict occurrences. A higher DOC value indicates more frequent vehicle-vehicle conflicts. Moreover, as a smaller TTC value indicates a more severe conflict, simulated DOCs are compared on three levels; $TTC < 2$, $TTC < 1.5$ and $TTC < 1$. The perception-reaction time of drivers is taken as 1s, as used in most junction studies. A DOC with $TTC < 1$ indicates a very severe conflict that is more likely to result in a sudden deceleration or collision. Table 5.14 summarises the average number of red-running violations per hour for each simulation scenario for the subject approach. From Table 5.14, the installation of RLC reduces the number of red-running violations at the approach in both the peak (−55%) and off-peak periods (−57%).

Table 5.14 Simulated red-running violations

Scenario	Traffic condition	No. of red-running violations
Scenario (1)	Peak (1,300pcu/h/approach)	13
Scenario (2)	Off-peak (580pcu/h/ approach)	9
Scenario (3)	Peak (1,300pcu/h/ approach)	29
Scenario (4)	Off-peak (580pcu/h/ approach)	21

To simplify simulation, U-turn vehicles are not simulated in this experiment. Vehicle-vehicle conflicts that may not be due to red light violations are classified as rear-end (Types (1) to (2) as shown in Table 5.1), lane-changing (Types (6) and (7)), and right-turn-against (Type (4)) which can be due to straight vehicles not

complying with red signals. Another conflict group, namely right-angle conflict (between movements from cross approaches), is always caused by red light violation and is also simulated. Simulated DOC for the four different conflict groups are summarised in Table 5.15. The safety impacts of RLCs in peak and off-peak hours for different conflict types are summarised in Figures 3a-3f (plotted in different scales). The safety impacts for each simulation scenario are calculated as: [(No. of DOC per vehicle without RLC installed – No. of DOC per vehicle with RLC installed)/ No. of DOC per vehicle without RLC installed] x100%. Positive values indicate favourable effects (reduction of conflict occurrences) of RLC installation, while negative values indicate unfavourable effects (increase in conflict occurrences). The safety impacts of RLCs on rear-end and right-turn-against conflicts are calculated separately for the green and amber/red signal phases.

Table 5.15 Average DOC per vehicle for each conflict type

Conflict type	Scenario	TTC < 2s	TTC <1.5s	TTC < 1.0s
Rear-end	1	0.22	0.17	0.04
	2	0.30	0.29	0.07
	3	0.26	0.17	0.05
	4	0.33	0.23	0.09
Lane-changing	1	0.03	0.02	0.01
	2	0.02	0.01	0.01
	3	0.03	0.02	0.02
	4	0.03	0.02	0.01
Right-angle (between movements from cross approaches)	1	0.06	0.03	< 0.01
	2	0.03	0.03	< 0.01
	3	0.40	0.09	0.06
	4	0.22	0.14	0.03
Right-turn-against (between movements from opposite approaches)	1	0.24	0.20	0.12
	2	0.26	0.21	0.15
	3	0.28	0.25	0.17
	4	0.34	0.28	0.22

According to Figures 5.20 and Table 5.15, the safety impact of RLC installation varies for the different conflict types and traffic conditions. Several conclusions can be drawn and are summarised as follows:

- 1) The overall impacts of RLCs on right-angle and right-turn-against conflicts are favourable. However, it is found that installation of RLCs increases rear-

end conflicts during amber/red phases. That is, due to the installation of RLCs, more vehicles tend to stop abruptly at the start of the amber/red phase. The more frequently sudden deceleration behaviours occur may lead to more rear-end and lane-changing conflicts at the junction approaches.

Figure 5.20 Safety impacts of RLC on different conflict types (simulation)

- 2) Among the four conflict types, the largest impact (in percentage terms) of RLC installation is the significant reduction of right-angle conflicts (85% and 86% for TTC < 2s during peak and off-peak hours, respectively). This finding corroborates with the situation that right-angle conflicts are principally caused by red running violations.
- 3) According to Figure 5.20, it is found that safety impact of RLCs on right-turn-against conflicts is more prominent during amber/red signal phases. The installation of RLCs reduces red running from opposing straight-through vehicles and thereby reduces occurrences of this kind of conflicts.

- 4) From Table 5.15, compared to the peak period (Scenarios 1 and 3), DOC per vehicle during the off-peak period (Scenarios 2 and 4) for rear-end and right-turn-against conflicts is higher, especially for more severe ones ($TTC < 1.5s$ and $TTC < 1s$). Right-angle conflicts are found to be less prevalent during off-peak hours, and no notable difference is found between peak and off-peak periods for lane-changing conflicts. Moreover, according to Table 5.15, it is found that the impacts of RLCs are more prominent during off-peak hours, especially for more severe conflicts.

5.6.3 Effect of RLC from crash records

Crash records are analysed by computing the crash occurrences at RLC and non-RLC junctions to estimate effect of RLC installation. The number of junctions with RLCs is obtained from an online GPS database (GPS Data Team, 2013). Altogether, there are nearly 100 junctions having approach(es) with RLCs (installed from 1986 to 1990), and about 1,300 non-RLC signalised junctions. Crash occurrences of different injury levels in 2009-2011 are computed per 100 junctions for both RLC and non-RLC junctions, as shown in Tables 5.16 and 5.17 (Singapore Police Force, 2012). In the database from Singapore Traffic Police, crash occurrences are classified into three classes, namely light injury, severe injury, and fatal. In Singapore's Road Traffic Act, "serious injury" means any injury which causes a person to be, for a period of 7 days, in severe bodily pain or unable to follow his ordinary pursuits.

Table 5.16 summarises crash counts per congested hour (7-9am, 5-7pm) while Table 5.17 summarises crash occurrences per quiet hour (7pm-7am, 9am-5pm) over recent years (2009-2011). The numbers in Tables 5.16 and 5.17 are calculated as crash counts per hour per 100 junctions. It is also found that, for all conflict movements, the rates of crash occurrence during off-peak periods are generally higher than during peak periods. The safety impacts of RLC installation for each conflict type are calculated as: $[(\text{No. of crashes per hour per 100 junctions without RLCs installed} - \text{No. of crashes per hour per 100 junctions with RLCs installed}) / \text{No. of crashes per hour per 100 junctions without RLCs installed}] \times 100\%$. As summarised in Figures 5.21, positive values represent favourable effects. If crash

occurrence for any conflict type at junctions without RLCs is 0, the impact of RLCs is not calculated. However, as RLCs are usually installed in locations with higher crash occurrences, the comparison between locations with RLCs and without RLCs would be affected by Regression To the Mean (RTM) biases. It should also be noted that the comparison was not able to account for the effect of the number of RLCs at a junction, as the accident statistics could not be disaggregated by approach.

Table 5.16 Accident occurrences (2009-2011) per congested hour

Conflict type	Accident counts per hour per 100 intersections					
	Light injury		Severe injury		Fatal	
	RLC	No RLC	RLC	No RLC	RLC	No RLC
Rear-end	0.50	1.46	0.00	0.00	0.00	0.04
Lane-changing	0.00	0.40	0.00	0.00	0.00	0.00
Right-angle	0.05	2.00	0.00	0.06	0.00	0.04
Right-turn-against	4.25	2.67	0.50	0.15	0.00	0.09

Table 5.17 Accident occurrences (2009-2011) per quiet hour

Conflict type	Accident counts per hour per 100 intersections					
	Light injury		Severe injury		Fatal	
	RLC	No RLC	RLC	No RLC	RLC	No RLC
Rear-end	0.25	0.87	0.05	0.02	0.05	0.02
Lane-changing	0.05	0.22	0.00	<0.01	0.00	<0.01
Right-angle	0.80	2.09	0.05	0.04	0.05	0.07
Right-turn-against	1.55	5.27	0.15	0.14	0.00	0.10

Figure 5.21 Safety impacts of RLC on different conflict types (accidents)

Results of crash analysis show similar characteristics to the simulation experiments in several aspects. Right-angle and right-turn-against accident occurrences at RLC junctions are more than 50% smaller than at non-RLC junctions in most severity levels. Severe rear-end accident occurrences (severe injury and fatal) are found to be higher at RLC junctions during off-peak hours. This finding is consistent with simulation results from the CA model, showing that the installation of RLCs will increase severe rear-end conflicts. For lane-changing accidents, simulation results show that accident occurrences are generally lower at RLC junctions. However, as lane-changing accidents at junctions are not frequent in Singapore, safety assessment of this conflict type through accident occurrences may not be reliable.

5.6.4 Discussion and conclusions

The model as developed in this study is useful in helping authorities make decisions on whether to install RLCs. As the design of signalised junctions entails a combination of control strategies under dynamic traffic demand, a micro-simulation model provides a quick and user-friendly tool to estimate conflict occurrences. In essence, the proposed CA model simulates traffic movements and, for safety assessment application, generates severity-graded traffic conflicts as the performance indicators. The CA model serves to provide an alternate solution methodology to complement conventional studies based on crash occurrences. The application of the CA model to the assessment of red running risk and efficacy of RLCs serves to demonstrate the functionality of the model.

However, as the time-dependent impacts of RLCs are affected with many other factors, such as knowledge of a RLC's presence and history of motorists being caught at a RLC junction, the proposed simulation model can be further refined to incorporate such additional factors when estimating the impacts of RLCs.

5.7 Chapter summary

In this chapter, a micro-simulation method for safety assessment is proposed. Compared to existing safety assessment methods, the contribution of the proposed micro-simulation model can be summarised as follows:

1) The proposed micro-simulation model is developed based on CA with several advantages. CA models allow local calibration on several aspects including car-following, lane-changing, and interaction between vehicles. Especially for signalised junctions, queuing behaviour and amber running behaviour can also be simulated and adjusted. With user-defined traffic characteristics, the proposed CA model can be more flexible and realistic compared to analytical models.

2) Although CA models have been widely used in simulating road traffic, the applications have mostly been on traffic capacity assessment. In this study, a CA model is used to assess safety performance by involving a proxy indicator from microscopic vehicle interactions. Simulation results of case junctions demonstrate that this approach is successful in estimating safety performance.

3) In contrast to conventional conflict techniques that rely on observation and rating, the proxy indicator (DOC) used in this research is based on simulation of vehicle interactions. Compared to SSAM, which is based on trajectories from VISSIM, the CA model is better able to simulate microscopic vehicle movements and dynamic decision-making by drivers.

CHAPTER 6 CA MODELS INCORPORATED WITH DECISION-MAKING TECHNIQUES

6.1 Chapter introduction

This chapter incorporates a conventional Cellular Automata (CA) model with decision-making techniques. First, Fuzzy Logic and traditional CA models are combined to develop a Fuzzy Cellular Automata (FCA) model to simulate vehicle movements at signalised junctions. Unlike other existing models and applications, the proposed FCA model utilises fuzzy sets and membership functions to simulate driver psychology and microscopic decision-making processes. Four fuzzy sets are applied for each movement process at signalised junctions: car-following, lane-changing, amber-running and right-turn filtering. Through microscopic validation and three simulation experiments, the proposed model is found to be able to simulate vehicle responses under various traffic conditions.

The second part of this chapter introduces a Neural Cellular Automata (NCA) model that incorporates an Artificial Neural Network (ANN) to simulate dynamic decision-making procedures. Shared lane usage, erratic behaviours and lateral movements of motorcycles are simulated. Based on various simulation experiments, the behaviour of mixed traffic flows, especially those involving motorcycles, are analysed.

6.2 Significance of incorporating decision-making techniques into CA model

With increasing computation technology, CA models, which require massive computing, are becoming popular for modelling and simulating complex scenarios (Lu et al., 2011; Mallikarjuna and Rao, 2009). However, upon reviewing current CA models, several limitations have been identified. In conventional CA models, be they deterministic or stochastic, control strategies for vehicle movements are not realistic enough. In deterministic models, vehicles' positions as well as velocities are represented by integers (Gundaliya et al., 2008), and the transition rules are inherently fixed. In stochastic models, probability distributions are used to estimate

vehicle movements, such as amber running and acceleration or deceleration. However, to achieve an accurate result, stochastic CA models require a large number of simulation runs and rigorous model calibration.

Fuzzy logic theory can be applied to overcome the limitations of CA models (Placzek, 2012). Compared to traditional logic with exact and fixed solutions, fuzzy logic contains uncertainty and approximation which are well suited to representing multiple co-operations, collaborations and even conflicts (Chiou and Huang, 2013). Incorporation of fuzzy control into micro-simulation is able to reduce overall cognitive dissonance in the modelling process. Fuzzy rules have been applied to describe driving behaviour of vehicles (Wu et al., 2000). Driver behaviour in the dilemma zone at signalised junctions has also been modelled by fuzzy sets (Hurwitz et al., 2012).

The concept of FCA has been developed and applied to several areas including image processing and fire spread simulations. Those models are found to be more intelligent in responding to environmental changes (Mraz et al., 2000; Patel et al., 2013).

Few studies have been found to apply FCA in simulating microscopic vehicle movements and interactions (Gong and Liu, 2010). Yeldan et al. (2012) incorporated fuzzy sets into a continuous CA model to simulate different vehicle movements along freeways, with fuzzy membership functions being developed for car-following and lane-changing rules. However, as only macroscopic outputs are analysed in that study, the impact of involving fuzzy sets into CA models is still not clear. Moreover, as most current traffic FCA models focus on velocity control of vehicles, dynamic decision-making of road users (such as disobeying signal control, gap acceptance, movement directions, lane usage and behaviour when conflict occurs) has not been well-studied so far.

6.3 Fuzzy sets and rules for vehicle movements at signalised junctions

In the proposed FCA model, four fuzzy sets are designed to model vehicle movements at signalised junctions. To simulate a driver's decision-making process,

different factors and linguistic terms are used for each fuzzy set, as shown in Tables 6.1 and 6.2. Detailed fuzzy rules are shown in Appendix I.

Table 6.1 Fuzzy sets and terms in the proposed FCA model

No.	Fuzzy set	Effect area	Inputs	Target
F ₁	Car-following (neighbouring traffic)	All	Current velocity (v_n); Relative velocity ($v_{n+1} - v_n$); Front gap (g_n)	Acceleration or deceleration (ϕ_a, ϕ_d)
F ₂ (F ₂₋₁ , F ₂₋₂) ¹	Car-following (signal phasing)	Junction approach only	Current velocity (v_n); Distance to stop-line (DS); Signal timing (t^s)	Acceleration or deceleration (ϕ_a, ϕ_d)
F ₃	Lane-changing	All	Current velocity (v_n); Front gap (current lane) (g_n); Front gap (target lane) (g_n^t); Rear gap (target lane) ($g_n^{t, rear}$); Rear velocity (target lane) ($v_n^{t, rear}$)	Lane-changing decision (Yes/No)
F ₄	Right-turn filtering	Right-turn vehicles only	Current velocity (v_n); Velocity of the opposing vehicle (v_n^o); Gap provided by opposing straight flow (g_n^o)	Filtering decision (Yes/No)

¹: F₂ is divided into 2 sub-sets (F₂₋₁ and F₂₋₂) to generate different driver response due to different stop-go decision during flashing green and amber phase.

6.3.1 Forwarding rules

Two fuzzy sets of rules (F₁ and F₂) are developed to determine ϕ_a (if accelerate) or ϕ_d (if decelerate) at the next time step, based on inputs from the current time step. For each vehicle, the acceleration ϕ_a depends on the following variables: current velocity (v_n) of the subject vehicle; relative velocity between front and subject vehicle ($v_{n+1} - v_n$); front gap (g_n); distance to stop-line (DS) and signal timing (t^s). Linguistic terms used in the fuzzy sets are summarised in Table 6.2. The first set of

fuzzy rules (F_1) estimate the impact of the front vehicle by including the first three inputs (v_n , $v_{n+1} - v_n$, and g_n), as shown in Figure 6.1 and Table 6.3. Inputs related to signal control (DS and t^s) are separated as the second fuzzy set of rules (Table 6.4). v_n is also included in F_2 to avoid unrealistic driver behaviour in simulation. The reason for developing two fuzzy sets of rules is to provide different movement strategies for vehicles before and after the stop-line. Vehicles before the stop-line are controlled by both F_1 and F_2 while vehicles after the stop-line are only controlled by F_1 . Suppose O_1 and O_2 are the outputs of F_1 and F_2 , respectively, the final driver response O (before stop-line) is computed as $O = \min(O_1, O_2)$.

Table 6.2 Linguistic terms in the proposed FCA model

No.	Input/output factor	Linguistic terms
Inputs	Current velocity (v_n)	High; Normal; Slow
	Relative velocity ($v_{n+1} - v_n$)	Opening fast; Opening; About zero; Closing; Closing fast
	Front gap (g_n)	Far; Medium; Close
	Distance to stop-line (DS)	Far; Medium; Close
	Signal timing (t^s)	Just became green; About to become amber; Amber; Just became red; About to become green
	Front gap (target lane) (g_n^t)	Far; Medium; Close
	Rear gap (target lane) ($g_n^{t, rear}$)	Far; Medium; Close
	Rear velocity (target lane) ($v_n^{t, rear}$)	High; Normal; Slow
	Velocity of the opposing vehicle (v_n^o)	High; Normal; Slow
	Gap provided by opposing straight-through flow (g_n^o)	Far; Medium; Close
Outputs	Acceleration or deceleration (ϕ_a, ϕ_d)	Strong acceleration (SA); Light acceleration (LA); No action (NA); Light deceleration (LD); Strong deceleration (SD);
	Lane-changing decision	Yes (Y); No (N)
	Filtering decision	Yes (Y); No (N)

Figure 6.1 Structure of F_1

The target decisions are the driver's response: Strong acceleration (SA); Light acceleration (LA); Maintain current velocity with no action (NA); Light deceleration (LD); and Strong deceleration (SD). Fuzzy rules are created based on common sense to describe the willingness to accelerate or decelerate of each driver, as summarised in Tables 6.3 and 6.4. In F_2 , when a signal is about to become amber or during amber phase, two responses are defined for drivers, who have to decide either to stop before or continue across the stop-line. The decisions (stop or cross) are computed based on a set of fuzzy rules described in Section 6.4.

Table 6.3 1st set of fuzzy rules (F_1)

	Current velocity (v_n)	Relative velocity ($v_{n+1} - v_n$)	Front gap (g_n)	Driver response (ϕ_a, ϕ_d)
1	Slow	Opening fast	Far	SA
2	Slow	Opening fast	Medium	SA
3	Slow	Opening fast	Close	LA
4	Slow	Opening	Far	SA
5	Slow	Opening	Medium	SA
6	Slow	Opening	Close	LA
...	...	...	...	...
41	High	Closing	Medium	SD
42	High	Closing	Close	SD
43	High	Closing fast	Far	LD
44	High	Closing fast	Medium	SD
45	High	Closing fast	Close	SD

Table 6.4 2nd set of fuzzy rules (F₂)

	Current velocity (v_n)	Distance to stop-line (DS)	Signal timing (t^s)	Driver response (ϕ_a, ϕ_d)
1	Slow	Far	Just became green	SA
2	Slow	Far	About to become amber	SA/NA
3	Slow	Far	Amber	SA/LD
4	Slow	Far	Just became red	LA
5	Slow	Far	About to become green	SA
6	Slow	Medium	Just became green	SA
7	Slow	Medium	About to become amber	SA/LD
...	...	...	...	...
40	Fast	Medium	About to become green	LD
41	Fast	Close	Just became green	NA
42	Fast	Close	About to become amber	NA/SD
43	Fast	Close	Amber	NA/SD
44	Fast	Close	Just became red	SD
45	Fast	Close	About to become green	LD

Stopping propensity of different vehicle types at the onset of amber are modelled by the following equations as described in Section 4.4.5. The variables include distance to stop-line (DS) and moving velocity (v_n).

$$p_s(\text{car}) = [1 + \exp\{-(-1.02 + 0.129DS_n - 0.54v_n)\}]^{-1} \quad (6-2)$$

$$p_s(\text{heavy vehicle}) = [1 + \exp\{-(-2.61 + 0.17DS_n - 0.31v_n)\}]^{-1} \quad (6-3)$$

$$p_s(\text{motorcycle}) = [1 + \exp\{-(2.59 + 0.08DS_n - 0.72v_n)\}]^{-1} \quad (6-4)$$

6.3.2 Lane-changing movements

At signalised junctions, vehicles change lanes very often along the approach and departure lanes. Two types of lane-changing are observed: Type (I) is to change to the lane (straight-through or turning) at the junction approach corresponding to the vehicle movement direction; Type (II) is to move to a more convenient lane (with shorter queue or being less congested). In the proposed lane-changing fuzzy model (F₃), input factors include current velocity (v_n), front gap (current lane) (g_n), front gap (target lane) (g_n^t), rear gap (target lane) ($g_n^{t, rear}$), and rear vehicle velocity (target lane) ($v_n^{t, rear}$). To model Type (I) lane-changing, an additional input, Distance to stop-line (DS), is involved. That is, with the same velocity and gaps, if the subject vehicle is closer to stop-line, the probability of making Type (I) lane-changing will be higher. Fuzzy rules are created as summarised in Figure 6.2.

Figure 6.2 Lane-changing fuzzy rules (F_3)

6.3.3 Gap acceptance of right-turn filtering

In Singapore, most signalised junctions are controlled with permissive right-turn signal control. During straight-through green phase, the right-turn vehicle needs to wait for appropriate gaps in the opposing straight-through traffic stream to make a right-turn (Wang and Abdel-Aty, 2007; Wang and Abdel-Aty, 2008). There is a risk of collision if a right-turn vehicle moves without enough gap or when the opposing straight-through vehicle is travelling too fast. Therefore, a set of fuzzy rules (F_4) is developed for right-turn vehicles to decide whether to stop or move according to the velocity and position of the subject and opposing vehicle. Input factors are current velocity of the subject vehicle (v_n), velocity of the opposing vehicle (v_n^o), and the gap provided by opposing straight flow (g_n^o). Fuzzy rules are created as summarised in Figure 6.3.

6.3.4 Membership functions

In this study, it is assumed that membership functions are triangular and trapezoidal for better computational efficiency. The applied membership functions for each set of input factors and target driver's responses are derived from previous studies by Groeger (2002) and Yeldan et al. (2012). As shown in Figure 6.4, μ is the membership degree with different values of input and output factors. Furthermore, as a smaller moving velocity is observed at the junction-box, different membership functions are applied for vehicles in the approach and departure lanes, and vehicle

within the junction-box area. In the proposed model, cycle length is assumed as 100s, with 30s of full green phase, 3s amber and 15s of right-turn green arrow for each approach.

Figure 6.3 Right-turn filtering fuzzy rules (F_4)

Figure 6.4 Membership functions

Figure 6.4 (cont.) Membership functions

6.4 Development and application of FCA model

6.4.1 Model development

In the proposed FCA model, fuzzy sets introduced in Section 6.3 are embedded within the CA model by using the Fuzzy Logic Toolbox of Matlab, as shown in Figure 6.5. The Toolbox allows users to define membership functions for each input and output. Based on the input membership functions, membership values for each function are computed proportional to make sure the summation of all memberships for each input value is 1. By using the 'Evafis' function in Matlab, the response of each vehicle at each time step will be computed according to dynamic traffic flow and signal timing. The output response will be used to provide the vehicle's velocity and position at the next time step, as shown in Figure 6.6.

Figure 6.5 Fuzzy sets and rules in Fuzzy Logic Toolbox (F₁)

Figure 6.6 Structure of the proposed FCA model

6.4.2 Model validation

The proposed FCA model is validated by comparison with observed traffic data on Sites No. 5 and No. 6 (as described in Appendix B) at both the macroscopic and microscopic levels.

i) Average travel time

To investigate the model validity, a simulation using observed vehicle characteristics, including traffic density, arrival distribution, and moving velocity, is performed for the two sites. The average travel time of each type of vehicles from observation and simulation after 20 signal cycles is shown in Table 6.5. The results of traffic delay show very good agreement. Therefore, the FCA model is demonstrated to be able to replicate realistic signalised junction traffic at the macroscopic level.

Table 6.5 Comparison of traffic delay (s) from CA simulation and field data

	Site No. 5			Site No. 6		
	Cars	Heavy vehicles	Motor-cycles	Cars	Heavy vehicles	Motor-cycles
Field data	97.48	101.87	74.39	109.85	122.37	92.53
CA simulation	94.30	103.98	76.63	115.61	118.63	95.38
Error	3.4%	-2.0%	2.9%	-5.0%	3.2%	-3%

ii) Comparison of movement characteristics

To further validate the FCA model, distributions of several movement characteristics are compared from simulation and field observations, as shown in Figures 6.7 to 6.9. The simulation and observation profiles are in close agreement.

6.4.3 Simulation experiment -1: Car-following and lane-changing behaviour

Two straight-through lanes at the junction approach, as shown in Figure 6.10, are selected for this experiment. With the geometric layout of the case junction (Site No. 2) as shown in Appendix B, Lanes 2 and 3 are selected for the experiment. In this two-lane system, each straight-through vehicle can choose whether to change to the other lane before or after the stop-line. To evaluate microscopic car-following and lane-changing movement, a subject vehicle is assigned which arrives at the start point of the junction approach (150m before stop-line) at 12s after the start of the green phase. Therefore, if the subject vehicle is moving forward with an average velocity higher than 30km/h, it is able to cross the stop-line before the onset of amber.

Figure 6.7 Comparison of velocity distribution

Figure 6.8 Comparison of acceleration and deceleration

Figure 6.9 Comparison of stop propensity

Figure 6.10 Studied two-lane system

Car-following and lane-changing are affected by traffic condition as well as signal control. Therefore, four factors are involved in the experiment, including: (1) traffic volume in the subject lane, vol_s , (2) traffic volume along the neighbouring lane, vol_n , (3) signal state, and (4) being before or after the stop-line. A total of 32 simulation scenarios are conducted as summarised in Tables 6.6 and 6.7, with different traffic volumes for each straight-through lane varying from 100pcu/h (saturation degree= 0.24) to 400pcu/h (saturation degree= 0.96). In Scenarios 1-16, only the subject vehicle is allowed to make lane-changing while all other vehicles are forbidden to change lane. In Scenarios 17-32, all simulated vehicles are free to make lane-changing.

To determine the number of vehicles for each vehicle type, vehicle composition is applied as Car: Heavy vehicle: Motorcycle=3:1:1 (in accordance with field observation). PCE values calibrated in Singapore are used for converting turning (Kok and How 1992) and straight-through vehicles (Pang and Meng 1990). The signal cycle time is 100s, the green time assigned for each movement direction is 30s for the straight-through green phase (with permissive right-turn) and 15s for the exclusive right-turn green phase. The simulation runs for 30 signal cycles, or approximately 50min. Simulation outputs are the average of 5 runs.

To assess the numerical simulation outputs, five evaluation measurements are selected: (1) travel time, t^t , (2) time and position of the 1st actual lane-changing, t_c , p_c , (3) average willingness of lane-changing, $\bar{w}_c$ (4) frequency of lane-changing along each lane $\bar{f}_c^1$, $\bar{f}_c^2$ and (5) frequency of lane-changing per vehicle during green and amber-red signal phase $\bar{f}_c^g$, $\bar{f}_c^{ar}$. Among them, measurements 1-3 are for the subject vehicle, while 4-5 are the average values for the overall traffic flow. The simulation results are summarised in Tables 6.6 and 6.7.

Overall, the simulation results of Tables 6.6 and 6.7 indicate that the FCA model is able to simulate vehicle responses under various traffic conditions and microscopic car-following and lane-changing behaviour of vehicles.

In addition, several conclusions can be made based on the simulation results.

Table 6.6 Numerical results under various traffic conditions
(lane-changing permitted to subject vehicle only)

Scenario	vol_s (pcu/h)	vol_n (pcu/h)	t^t (s)	t_c (s)	p_c (m)	$\bar{w}_c$
Scenario-1	100	100	65.9	53	+43	0.23
Scenario-2	100	200	76.2	NA	NA	0.21
Scenario-3	100	300	73.6	NA	NA	0.18
Scenario-4	100	400	71.7	NA	NA	0.13
Scenario-5	200	100	92.6	20	+28	0.32
Scenario-6	200	200	96.3	NA	NA	0.29
Scenario-7	200	300	104.1	NA	NA	0.26
Scenario-8	200	400	99.3	NA	NA	0.18
Scenario-9	300	100	127.5	11	-45	0.63
Scenario-10	300	200	132	18	+17	0.55
Scenario-11	300	300	129.8	25	+35	0.39
Scenario-12	300	400	130.1	NA	NA	0.24
Scenario-13	400	100	170.9	4	-72	0.82
Scenario-14	400	200	180.2	8	-46	0.70
Scenario-15	400	300	184.0	45	-15	0.53
Scenario-16	400	400	182.4	62	+29	0.38

- 1) From Tables 6.6 and 6.7, whether free lane-changing is allowed or not, the travel time of the subject vehicle (in lane 1) is affected by the traffic volume in both that lane and the neighbouring lane. However, it is found that when all simulated vehicles are allowed to change lane, the impact of the traffic volume in the neighbouring lane is higher.
- 2) According to Table 6.7, if free lane-changing is allowed, more lane-changing is observed from the lane with the higher traffic volume to the lane with the lower traffic volume. The two-lane system is found to be able to self-organise itself to achieve a more balanced condition through lane-changing, when all vehicles are free to change lane.

Table 6.7 Numerical results under various traffic conditions (free lane-changing)

Scenario	vol_s (pcu/h)	vol_n (pcu/h)	t^t (s)	t_c (s)	p_c (m)	$\bar{w}_c$	$\bar{f}_c^1$	$\bar{f}_c^2$	$\bar{f}_c^g$	$\bar{f}_c^{ar}$
Scenario-17	100	100	68.8	NA	NA	0.21	4%	4%	2%	6%
Scenario-18	100	200	106.0	NA	NA	0.28	5%	52%	12%	45%
Scenario-19	100	300	125.9	NA	NA	0.35	9%	28%	8%	29%
Scenario-20	100	400	131.7	NA	NA	0.41	12%	39%	10%	41%
Scenario-21	200	100	82.6	NA	NA	0.27	52%	5%	12%	45%
Scenario-22	200	200	108.3	NA	NA	0.36	8%	8%	4%	12%
Scenario-23	200	300	132.2	NA	NA	0.40	10%	23%	8%	25%
Scenario-24	200	400	142.4	NA	NA	0.33	7%	27%	5%	29%
Scenario-25	300	100	96.0	23	+32	0.36	32%	9%	9%	25%
Scenario-26	300	200	132.1	30	+52	0.41	23%	10%	10%	24%
Scenario-27	300	300	147.3	NA	NA	0.30	6%	6%	7%	24%
Scenario-28	300	400	146.6	NA	NA	0.26	7%	14%	9%	23%
Scenario-29	400	100	153.5	15	-18	0.45	39%	12%	9%	28%
Scenario-30	400	200	165.4	5	-54	0.33	27%	8%	10%	22%
Scenario-31	400	300	173.3	NA	NA	0.26	14%	7%	9%	23%
Scenario-32	400	400	178.9	NA	NA	0.17	4%	4%	5%	24%

3) Moreover, in Table 6.7, lane-changing frequencies before the stop-line during the green signal period are found to be much fewer than during the amber and red signal period, especially in scenarios with higher traffic volumes. This phenomenon has two causes. First, most vehicles change lane before the stop-line to enter a shorter queue, so most lane-changing occurrences are during the amber and red periods. Second, vehicles usually travel at a relatively higher velocity during the green period and this deters lane-changing.

6.4.4 Simulation experiment-2: Right-turn filtering behaviour

This experiment is designed to find out whether filtering is affected by overall traffic conditions. Two factors are involved in the experiment according to the 4th fuzzy set (filtering), namely: (1) traffic volume in the right-turn lane, vol_r , (2) traffic volume in the opposing straight-through lane, vol_{os} . A total of 16 simulation scenarios are conducted with different traffic volumes varying from 60pcu/h (saturation degree= 0.24) to 240pcu/h (saturation degree= 0.96) for the right-turn lane and 100pcu/h (saturation degree= 0.24) to 400pcu/h (saturation degree= 0.96)

for the opposing straight-through lane as, similarly to Experiment-1. In this experiment, the same vehicle compositions and signal timings are applied.

To assess right-turn filtering behaviour, five evaluation measurements are selected according to the 4th fuzzy set (filtering): (1) average velocity of the right-turn vehicle before filtering, $\bar{v}_{rt}$, (2) average velocity of the opposite straight-through vehicle before filtering, $\bar{v}_o$, (3) average available gap in the opposing vehicle stream before filtering, $\bar{g}_o$, (4) average travel time of right-turn vehicles, $\bar{t}_{rt}$, and (5) average willingness to filter of all right-turn vehicles during the straight-through green period, $\bar{w}_f$. Simulation results are summarised in Figure 6.11.

As shown in Figure 6.11, it is very clear that the filtering behaviour of right-turn vehicles is affected by general traffic conditions. When the right-turn traffic volume increases, the average right-turn velocity to filtering vehicle also increases. The average travel time and average willingness filter are also increased. However, the average opposing straight-through velocity and opposing gap provided when the vehicle filters through the opposing flow, are reduced as the right-turn traffic volume increases.

The opposing straight-through traffic volume is also found to affect filtering behaviour. When the opposing straight-through traffic volume increases, filtering willingness, average right-turn vehicle velocity and average gap available in the opposing straight-through vehicle stream decrease, while the average opposing vehicle velocity and the travel time of right-turn vehicles increase.

6.4.5 Simulation experiment-3: Impacts of risky driving

It is found that traffic performance and accident occurrences are affected by human factors (Grayson and Maycock, 1988; Sabey and Taylor, 1980). Risk-taking behaviour, which means drivers tend to increase the possibility of negative health outcomes for themselves and other drivers, is mainly affected by human factors and will result in unfavourable safety performance (Ulleberg and Rundmo, 2003).

Figure 6.11 Simulation outputs in different traffic conditions

Drivers can be risk-averse or risk-affine (Xiao and Lo, 2013). Risk-averse (risk-avoiding) drivers are usually more conservative than normal. They usually drive with a lower speed, maintain a larger front gap and are less likely to change lanes. On the other hand, risk-affine (risk-seeking) drivers are usually more aggressive in car-following and lane-changing. The concept of being risk-averse and risk-affine is developed and applied in many driving aspects, including dynamic route choices and traffic safety assessment (Bell and Cassir, 2002; Chi et al., 2013). Ulleberg and

Rundmo (2003) measured the risk-affinity of drivers, using characteristics such as aggression, altruism and anxiety, through a questionnaire study.

Numerous previous researchers have found different perspectives of cognitive antecedents to explain the differences in risk-taking behaviour for each driver (Parker et al., 1998). According to various psychological models, such as Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB) and health belief models (Ajzen, 1988; Rosenstock, 1974; Rutter et al., 1995), various variables are found to be associated with risk-taking behaviour, such as drivers attitude, perceived risk, as well as perceived behavioural control (Parker et al, 1992; Hu et al., 2013).

Risk-related attitude is defined as a psychological intent towards favourable/unfavourable risky driving behaviour as well (Falk and Montgomery, 2009). A driver's attitude is found to affect driver behaviour by way of aggressive driving, fast driving and involvement in traffic accidents (Parker et al., 1998; Iversen, 2004). Perceived risk is defined as driver's perception of a potential danger (Baron et al., 2000). Some studies found that risk perception directly affects traffic safety (Nordfjærn and Rundmo, 2012). When drivers are more easily seeing themselves to be in a situation of danger, the driver is more likely to not drive in a manner risky to himself or herself (Rundmo and Iversen, 2004; Hayakawa et al., 2000). Another cognitive antecedent, namely perceived behavioural control (PBC), represents driver's perception of his or her ability to perform a behaviour, such as braking or lane-changing (Ajzen, 1991). PBC is known as a multi-dimensional construct that involves both attitude and perception aspects (Kraft et al., 2011). It is clear that PBC also affects drivers' decision-making process. Cestac et al. (2011) conducted a questionnaire survey to understand PBC and drivers' intention of speeding. It is found that PBC has a strong impact on speeding, especially for more experienced drivers.

ii) Simulation of risky driving behaviour

In this study, three types of drivers (risk-averse, risk-neural and risk-affine) are simulated. Type (II) drivers are risk-neural drivers. Compared to Type (II) drivers,

Types (I) drivers are risk-averse drivers, and are more conservative in detecting perceived risk and more likely to avoid possible risks. Types (III) drivers are risk-affine drivers compared to Type (II) drivers. These drivers are more aggressive, less likely to notice perceived risk and more risk-taking in making decisions.

In each fuzzy set, membership functions and fuzzy rules are constructed to simulate different driver types. The modification of membership functions reflects driver's perception about the vehicle he or she is driving, neighbouring traffic, and signal phase. A Type (I) driver is more likely to detect risks in neighbouring traffic, such as a small front gap and fast current velocity, and is more likely to cross the stop-line. However, a Type (III) driver is less likely to detect or heed such risks. In the proposed FCA model, membership functions are constructed (along directions based on the definitions of risk-averse and affine) for each type of driver, as shown in Tables 6.8 and 6.9. μ is the membership degree with different values of input and output factors.

Fuzzy rules are constructed that represent different decisions affected by drivers' attitude. Rules in F_1 and F_2 are constructed as shown in Table 6.10. According to Table 6.10, a Type (I) driver decelerates strongly (SD), a Type (II) driver does decelerates lightly (LD) and a Type (III) driver does not decelerate (NA).

Rules in F_3 and F_4 are also modified to generate the response of drivers. For example, for a Type (I) driver, when current velocity is low; front gap is small; front gap in target lane is medium; rear velocity in current lane is normal; and rear velocity in target lane is normal, the subject vehicle does not change lane. However, a Type (III) driver (risk-affine) with the same inputs changes to the target lane.

Table 6.8 Fuzzy memberships applied in F₁

v) Experimental design

To assess capacity and safety impacts of risk-taking driving behaviour, microscopic simulation experiments are conducted. To simplify the simulation experiment, only two driver types (Types (I) and (III)) are simulated. A total of 11 simulation scenarios are designed with different mixes of two driver types, as shown in Table 6.11.

Table 6.9 Fuzzy memberships applied in F₂

Table 6.10 Modified response for drivers with risky attitude

Type (II) Risk-averse	Type (I) Normal drivers	Type (III) Risk-affine
SD	SD (Strong deceleration)	LD
SD	LD (Light deceleration)	NA
LD	NA (No action)	LA
NA	LA (Light acceleration)	SA
LA	SA (Strong acceleration)	SA

In the simulation, overall traffic volume is fixed as 800 pcu/h (saturation degree=0.67) per junction approach. To determine the input number of vehicles for each vehicle type, vehicle composition is applied as Car: Heavy vehicle: Motorcycle=3:1:1 according to field observations. Passenger Car Equivalent (PCE) values calibrated in Singapore are used for converting turning (Kok and How 1992) and straight-through vehicles (Pang and Meng 1990). The signal cycle time is 120s,

green time assigned for each movement direction is 30s for the straight-through green phase (with permissive right-turn) and 20s for the exclusive right-turn green phase. The simulation runs for 30 signal cycles, or approximately 1 hour. Simulation outputs are the averages of five runs, as suggested by Pasin and Giroux (2011).

To assess safety impacts of risk-taking driving behaviour, seven vehicle-vehicle conflict types are defined in Chapter 5. For each type of conflict, occurrences are estimated by a proxy indicator, “Deceleration Occurrence caused by Conflicts (DOC)” (Chai and Wong, 2014a). Average Time to Collision (TTC) is computed to estimate the severity of each type of conflict (Lee, 1976). A lower TCC value means a very short time for vehicles to avoid collision.

Table 6.11 Designed simulation scenarios

Scenarios	Type (I) driver	Type (III) driver
1	100%	0%
2	90%	10%
3	80%	20%
4	70%	30%
5	60%	40%
6	50%	50%
7	40%	60%
8	30%	70%
9	20%	80%
10	10%	90%
11	0%	100%

vi) Capacity and safety impacts of risky driving behaviour

To assess the capacity impact of risky driving behaviour, the average travel time per vehicle is computed for each scenario, as shown in Figure 6.12. Since travel time per vehicle is averaged by simulation time of one hour and five individual simulation runs, temporary reduction in capacity due to rapid deceleration following front vehicles, known as “shock-waves”, are not shown in Figure 6.12.

Figure 6.12 Average travel time with risky perceptions

Simulation results presented in Figures 6.12 indicate that the proposed FCA model is able to simulate and assess traffic performance with drivers who have different risk-taking behaviour (averse and affine). According to Figure 6.12, in capacity aspect, when a higher proportion of Type (III) (risk-affine) drivers and lower proportion of Type (I) (risk-averse) drivers are present, the average travel time decreases. Compared to Type (III) drivers, Type (I) (risk-averse) drivers are likely to detect risky situations and be more ready and quicker to engage braking. On the contrary, risk-affine drivers will adopt aggressive behaviours, such as higher velocity, less braking and a smaller front gap.

Occurrences (DOC) and severity (average TTC) for each conflict type are computed for each simulation scenario, as summarised in Figure 6.13. Simulation results from Figure 6.13 suggest that the “shock-wave” effect may exist due to average DOC per vehicle for Conflict Types 3,4,5,7 not decreasing when more drivers are risk-affine.

Figure 6.13 Occurrences and severity of vehicle-vehicle conflicts affected by driver's risk behaviour

Occurrences of vehicle conflicts (DOC) decrease when there are more Type (III) (risk-affine) Drivers for Conflict Types 1,2,6,7. This is caused by less ready braking of Type (III) Drivers. However, occurrences of Conflict Type 4 (between right-turn filtering and opposing straight-through vehicles) slightly increase with more Type (III) Drivers. Compared to Type (III) (risk-affine) Drivers, Type (I) (risk-averse) Drivers are less likely to filter through the stream of opposing straight-through vehicles.

Moreover, average TTC per conflict for all the 7 conflict types are reduced with more Type (III) (risk-affine) drivers. Several reasons are plausible to explain this trend. Firstly, Type (III) (risk-affine) drivers are likely to travel in a relatively higher velocity. In addition, compared to Type (II) drivers, Type (III) drivers are less likely to detect latent risks. Therefore, as lower TTC represents more severe vehicle conflicts, being risk-averse is found to result in favourable safety performance. In contrast, being risk-affine is found to result in unfavourable overall safety performance.

6.5 Neural Cellular Automata (NCA) model for dynamic decision-making

6.5.1 Background

Numerous researchers have applied CA models to simulate urban traffic conditions, especially at signalised junctions. However, designing a proper CA model for more complex tasks, such as a traffic system with many factors affecting vehicle movements, is usually difficult. Artificial Computation Intelligence (ACI) technologies are developed to solve such problems. In previous studies, a self-organised CA model with Artificial Neural Network (ANN) control has been developed and found to provide feasible solutions (Tavares et al., 2000; Elmenreich and Fehérvári, 2011). However, as vehicle movements are not solely defined by neighbouring cells in traffic systems, current models have not been applied to traffic simulation so far.

Unlike the previous CA models, with ANN control, the network is built between road users and input factors rather than among cells. Therefore, in this study, by involving an ANN into the micro-simulation, interactions between components (including signal control, geometric layout and neighbouring vehicles) can be represented coherently. In the Neural Cellular Automata (NCA) model, vehicle lane choices are decided using a Neural Network built according to field observations. Compared to other mathematical approaches which are used to estimate the capacity of a shared lane, the NCA model is more flexible in accommodating different vehicle types, traffic movements and simulating microscopic behaviour of vehicles.

6.5.2 Shared lane and blockage modelling based on ANN

In this study, an ANN is built and trained, so that a particular input leads to a specific target output, as shown in Figure 6.14. Here, the ANN is adjusted, based on a comparison of the output and the target, until the network output matches the target.

The decision-making of each driver on whether to use the shared lane or exclusive lane is controlled by a pre-trained network. Seven inputs, including current lane, vehicle type, vehicle movement (right-turn or straight-through), moving velocity, signal phase, and queue length along exclusive or shared lane, are taken into consideration. The input variables and target decision (using shared lane or exclusive lane) are extracted from 2 hours' continuous field observations. A two-layer perception network with back propagation and weighted sum of inputs and bias term is built to produce the output. The learning algorithm used is Gradient Descent with Momentum and Adaptive Linear Regression to get a stable result (Graepel and Schraudolph, 2002). To get a 0-1 decision, Log-Sigmoid transfer function is used to calculate a layer's output from its net input and round into [0, 1]. After several trails, the final network has two layers and 25 neurons. As all training samples pass through the learning algorithm simultaneously in one epoch before weights of each input are updated, the best performance (Mean Square Error) is 0.0734 which occurs at epoch 992.

The network is built inside NCA model to produce a decision for each vehicle at the beginning of the junction approach. However, during the green phase, if there is enough gap provided in the neighbouring exclusive lane, some vehicles queuing in the shared lane will change to the exclusive lane based on the multi-lane NaSch model. The lane-changing decision is simulated based on a similar pre-trained network based on on-site observations of a stream of 100 queuing vehicles.

6.5.3 Lateral movement of motorcycles

In this study, a lane is represented as four rows of cells in the NCA model. Therefore four lateral positions are defined accordingly, as shown in Figure 6.15. Positions (1) and (4) are the boundary cells of an approach lane while Positions (2) and (3) are the inner cells. According to vehicle trajectories from field observations of three different junction approaches during the peak hour, several differences of lateral positions between vehicle types are found as follows:

1) Motorcycles are more likely to occupy Positions (1) and (4) than cars and heavy vehicles. About one in three (34%) of all observed motorcycle positions are occupy either Position (1) or (4), while 8% of observed cars and 6% of heavy vehicles occupy these two positions. Moreover, when motorcycles are occupying Positions (1) and (4), there are cars or heavy vehicles concurrently occupying the same lane in three out of five times (63%). When motorcycles are occupying Position (2) and (3), in less than one out of five times (18%), there are cars or heavy vehicles occupying the same lane.

2) Motorcycle occupation of Position (1) is 30% more frequent than the Position (4) along a lane. Similar results have been found by Meng et al. in China where vehicles are travelling on the right side (US convention), in which motorcycles are more likely to move in the right position (Meng et al., 2007).

3) During the red signal phase, about half (48%) of the motorcycles will move to the front and queue beside other vehicles, with additional motorcycles queuing behind them. It is also found that more motorcycles queue behind a heavy vehicle than a car.

To simulate erratic motorcycle behaviour at junction approaches, a pre-trained ANN is embedded in the NCA model, as shown in Figure 6.14 (Elmenreich and Fehérvári, 2011). The network is obtained from observations that produce motorcyclists' decisions at each time step. Input factors include distance to stop-line (DS), signal phasing (SP), moving velocity (v_n), front and lateral gaps for left and right sides (g_n, g_n^l, g_n^r), the i^{th} front gap alongside ($g_a(i)$), front gap in the i^{th} neighbouring lane ($g_l(i)$) and also vehicle type (T), position and velocity of the front and neighbouring vehicles (x_j^i, v_j^i for the n^{th} vehicle, where the j^{th} vehicle along the i^{th} lane is within an extended Moore Neighbourhood). Target decisions are whether to make lateral movements in one or other directions. Inputs and target decisions extracted from two hours of continuous observations at three different junction approaches during peak hours are used to train the network. Compared to the network defined in Section 6.5.2, this decision-making process involves more input factors. Therefore, a three-layer perceptron network with back propagation, and weighted sum of inputs and bias term, is built to produce the output. The learning algorithm used is Gradient Descent with Momentum and Adaptive Linear Regression to get a stable result (Graepel and Schraudolph, 2002). After several trials, the final network has three layers and 76 neurons. The best performance (Mean Square Error) is 0.019 that occurs at epoch 1023.

Figure 6.14 CA model embedded with ANN for decision-making of lateral movements

Figure 6.15 Lateral position and gaps provided for motorcycle decision-making

6.5.4 Application of the NCA model: erratic movement of motorcycles

i) Simulation set up

In this study, simulation experiments are conducted on a signalised cross-junction. Pure car traffic, mixed traffic with cars and heavy vehicles, as well as mixed traffic with cars, heavy vehicles and motorcycles, are simulated. Traffic performance, in terms of average travel time of different vehicle types, is estimated under various traffic conditions.

As per field observations, the cycle length of junctions with studied geometric layout is around 120s during peak hours and 100s during off-peak hours. Therefore, in the simulation, if the saturation degree is over 0.5, the cycle length is set to 120s, otherwise the cycle length is set to 100s. Moreover, in each simulation scenario, the same traffic volumes are applied at each junction approach, with the straight-through and right-turn volumes being kept at the same level. Therefore, as permissive right-turn is not applied, based on Webster's signal timing method, the

green time (straight-through or right-turn) for each approach is 27s (cycle length =120s) or 22s (cycle length). A 3s amber and 1s all-red are applied after each straight-through green phase, and a 2s all-red is applied after each right-turn green phase. The capacity of the whole approach is calculated as 806pcu/h (cycle length =120s) and 748pcu/h (cycle length=100s) (Akçelik, 1988). The input traffic volume is calculated based on different degrees of saturation of the approach capacity. In this study, the Passenger Car Equivalent (PCE) for turning and straight-through vehicles are estimated for Singapore junctions (Pang and Meng, 1990; Kok and How, 1992). Arrival distributions are calibrated as Negative Binomial distributions from field observations at 3 different locations (Sites No. 2, 5 and 6).

ii) Mixed traffic flow with cars and heavy vehicles

In order to analyse mixed traffic flow for the NCA model, mixed traffic with cars and heavy vehicles are first simulated. Four scenarios with different car-heavy vehicle ratios (hereinafter C:H = 3:1, 2:1, 1:1, 1:2) are simulated, while the degree of saturation varies from 0.1 to 1.0 in 0.1 intervals. The average travel times for cars and heavy vehicles are based on the results of five simulation runs (Figures 6.16 and 6.17). 100% car traffic with the same degree of saturation is simulated as a comparison.

According to Figures 6.16 and 6.17, in all the simulation scenarios, the travel times of both vehicle types increase with the degree of saturation. The scenario with 100% cars has the shortest average travel time. The travel times for both vehicle types increase with the proportion of heavy vehicles. It is also found that travel times for heavy vehicles are higher than for cars within the same scenario, as shown in Figure 6.18. This is because of the differences of movement characteristics between the two vehicle types in the NCA model, such as maximum velocities, acceleration and deceleration rates, as well as minimum clearance between vehicles.

Figure 6.16 Average travel times of cars

Figure 6.17 Average travel times of heavy vehicles

Figure 6.18 Average travel time of cars and heavy vehicles (C:H= 2:1)

iii) Mixed traffic flow with motorcycles

To estimate erratic behaviour and dynamic decision-making of motorcycles, mixed traffic flow with cars, heavy vehicles and motorcycles in different proportions are simulated. To control the impact of heavy vehicles, in this part, C:H is kept as 3:1 in accordance with field observations. Four cases with different proportions of motorcycles are simulated (hereinafter C:H:M= 3:1:1, 3:1:2, 3:1:4, 3:1:8). Within

each simulation case, three different movement strategies for motorcycles are simulated as follows:

Strategy 1: All of the motorcycles do not overtake or queue beside cars and heavy vehicles;

Strategy 2: All motorcycles overtake or queue beside cars and heavy vehicles wherever alongside gaps exist; and

Strategy 3: Motorcycle riders make dynamic decisions in adopting strategy 1 or 2 for every time step according to the pre-trained ANN described in earlier sections.

For simulations conducted with Strategy 3, motorcycles can make lateral movement decisions based on signal and traffic conditions. Figures 6.19 to 6.21 show the “space-time” plot of simulated vehicles in lane 2 (Lárraga and Alvarez-Icaza, 2010). In Figure 6.19, only cars (in black colour) and heavy vehicles (in blue colour) are simulated. In Figure 6.21, all the three types of vehicles (motorcycles in red colour) are simulated with Strategy 3. In Figure 6.21, “red” motorcycles are following cars or heavy vehicles while “green” motorcycles are travelling beside other vehicles.

Figure 6.19 “Space-time” plot of mixed traffic flow with cars and heavy vehicles (C:H= 3:1)

Figure 6.20 “Space-time” plot of mixed traffic flow with cars (black), heavy vehicles and motorcycles (blue)
(C:H:M= 3:1:2, Strategy 1, Cars: black; Heavy vehicles: blue; Motorcycles: red)

Figure 6.21 “Space-time” plot of mixed traffic flow with cars, heavy vehicles and motorcycles
(C:H:M= 3:1:8, Strategy 3, Cars: black; Heavy vehicles: blue; Motorcycles following: red; Motorcycles beside: green)

Vehicles coming to the stop-line during the amber/red signal phase slow down and queue for a while. Then after the onset of the green phase, they start to accelerate and move forward. According to Figure 6.21, the green lines show the trajectories of motorcycles overtaking and riding/queuing beside cars and heavy vehicles in the same lane. For most of the motorcycles queuing beside cars and heavy vehicles, a shorter queuing time is observed. As most of the plotted trajectories within lane 2 are completed (without lane change), it can also be found that very few lane-changes are observed within the plotted area ($\pm 30\text{m}$ from the stop-line).

Similar to earlier sections, the average travel times for all vehicle types in different vehicle proportions and motorcycle movement strategies are calculated with degree of saturations from 0.1 to 1, as shown in Figure 6.22.

Figure 6.22 Average travel time for mixed traffic flow with motorcycles

According to Figure 6.22, several observations are made.

1) For mixed traffic flow with motorcycle movement Strategy 1, as all motorcycles are following cars and heavy vehicles, the average travel times of cars and heavy vehicles are similar to the travel time of motorcycles. As the saturation degree

increases, the travel time for all vehicle types increases. It is also found that with an increase in the proportion of motorcycles, the travel time also increases due to the smaller maximum velocity and acceleration rates.

2) For mixed traffic flow with motorcycle movement Strategy 2, the average travel time of cars and heavy vehicles are not affected by an increase in the proportion of motorcycles as all motorcycles, are travelling beside them. As motorcycles travelling beside cars and heavy vehicles increase the capacity of junction approach, the average travel times of all vehicle types are smaller compared to Strategy 1.

3) For mixed traffic flow with motorcycle movement Strategy 3, travel times for all vehicle types are found to be affected by the proportion of motorcycles. However, the impacts are smaller than for Strategy 1, as Strategy 3 entails some motorcycles travelling beside cars or heavy vehicles.

6.6 Chapter summary

In this chapter, CA model is extended to incorporate with decision-making techniques to simulate microscopic vehicle movements and driver responses. First, a FCA model is developed by incorporating fuzzy sets and rules to simulate driver responses at signalised junctions. Four fuzzy sets are designed to simulate car-following, lane-changing, amber running and right-turn filtering behaviour. The proposed FCA model is applied in various experiments to study drivers' behaviour, including lane-changing, filtering and risky driving. It is found that microscopic driver behaviour at signalised junctions is affected by risky driving behaviour, as well as junction design and operation.

In the second part of this chapter, a NCA model is developed. To simulate traffic movements, decision-making modules based on ANN for drivers' lane choices are built, based on field observations. The NCA model is validated at both the microscopic and macroscopic levels, and is well-suited for modelling the performance of shared lanes at signalised junctions. With an embedded decision-making network, the proposed model is able to simulate the influences of environment and driver decisions on shared lane usage. Comparisons of simulation

results and field data demonstrate that this CA model could replicate realistic traffic flows at both the macroscopic and microscopic levels. Simulation results show that the decision-making of motorcyclists, the interaction between motorcycles and other vehicle types, affects the overall traffic performance.

Compared to CA models introduced in Chapters 4 and 5, the proposed FCA and NCA models are more able to estimate dynamic driver responses due to different control strategies and surrounding vehicles. Simulation results for case studies demonstrate that this approach is able to model microscopic lane-changing and right-turn filtering behaviour. Moreover, in the proposed FCA model, various driver types with different driving behaviour can be simulated. The proposed FCA and NCA models provide valuable tools to estimate microscopic decision-making of each driver. Moreover, through creating simulation experiments, the relationships are established between driver behaviour with other factors, including external factors such as geometric layout and signal timing, and internal factors, such as perception and attitude.

CHAPTER 7 SUMMARY AND CONCLUSIONS

This concluding chapter includes four main parts namely, research methodology, summary of key findings, main contributions of the research and finally the recommendations for continued work. Furthermore, a number of the findings have been published manuscripts in journals and conferences and the papers are contained in Appendix J.

7.1 Research methodology

This study encompasses 4 stages. The first stage is data collection through video and image-based technologies. By developing image and video processing algorithms, traffic data are collected manually as well as by automatic vehicle detection and tracking. Traffic flow characteristics for vehicles and pedestrians are estimated through data analysis and fitting

Model development is conducted in the second stage on two aspects, homogenous and heterogeneous vehicle movements. Through several modifications of conventional CA models, an improved CA model with multiple cell sizes is developed to simulate homogenous vehicle movements. The model is applied to estimate traffic performance at shared lanes. To simulate heterogeneous vehicle movements, a CA model for mixed traffic flow is developed. The model is able to simulate three vehicle types, namely cars, heavy vehicles and motorcycles, in different movement characteristics.

In the next stage, the CA models are modified for safety assessment. Deceleration Occurrence caused by Conflict (DOC) and other selected safety indicators (TTC, PET, and CI) are generated through simulation. Through assessing the values of safety indicators, the occurrences and severity of vehicle conflicts are estimated. The proposed method is applied in several aspects such as estimating the safety impact of a permissive right-turn, a shared lane and Red Light Cameras (RLC).

The 4th stage is incorporating the CA model with decision-making techniques such as Fuzzy Logic (FL) and Artificial Neural Network (ANN). A Fuzzy Cellular Automata (FCA) model is developed through using fuzzy sets and memberships to simulate drivers' response to traffic condition and signal phasing. Moreover, by embedding pre-trained ANN to simulate decision-making procedures, a Neural Cellular Automata (NCA) model is developed. The models are validated on the microscopic level and are used to simulate driver behaviours such as risky driving and erratic behaviour of motorcycles.

7.2 Summary of key findings

7.2.1 Simulation performance of improved CA models

The major advantage of conventional CA is computing efficiency provided by discrete parameters and simple transition rules. However, being discrete models, conventional CA models usually suffer from low simulation accuracy. This study improves the conventional CA model by using smaller cell sizes to form the mesh in simulating complex movements at signalised junctions.

Simulation results have demonstrated that, with sufficient improvements, CA models are able to simulate realistic vehicle movements. Several findings are established from the CA simulations.

Firstly, lateral drift of vehicles as well as lane-splitting of motorcycles are simulated and estimated. Simulation results show that the decisions of motorcyclists on whether to lane-split do affect traffic performance for both motorcycles and other vehicle types.

Traffic performance of a shared-lane is simulated through the modification of transition rules. It is found that the simulated proportions of drivers' decisions on whether to use a shared lane is close to observed proportions, and the average travel time for all vehicles is very close to its minimum. This indicates that, as a self-

organising system, the traffic on the whole approach tends to the minimum overall traffic delay.

On the safety aspect, the CA approach is found to be able to generate realistic conflicts through comparing with SSAM and observed conflicts. A risk degree analysis based on the clustering of simulated conflicts found that the overall risk degree of seven conflict types is crossing> rear-end> lane-changing. Moreover, the simulated conflicts from quiet scenarios are found to be more severe than those from congested scenarios. The analysis of crash occurrences also reaffirms these simulation findings.

7.2.2 Comparison between CA and other approaches

Through this study, several advantages and limitations of CA approach can be made compared to the other approaches. Firstly, compared to approaches based on empirical formulas, the CA approach not only provides quantitative assessment through simulation outputs but also shows the underlying vehicle movements. For example, both CA and empirical formulas are able to assess the quantitative reduction of travel time for right-turn vehicles when the permissive right-turn is applied. However, the CA approach is able to provide details such as the proportion of right-turn vehicles that filtered through and the conflict occurrences between vehicles.

Moreover, for safety assessment, the majority of traditional approaches at signalised intersections are based on statistical analyse of crash occurrences. However, a successful statistical analysis is subjected to several conditions including a large sample size, sufficient and accurate details for each accident, and availability of before-after data in order to study a certain action. In practice, when there are insufficient crash records for analysis, the CA approach provides an alternative method for safety assessment. Furthermore, compared to crash records, the CA approach provides extra details of vehicle movements and responses due to the neighbouring vehicles, and thus allows users to understand the contributory factors to

the crashes. In addition, the CA approach allows users to predict safety performance of future designs where crash records are not obtainable.

7.2.3 Impact of junction control strategies

i) Application of shared straight-through and right-turn lane

Simulation results of a lane group with one shared lane suggest that for the whole approach, when one of the traffic volumes of two moving directions is particularly heavy, the shared lane usage could increase the traffic delay. According to the simulation conducted with adjusted signal timing (larger green time for heavier vehicle movement), even though capacity of the exclusive lane is improved, the blockage effect along shared lane will still reduce the capacity of lane-group significantly especially when more vehicles are using the shared lane. The CA simulation also shows that the relative proportion between traffic volumes of the two streams will affect the utility of a shared lane. Though a shared lane is arranged because of heavy right-turn traffic volume, straight-through traffic volume should also be examined carefully, as the shared lane will not function efficiently if the straight-through volume is relatively low.

The traffic performance of the shared lane is quite different when considering different traffic volume of the two vehicle movements. Therefore, as traffic volume changes during different times of a day, the shared lane will only be beneficial during particular hours. On the safety aspect, a shared right-turn and straight-through lane is found to increase both rear-end conflicts between straight-through and right-turn vehicles as well as crossing conflicts between right-turn vehicles and opposing straight-through vehicles.

ii) Installation of RLCs

Four conflict types involving rear-end, lane-changing, right-angle and right-turn-against conflicts are simulated. The impact of RLCs during peak and off-peak periods are estimated through the comparison of simulation results at junctions with and without RLCs. The overall impacts of RLCs on right-angle and right-turn against

conflicts are favorable. However, unfavorable impacts are found for RLCs on rear-end conflicts (especially during red/amber signal phases). A similar conclusion is also found from analysis of accident occurrences.

7.3 Research contributions

This study focuses on microscopic vehicle movements at signalised junctions and provides valuable tools and findings for transport professionals in designing and managing signalised junctions. With the addition of new technologies, such as video processing and CA modelling, vehicle movements and the impacts of junction design issues are better understood, which is of great value both in academic research and in practice. Research contributions of this study can be summarised as:

- 1) Improved video processing techniques for traffic data acquisition;
- 2) Improved CA models for homogenous and heterogeneous vehicle movements;
- 3) Application of CA models to safety assessment; and
- 4) CA models incorporated with decision-making techniques.

7.3.1 Improved video processing techniques

An automatic vehicle detection and tracking programme is built in MATLAB based on the Computer Vision System Toolbox. The programme is able to compute traffic parameters including a vehicle's position and velocity profile. Through error testing, the programme is validated as most of the vehicles can be detected. An automatic vehicle classification and tracking method for estimating traffic parameters of vehicle movements is proposed. The method is specially designed for signalised junction areas, as it is powerful and accurate in dealing with the changes of vehicle shape and size. Based on a projective transformation, global co-ordinates are applied to each video frame. A classifier is designed based on the size of vehicles to accurately separate vehicles into different categories. Several features, including vehicle position, type, size and velocity can be automatically extracted. Then, the vehicle's two-

dimensional movements and velocity profiles are used to analyse traffic parameters of vehicle movements at signalised junctions. The contributions of the proposed method developed in this research include the following.

- 1) A projective transformation method based on camera calibration is proposed. A vehicle's position in a global coordinate system can be estimated directly. The transformation forms the basis of an automatic vehicle classification algorithm as vehicles sizes are unified and no longer related to the camera's position and angle.
- 2) A new classification algorithm is developed to categorise vehicles and non-motorised traffic (pedestrians and bicycles) based on their sizes. Compared to feature-based algorithms, the classification method is more suitable at signalised junctions as the vehicle shape in a perspective view changes for turning vehicles.
- 3) Several add-on modules are developed to improve an existing vehicle detection algorithm. The improved optical flow method is able to detect multiple vehicle types as well as produce continuous vehicle trajectories.
- 4) Two-dimensional movements and turning paths of right-turn and U-turn vehicles are estimated. The velocity profiles of vehicles are analysed and classified into three groups. The results can provide sufficient data for building path and velocity control schemes of intelligent vehicles.

7.3.2 Improved CA model of homogenous and heterogeneous traffic

Microscopic CA models are developed to simulate homogenous and heterogeneous traffic flow at signalised junctions. Compared to existing CA models, the proposed models use a smaller and multiple cell size to simulate traffic flow. Vehicle types and transition rules are calibrated to represent real traffic flow at the signalised junctions. Traffic flow characteristics, such as arrival distribution, spacing of queuing vehicles, maximum velocity, maximum acceleration and deceleration rates are calibrated for Singapore's local traffic conditions and assigned differently to each vehicle type.

The proposed models are efficient in computation while accounting for various junction design issues, such as signalised control, shared lane, short storage lane, amber running and right-turn waiting area. Comparison of simulation results and field data demonstrate that the proposed models can replicate realistic traffic flows at both the macroscopic and microscopic levels.

Although a CA model is not yet very popular among traffic engineers due to the lack of user-friendly software, it is widely used in academic research and producing very valuable results in helping the engineers to make decisions. The CA model developed in this research would be able to help authorities to estimate the capacity of a junction before installation (or construction). Apart from calculating the capacity of a shared lane according to quantitative models, the microscopic simulation would help engineers to assess the traffic performance of their design in various traffic conditions and signal timings. However, since vehicle movements are not solely determined by neighbouring cells, the proposed CA model can be further improved by involving driving behaviour.

7.3.3 CA model for safety assessment

The study evaluates the occurrence of conflicts at signalised junction through microscopic simulation based on Cellular Automata (CA). Safety indicators are estimated through vehicle interactions at the conflict area.

Compared to existing safety assessment methods, the contribution of the proposed micro-simulation model can be summarised as follows.

- 1) The proposed micro-simulation model is developed based on CA with several advantages. CA models allow local calibration on several aspects including car-following, lane-changing, and interaction between vehicles. Especially for signalised junctions, queuing behaviour and amber running behaviour can also be simulated and adjusted. With user-defined traffic characteristics, the proposed CA model can be more flexible and accurate compared to analytical models.

2) Although a CA model is widely used by researchers in simulating road traffic, the application has mostly been on traffic capacity assessment. In this research, a CA model is applied for assessing safety performance by involving proxy indicators from microscopic vehicle interactions. Simulation results of case junctions demonstrate that this simple approach is successful in using CA models to estimate safety performance.

3) In essence, the proposed CA model simulates traffic movements and, for safety assessment application, generates severity-graded traffic conflicts as the performance indicators. The CA model serves to provide an alternate solution methodology to complement conventional studies based on crash occurrences. Whereas the conventional approach relies on historical crash data (which require adequate accident counts, hence lengthy occurrence period, for numeral stability), CA model simulates traffic movements and generates severity-graded traffic conflicts for safety assessment application. Compared to SSAM, which is based on trajectories from VISSIM, the CA model is better able to simulate microscopic vehicle movements and dynamic decision-making of drivers.

3) It is found that the impacts of junction design and traffic factors on the occurrence of vehicle conflicts match well with observation data. Apart from the proposed junction layout, the CA model can also be applied to estimate safety performance in various junction layouts, signal sequences and traffic conditions.

The proposed model is versatile and, with relevant definition of performance indicators coupled with proper calibration, is customisable for many applications. In essence, the CA model simulates traffic conflicts rather than real crashes. The application of the CA model to the assessment of RLCs and permissive right-turn serves to demonstrate the functionality of the model.

As the design of a signalised junction entails a combination of control strategies under dynamic traffic demand, the micro-simulation model provides a user-friendly tool to estimate conflict occurrences. Through the proposed approach, prediction models of

traffic conflicts can be developed for various geometric layouts and traffic control strategies.

7.3.4 CA models with decision-making capacity

FCA and NCA models are developed to involve decision-making of drivers as vehicle movements are not solely defined by neighbouring cells. Compared to existing CA methods, both deterministic and stochastic (as introduced in Chapters 4 and 5), contributions of the proposed FCA and NCA models can be summarised as follows.

1) The proposed micro-simulation models based on FCA and NCA have several improvements over the conventional CA models. The proposed models allow calibration from both field observation and driver survey (questionnaire and driver simulator) of driving behaviour and human factors. In particular, queuing behaviour and amber running behaviour can also be simulated and adjusted. With user-defined fuzzy membership functions or neural networks, the proposed CA model can be more flexible and realistic compared to the analytical models.

2) With improvements of aspects of the decision-making process, the proposed FCA and NCA models are more able to estimate dynamic driver responses due to different control strategies and surrounding vehicles. Simulation results for a case study demonstrated that this approach is able to assess lane-changing and right-turn filtering behaviour.

3) Compared to conventional CA models, the proposed FCA and NCA models are able to replicate the decision-making procedures of individual drivers. Through applying different fuzzy rules, membership functions and neural networks, various driver types with different perception and attitude can be simulated. From the findings in the experiments conducted in this study, the proposed models should be able to help researchers and authorities estimate driver responses as affected by various factors. The proposed models provide an alternative tool to estimate the impact of human factors on traffic performance. With validation, the proposed approach can be

applied in many aspects, such as estimating the effects of traffic signs and simulating distracted drivers.

7.4 Recommendations

7.4.1 Recommendations on model development

Another contribution of this research is to serve as a reference to future researchers, traffic authorities, and industry. Several recommendations are made for further enhancement and improvement.

First, it is found that traffic performances, in both capacity and safety aspects, are affected by drivers' behaviour and interactions. Therefore, more research needs to be conducted on understanding and modelling the human factors in microscopic simulation models. Notwithstanding the many extensions being made on current CA models in this research, it is possible to further develop even more sophisticated CA models to simulate human factors with greater complexity.

Moreover, although CA models have both flexibility and great computational efficiency, they are not widely used by the traffic authorities and the industry so far, as current CA models have certain limitations. Through this research, the application of current CA models is extended to cover complex vehicle movements at the signalised junctions and the associated safety aspects. Another constraint is the lack of software or interfaces to allow traffic authorities and industry to apply CA models. Hence, user-friendly software that is able to generate flexible simulation scenarios and automatically analyse simulation results should be developed.

Last but not least, the application of the CA model on the assessment of running risk and efficacy of RLCs serves to demonstrate functionality of the model. For further research, the proposed simulation model can be further refined to study the time-dependent impacts of RLCs by incorporating additional factors such as knowledge of RLC's presence or motorists being caught at RLC junctions. Moreover, as spillover

effect may occur at all junctions within an area with RLC enforcement (Retting et al., 2003), this study can be improved through field observations at completely un-enforced area to fully control spillover effect.

7.4.2 Recommendations on junction design and operation

For the traffic authorities, this study provides a flexible assessment tool to estimate the impacts of various traffic strategies. According to simulation experiments, the impact of a traffic management strategy at a certain junction, such as a permissive right-turn or the installation of a Red Light Camera (RLC), will be different under various traffic conditions. Therefore, it shall be helpful if different control strategies are applied according to traffic condition, such as flexible lane-markings and permissive right-turn.

As traffic performance of a shared lane varies under different traffic conditions, one of the solutions is to make the lane markings changeable, by way of Dynamic Lane Markings (DLM). For example, a digital board could be used ahead of the approach area to display real-time lane arrangement due to detected traffic volume. LED road markers placed on road surface can also help to change the channelisation of approaches. These technologies are being studied and designed in several countries including Australia, U.K. and Netherland.

Moreover, a permissive right-turn is found to increase conflicts between right-turn vehicles and opposing straight-through vehicles, which is the most severe conflict type. Thus, for traffic engineers, when applying the permissive right-turn control, management of crossing conflicts should be first taken into consideration. There should be situations that opposing straight-through traffic is not too heavy so that enough gaps can be provided for right-turn vehicles to filter through and complete the turn. The geometric layout of junction approach should also be taken into consideration as permissive right-turn can help to reduce vehicle conflicts along approach with shared lane.

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