THE UNIVERSITY OF QUEENSLAND

AUSTRALIA

Network-Wide Analysis and Design of Transit Priority Treatments

Mehdi Bagherian

B.Eng. (Hons), M.Sc.

A thesis submitted for the degree of Doctor of Philosophy at

The University of Queensland in 2017

School of Civil Engineering

Abstract

A rapid increase in traffic congestion on urban roads and limitations in developing infrastructure urges a better operation of available transport facilities. To this end, maximizing the efficiency of public transport by deploying transit priority strategies can play a crucial role since a decent transit service can serve more demand and mitigate traffic congestion.

A wide range of strategies has been suggested to improve public transportation performance in urban networks. They range from introducing Transit Priority Lanes (TPL) on a segment to Transit Signal Priority (TSP) strategies that seek to decrease bus delays and travel time variability at intersections. Despite the fact that these strategies can improve the performance of transit operation, their potential negative impacts on the competent modes raise concerns on their deployment and urges a thorough validation before implementation.

The main goal of this research is to develop and validate a planning tool to evaluate and design priority strategies at the network level. By developing inspection, evaluation, and design modules, the tool can help practitioners and planners to find the best strategy considering all of the system-wide impacts of TSP implementation at intersections. Furthermore, this tool would reflect TSP deployment when it is combined with planning-level solutions like bus-exclusive lanes.

This study adds a set of contributions to the existing works in the transit priority area. The main contribution of this research is the development of an optimization framework to find the optimal location of priority strategies in the network. In this regard, a set of methods were developed for finding the location of transit priority strategies. Simulation-based network-wide optimization framework of Transit Signal Priority (TSP) strategies as well as analytical evaluation and optimization of TSP and Transit Priority Lanes (TPL) integration are the main contribution of this study.

In addition, a handful of other contributions were made in this study. For example, the study proposed two analytical approaches to evaluate the performance of priority strategies in a network, A tool and two passenger oriented delay and variability metrics were introduced to identify prone areas for possible strategies using smart card data. The study also proposed the implementation of Vehicle-to-Infrastructure (V2I) communication to reduce bus fuel consumption at intersections and its integration with TSP strategies. Finally, the study analyzed the application of Binary Particle Swarm Optimization(BPSO) algorithm for finding the optimum location of priority strategies are the other contributions of this work.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due references have been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my research higher degree candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

I acknowledge that an electronic copy of my thesis must be lodged with the University Library and, subject to the policy and procedures of The University of Queensland, the thesis be made available for research and study in accordance with the Copyright Act 1968 unless a period of embargo has been approved by the Dean of the Graduate School.

I acknowledge that copyright of all material contained in my thesis resides with the copyright holder(s) of that material. Where appropriate I have obtained copyright permission from the copyright holder to reproduce material in this thesis.

Publications during candidature

Refereed Journal Papers

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. 2014a. Using delay functions to evaluate transit priority at signals. *Public Transport*, 7**,** 61-75.

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. An Integrated Transit Signal Priority and Vehicle-to-Infrastructure Communication to reduce bus fuel consumption. Transport Policy: Case Studies on Transport Policy (Accepted for Publication)

Peer-Reviewed Conference Papers

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. An Integrated Transit Signal Priority and Vehicle-to-Infrastructure Communication to reduce bus fuel consumption. World Conference on Transport Research - WCTR 2016a Shanghai.

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. 2016b. Using Vehicle to Infrastructure Communication to Reduce Bus Fuel Consumption at Intersections. *95td Annual Meeting for Transport Research Board (TRB).* Washington, D.C., USA.

BAGHERIAN, M., MESBAH, M., FERREIRA, L., CHARLES, P. & KHALILIKHAH, M. 2014b. Network-Wide Optimization of Transit Signal Priority. *94td Annual Meeting for Transport Research Board (TRB).* Washington, D.C., USA.

BAGHERIAN, M., MASSAH, S. & KERMANSHAHI, S. “A Swarm Based Method for Solving Transit Network Design Problem”. Australasian Transport Research Forum (ATRF), 36th, 2013, Brisbane, Queensland, Australia, 2013.

BAGHERIAN, M., CATS, O. ,VAN OORT, N., and HICKMAN, M. “Measuring Passenger Travel Time Reliability Using Smart Card Data.” Triennial Symposium on Transportation Analysis (TRISTAN IX), 9th, 2016, Orangestad , Aruba, 2016(extended asbtract).

BAGHERIAN, M., HICKMAN, M., CATS, O., and VAN OORT, N., “Measuring Passenger Travel Time Punctuality for Multi-Leg Trips” , International Workshop on Automated Data Collection Systems, 2nd, 2016, Boston, US, 2016(extended asbtract).

Publications included in this thesis

No publications included

Contributions by others to the thesis

No contributions by others.

Statement of parts of the thesis submitted to qualify for the award of another degree

None.

Acknowledgements

This thesis could never exist without the advice, encouragement and continuous support of many people whom I would like to acknowledge:

I would like to extend my sincere gratitude to *Dr Mahmoud Mesbah*, *Professor Luis Ferreira*, and *Professor Charles* for their supports and endless patience, and guidance during my PhD program. Their drive toward excellence has not only aided my research but made me a stronger professional.

Also, thank you *professor Mark Hickman* for providing me the opportunity of broadening my professional horizon by your endless support in a number of projects. Having the opportunity of working with you in these projects was indeed great.

During my PhD program, I had the chance of being a visiting scholar at the Department of Transport and Planning of TUDelft, Netherlands. I would like to express my gratitude to *Oded Cats*, *Niels Van Oort*, and PhD students and staff of TUDelft for making that three months in Delft invaluably beneficial to me. Oded and Niels, thanks heaps for everything!

I would also like to appreciate the people who have expanded my insight and helped me unconditionally during my PhD program, particularly *Dr Ahmad Tavassoli* for his support during my career at UQ, Dr *Shahab Kermanshahi* (Rahshahr International Group), *Majid Khalilikhah* at Virginia Tech, and *Mehdi Keyvan Ekbatani* at TUDelft. Also, I would like to appreciate the patience of my special friend *Saghar Massah*, who made my move feasible with her patience and unforgettable positive vibes.

Finally, my sincere appreciations go to my lovely parents and sister back in Iran for their unconditional love and positive vibes they sent me continuously from thousands of miles distant. Thanks you for your patient and love that have made my achievements possible.

Keywords

Transit signal priority, transit priority, transit operation, optimization, particle swarm optimization, transit service reliability, transit punctuality

Australian and New Zealand Standard Research Classifications (ANZSRC)

090507: Transport Engineering (100%)

Fields of Research (FoR) Classification

0601: Civil Engineering, 100%

Table of Contents

List of Figures

List of Tables

1. Introduction

1.1. Background

A rapid increase in traffic congestion on urban roads and limitations in developing infrastructure urges a better operation of available transport facilities. To this end, maximizing the efficiency of public transport by deploying transit priority strategies can play a crucial role since a decent transit service can serve more demand and mitigate traffic congestion.

A wide range of strategies have been suggested to improve public transportation performance in urban networks. They range from introducing Transit Priority Lanes (TPL) on a segment to Transit Signal Priority (TSP) strategies that seek to decrease bus delays and travel time variability at intersections. Despite these strategies can improve the performance of transit operation, their potential negative impacts on the competent modes raises concerns on their deployment and urges a thorough validation before implementation. In addition, considering the effect of priority strategies in a network is a challenging task and a systematic approach to measure their network-wide performance with a feasible computational cost is demanding.

To evaluate transit priority strategies in a network, several components are required. Firstly, the strategies should be modeled in an existing macro- or micro-simulation environment. They can range from an adjustment in signal timings to deploying a dedicated lane along a corridor. Secondly, an appropriate formulation is required to measure the performance of a developed model, using as many details as available. Such metrics can be an aggregated model for planning purposed or an agent-based one that uses the individual trajectories and reflects variability or fuel consumption changes. Finally, considering the large size of the metropolitan areas and possible limitations in computational costs, it is crucial to develop an inspecting tool to capture the status of the network in terms of delays the passengers may experience. Such an inspection tool can be implemented to identify transit routes, segments, or intersections that need a special attention such as deploying transit priority strategies.

Feasibility of capturing the network status and modeling and evaluating different priority strategies makes it possible to design (or reshape) the location and settings of these strategies in order to optimize a targeted objective (e.g. minimizing total travel time of the network, minimizing the amount of bus fuel consumption etc.) in the study area. This task can be performed by developing a systematic approach of search-select-evaluate-learn cycle that is relying on the existing developed components.

1.2. Research Aims and Objectives

Numerous research studies have acknowledged the importance of prioritizing transit services and proposed different priority strategies. The main goal of this research was to develop a planning tool to evaluate and design the priority strategies at the network level. To this end, developing analytical and simulation based approaches that can be implemented for network-wide evaluation of priority schemes was firstly targeted. In addition, developing an optimization framework to search for optimal priority solution was needed to be made. We also targeted the priority logics and considered their improvements using the emerging technologies and data availability.The tool can help the practitioners and planners find the best strategy considering all the system-wide impacts of priority strategies' implementation. Furthermore, this model would be able to reflect TSP deployment when is combined with planning-level solutions like bus exclusive lanes.

1.3. Research Contributions

This research adds the following contributions to the existing works in transit priority area:

- Two novel analytical approaches to evaluate the performance of priority strategies. The first method uses delay functions to evaluate priority schemes while the second approach is based on adjustment factors and capacity changes.
- A simulation based network-wide optimization framework of Transit Signal Priority (TSP) strategies where metaheuristic algorithms are integrated into the developed evaluation tools.
- A set of developed measures of performance, considering travel time value and reliability and bus fuel consumption value.
- A tool and two passenger oriented metrics to identify prone areas for possible strategies using smart card data. The metrics reflect the experienced day to day variation and schedule deviation of the services by passengers.
- Using Vehicle-to-Infrastructure (V2I) Communication to Reduce Bus Fuel Consumption at Intersections.
- An Integrated Transit Signal Priority (TSP) and V2I Communication to reduce bus fuel consumption with minimum delay at intersections.
- Analytical evaluation of the effect of TSP and Transit Priority Lanes (TPL) integration in a given network. The developed model is relying on the proposed analytical tools to capture the effect of TSP and TPL integration.
- An analytical optimization framework to locate different priority strategies in a network. The framework is implementing integration, evaluation, and optimization components.

1.4. Thesis Outline and Structure

Figure 1-1 shows the structure of this thesis and provided chapters. The thesis is classified into three main parts. Firstly, a review of the existing research in transit priority realm and related areas are provided and research gaps are identified. The second part is dedicated to the fundamental developed models to capture the network status, developing a set of priority strategies, and proposed measures of performance. Finally, through the Model Application part, developed methodologies to evaluate different preferential strategies as well as optimization modules to find the best location of such strategies are elaborated.

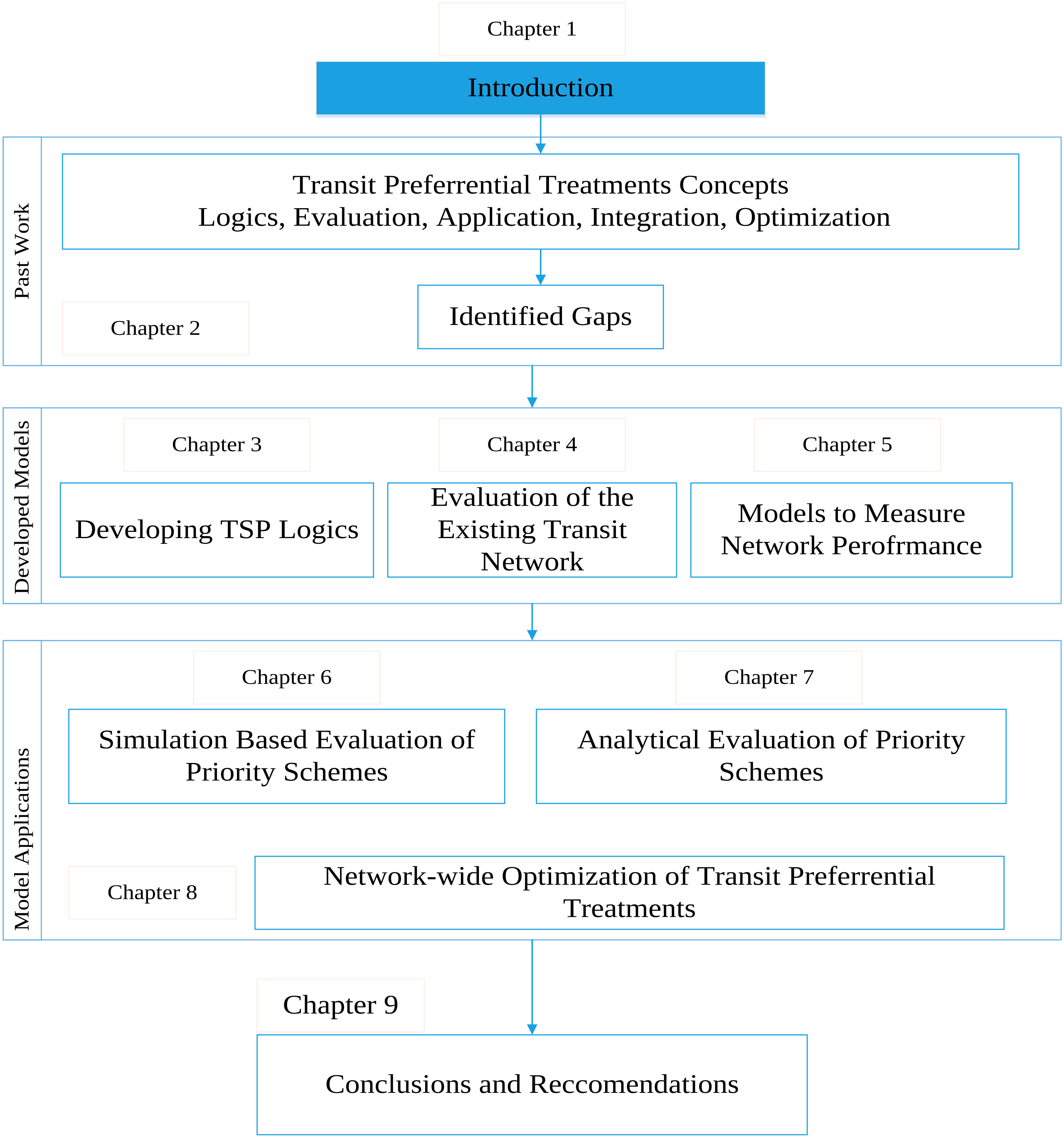


Figure 1-1 Research structure and the thesis chapters

The rest of dissertation is presented as follows. Chapter 2 reviews the existing literature and identifies research gaps of this research. In chapter 3 the developed priority logics are discussed. Chapter 4 presents the developed measures of performance to evaluate the effect of different priority strategies on different modes. In chapter 5, a novel methodology to inspect the passenger experienced delays in the network to support priority strategies deployment is presented. Chapter 6 is dedicated to the simulation-based methods to evaluate transit priority strategies in the selected area of study. Similarly, the proposed analytical approaches to evaluate such strategies is presented in chapter 7. In chapter 8 the methods presented in the previous two chapters are integrated to a set of optimization tools, aiming at finding the optimum location of TSP and TPL strategies so as to minimize the defined objective functions. Finally, conclusions, recommendations, and future areas of research are presented in chapter 9 of this study.

2. Transit Priority Strategies: A Review on the Literature

A review on the available literature in the realm of the study is presented in this section. The literature is classified into four parts. First, an overview on transit preferential strategies including the preliminary concepts of giving priority and different kinds of strategies are presented. These strategies can be classified as either the ones that can be applied on the link segments or intersections. The main focus of section 2.2 is on different transit signal priority strategies and their application in different scenarios. Different kinds of TSP strategies, customized TSP logics, methods to evaluate TSP performance, and performed efforts on the optimization of TSP setting and characteristics are reviewed in this part of the report. In section 2.3, an analysis on the application of smart card data to observe the delay and variability in transit network is presented. Finally, a review on the recent optimization tools that are implemented in this study is presented. This chapter is concluded by summarizing the overall trend, highlighting research gaps, and presenting the research structure. Figure 3-1 depicts the relationship of this section and the entire study.

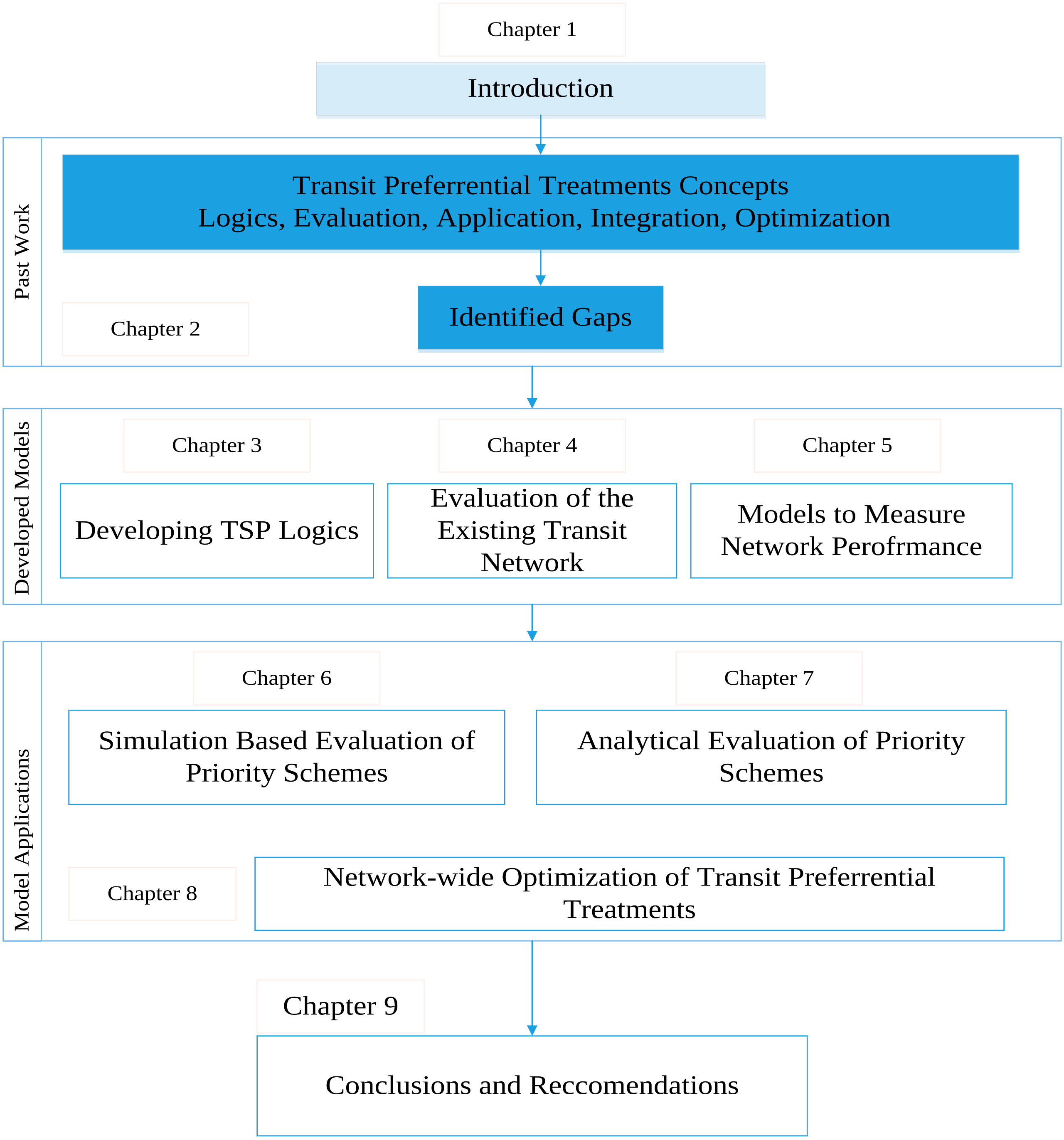


Figure 2-1 Thesis outline and highlighted current chapter

2.1. Transit Preferential Strategies

A wide range of strategies have been suggested to improve public transportation performance in urban networks. These treatments, known as Transit preferential strategies, seek to allocate time or space in favour of buses. They may increase reliability(Jin et al., 2015), reduce transit operating costs, and provide greater ridership (Skabardonis, 2000). They range from considering exclusive transit lanes along a segment to strategies seeking to decrease bus delay at intersections. Danaher (2010) performed a comprehensive study on different preferential strategies which are implemented so far.

Considering the transportation network as a set of nodes and links, they classified them in two sets: the ones related to roadway segments and the strategies to improve transit performance at intersections. A review on this classification and application of the proposed strategies is presented in this section.

2.1.1 *Strategies at the Roadway Segments*

The first set of strategies seeks to give priority to public transport along the segments. They can be applied along a specific length of road segments, often seeking to minimize the negative effect of the interactions between transit and the cars flow. Median transit-ways, exclusive curb-side lanes, and stop spacing and consolidations are three common types of roadway segment strategies.

Median transit-ways are exclusive transit facilities, designated in the median of an urban street. Exclusive transit lanes are the new lanes developed along a roadway (by either widening or dedication of existing facilities to transit use). Four kinds of exclusive lanes are available:

- Concurrent flow: designated lane for transit movement in the direction of general flow
- Contraflow: creating a transit exclusive lane in the opposite direction of general traffic (in one way streets)
- Bi-directional: having an exclusive lane for both directions
- Intermittent lane: a restricted lane for short time duration.

Stop Modifications are another type of strategies that can be applied along roadway segments. Modifications of the location of the bus stops can lead to a saving in delay and make transit service operates more efficient. Two types of stop modification are reviewed by Danaher (2010), namely stop relocations along a corridor and moving specific stops in favour of the other strategies. The former strategy will be applied when a new BRT or express bus is operation along a corridor. Elimination of some bus stops or moving them to other spots can provide overall benefits for the transit service. With regard to the latter, since the performance of the other strategies may be dependent on the bus stop location, moving the bus stop to a specific location (most of the times at an intersection) can help the other treatment strategies perform better. A quintessence of this strategy is to move a near-side bus stop to the far-side of an intersection to make transit signal priority strategies perform better (Sayed and Abdelfatah, 2004). Numerous studies on optimization of transit priority strategies along the links is available in literature that may be referred to (e.g. Mesbah et al., 2010, Mesbah et al., 2011)

2.1.2 *Strategies at the Intersections*

Among the strategies at the nodes, the following four strategies can be mentioned:

1. Transit Signal Priority
2. Special Signal Phasing
3. Queue jump and Bypass lanes
4. Curb extensions

Transit Signal Priority (TSP) is an operational strategy that facilitates the movement of transit vehicles (either buses or streetcars) through traffic signal controlled intersections (Baker et al., 2004). TSP is known as a viable solution for giving priority to bus services with negligible negative effect on vehicular traffic flow(Garrow and Machemehl, 1997) and is increasingly a common strategy to enhance transit service performance. As TSP forms the main core of this study, a comprehensive discussion on the performed studies on it is presented in section 2.2 of this study.

Special Signal Phasing is another strategy for prioritizing transit vehicles at the intersections. This strategy is similar to TSP but rather than adjusting signal timings, it seeks to improve transit performance by suggesting a transit-only signal phase into the signal phases of the intersections. Making a transit vehicle able to have a dedicated left turn (in a right-hand system) is an example of the application of this strategy. This strategy is not modelled in out TSP logics but can be evaluated using the proposed analytical tools.

Queue Jumpers are another transit priority strategy where a short lane would be defined for transit vehicles to skip the queue of general traffic at an intersection. This treatment combines a short stretch of special lane with a leading transit signal phase interval to allow buses to bypass a waiting traffic queue. Zhou and Gan (2005) reported that queue jumper lanes, or simply “Queue Jumpers” are the most effective strategies in congested traffic conditions, when long queues prevent transit vehicles to efficiently clear an intersection. Queue jumpers exploits the space in favour of the buses and reduce the capacity of the intersection thus can have negative impacts on the traffic state. There are some studies that have evaluated the effect of integrating queue jumpers and TSP strategies to enhance transit operation performance (Lahon, 2009, Zhou et al., 2006, Zhou and Gan, 2005, Zlatkovic et al., 2013). Nevertheless, these studies are limited to evaluate the effects of a set of scenarios on the intersection performance. To our best of knowledge, there exist only limited research (Zlatkovic et al., 2013) seeking to develop an optimization model for both space (here the queue jumpers) and time (i.e. TSP). In addition, application of these multi-policy strategies are limited to isolated intersection or a corridor while their impacts on larger networks are not addressed yet.

Curb Extension is the fourth transit preferential treatment at the intersections. The concept involves extending the sidewalk area into the street so that buses do not have to pull out of a travel lane to serve passengers at a stop. As a result, bus delay at the intersection would be reduced since there is no longer any queue in front of the bus. In addition, the bus does not need to seek for a gap to pull back into the lane. They may also provide added space for landscaping and passenger amenities. On the other hand, they might have negative effects on the car flow by reducing the capacity of the segment. Consequently, it is recommended to be implemented where the traffic flow is relatively low, right turn volumes are low-to-moderate, and there exists at least two lanes in each direction (Danaher, 2010). Similar to queue jumpers, developing a model to evaluate the performance of curb extension and TSP combination on the network might be a suitable area of research.

2.2. Transit Signal Priority

Among the available priority strategies, Transit Signal Priority has attracted considerable attention in the literature. The most common TSP type is to shorten the red time (red truncation) or to extend the green time to let the bus pass the intersection before changing the phase status to red (green extension) (Danaher, 2010). TSP strategies can be classified to passive, active, and real-time ones(Baker et al., 2004). Passive strategies establish a pre-set timing considering the arrival of transit services. They are useful when the transit arrival is predictable. Active TSP strategies utilize detectors and update signal timing after detecting a bus approaching an intersection. They can either be unconditional (giving priority to all vehicles) or conditional (considering criteria such as number of passengers, being behind schedule). Finally, real-time strategies adjust signal timings based on both transit and general traffic states. while the latter is rarely addressed in the literature, active and passive strategies have attracted a lot of attention in this realm. An overview on these TSP strategies is presented in this section. Further explanations on different TSP strategies can be found in references such as (Danaher, 2010, Smith et al., 2005, Baker et al., 2004).

2.2.1 *TSP Strategies*

Depending on the budget, available equipment, and intersection characteristics, different types of TSP strategies can be implemented. These strategies can be classified in either passive or active ones. Passive strategies are not using real-time data and the equipment like detectors and communication systems. They are basically developed using the general characteristics of the bus services (e.g. headways, expected arrival times, etc.) and no real-time data is available there. On the other hand, active strategies rely on much more amount of data, mainly real-time ones which are obtained from detectors, GPS data, or any other source. In this section, a review on these strategies is presented.

Passive TSP Strategies

Passive strategies do not require any specific investment in terms of hardware, detectors, TSP request generation system, or software. Indeed, they provide priority for buses through pre-timed adjustments of signal timing (cycle length, green times, and offsets), regardless the transit vehicle is present at the intersection or not (Smith et al., 2005). When transit operation is predictable and there exists less variability with them, these kinds of policies can be effective. The following strategies can be mentioned as the main passive strategies:

1. Signal coordination adjustments
2. Additional green time for the movements that serve transit vehicles (e.g. using person-based delay instead of vehicle based one)
3. Using as low cycle lengths as possible to account for operational characteristics(e.g. average dwell time and its variability)

Wanjing and Xiaoguang (2007) presented a passive TSP approach to enhance the reliability of bus services (keeping buses on schedule or preserve their adherence to the defined headway). They mathematically illustrated the dependency of TSP performance on bus frequency, cycle length, and the number of Different Signal Statuses (DSS). Then a logic for TSP was developed to passively give priority to buses. Adding green time to the phase serving buses, green phase rotation, and splitting the green phases were three passive strategies implemented in their study. To be able to utilize the proposed approach, relationship between bus frequency, cycle length, and the number of DSSes as well as the possible control strategies for different numbers of DSSes were analysed. They applied their model on an isolated intersection and confirmed its effectiveness using a microsimulation analysis.

Estrada et al. (2009) presented a simulation-based model to find optimum relative signal offsets of a set of intersections. Their objective was defined as minimization of total travel time of buses and cars when a Genetic Algorithm was used as the searching method. They reported 13%-26% reduction in travel time when the model was applied to a set of grid networks, depending on the network size.

Furth et al. (2010) analysed the effect of different transit signal priority strategies on an intersection near a major bus terminal where the frequency of the buses reach even four buses per signal cycle. Their strategy relied on providing green wave for buses to cause them stop at most once, when the delay at the intersection itself is reduced by coupled strategies.

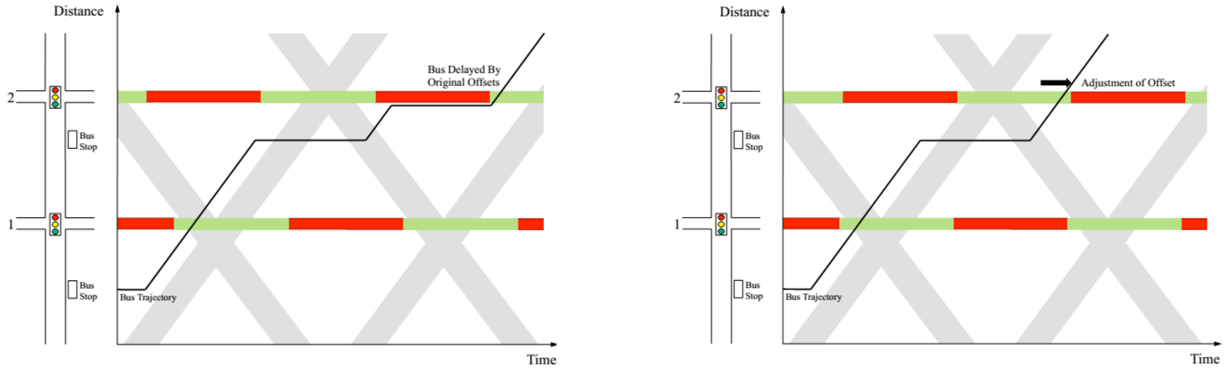
To sum up, passive priority strategies are inexpensive tools for adjusting signal timings in favour of the transit vehicles. Nevertheless, their performance depends on the level of variability of the intersection and traffic condition. Negligible variability of traffic volumes, deterministic dwell times, and in general accurate knowledge of their arrival time are the parameters that make passive strategies more competent. These conditions can be rarely seen in reality thus the application of passive strategies is limited to specific and rare cases.

Active TSP Strategies

Active priority strategies are another type of TSP strategies. On the contrary to passive strategies, active methods benefit from available real-time data of the intersection. In these strategies, transit services would be tracked and the priority can be granted using its observed bus position that is enriched by arrival prediction models. Thanks to the available information, active strategies are much more flexible and technically more effective than passive priority strategies. A number of active TSP strategies can be found in the literature:

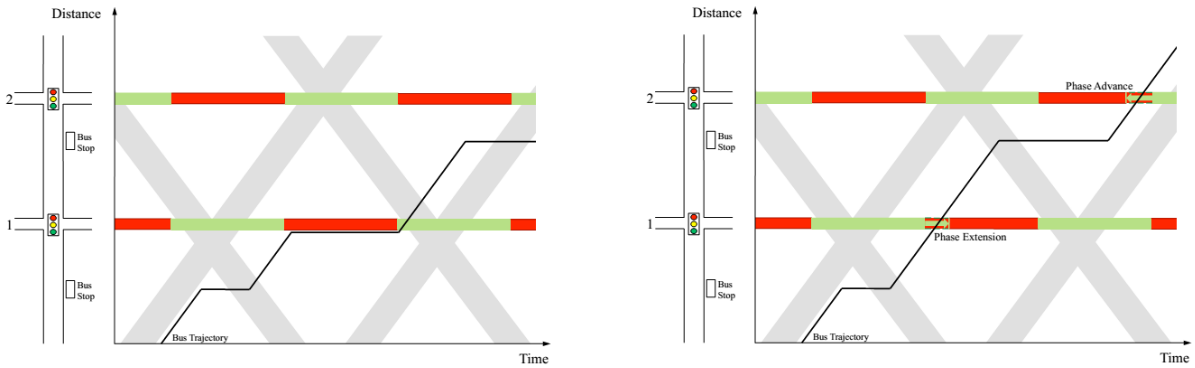
1. Green extension
2. Early green (red truncation)
3. Phase insertion
4. Phase rotation

Green extension is the most common active strategy in the literature. When a bus is approaching the intersection and the signal is green for that movement, green extension strategies can be applied. In this situation, in case the bus cannot clear out of the intersection during the allocated green time, the length of that phase would be extended to let the bus leave the intersection (Smith et al., 2005). Early green (or red truncation) shortens the green time of the other phases so that next green for the bus will be activated earlier. As the result, the prioritized buses will be imposed less delay than the normal signal timing. Phase insertion is the third type of active strategies which means introducing an especial phase within the normal sequence and serving the bus (in case of TSP request) in that phase. Finally, Phase rotation refers to changing the order of the pre-set phase sequences and rotating them such that the green phase for the bus will be appeared earlier. Figure 2-2 shows a schematic representation of different TSP strategies. Adjusted offset as a passive treatment as well as the common active strategies (namely green extension, early green, phase rotation, and phase insertion) are schematically shown in this figure.



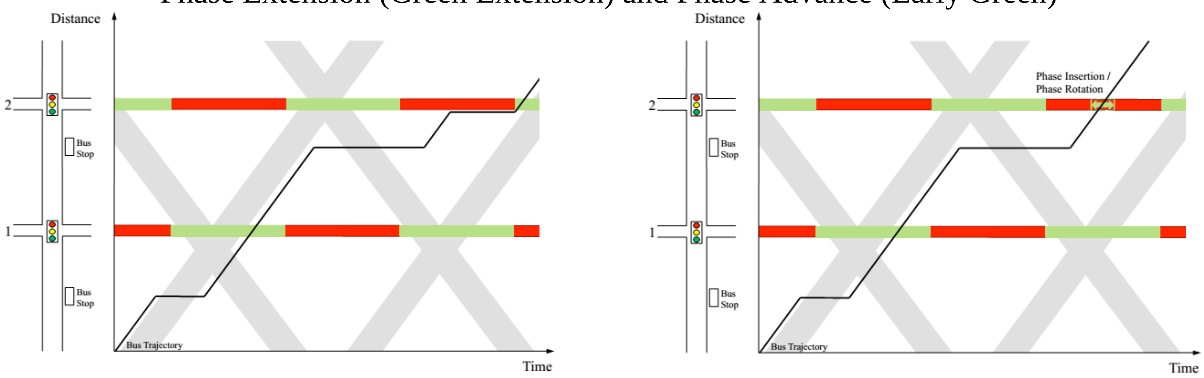
(a) Initial Signal Settings (b) Adjusted Offset

Adjusted Offset



(a) Initial Signal Settings (b) Phase Advance and Phase Extension

Phase Extension (Green Extension) and Phase Advance (Early Green)



(a) Initial Signal Settings (b) Phase Insertion/Phase Rotation

Phase Insertion or Phase Rotation

Figure 2-2 Schematic view of the different TSP strategies (source: Christofa (2012))

In practice, green extension and red truncation strategies are more common than the other ones and the majority of the literature (e.g. (Stevanovic et al., 2008, Stevanovic et al., 2011, Skabardonis and Christofa, 2011, Ekeila et al., 2009, Liu et al., 2012, Zlatkovic et al., 2010)) developed models based on these two strategies. These two strategies do not require additional clearance time thus do not increase in the lost time of cycle. In addition, they are less disruptive than the other strategies for the drivers. Finally, green extension and early green can be applied with no change in phase sequence and cycle length so that less interruption in the progression of the vehicle platoons will be expected (Christofa and Skabardonis, 2011a). Table 2-1 provides a summary of the application of TSP strategies in different studies. As can be seen in this table, the majority of TSP strategies employed early green (EG) and green extension (GE) strategies.

Table 2-1 Implemented TSP strategy by agency. Source: (Baker et al., 2004)

Location	Transit Type	No. Of Intersections	TSP Strategy	Benefits/Impacts
Portland, OR Tualatin Valley Hwy.	Bus	13	early green, green extension	• Bus travel time savings of 1.7 to 14.2% per trip •2 to 13 seconds reduction in per intersection delay • Up to 3.4% reduction in travel time variability
Europe	Bus	Five Case Studies	Various	• 10 seconds/intersection average reduction in transit signal delay • 40 to 80% potential reduction in transit signal delay • 6 to 42% reduction in transit travel times in England and France •0.3 to 2.5% increase in auto travel times • 1 to 2 year payback period for installation of transit priority systems
Seattle, WA(Rainier Ave)	Bus	20	early green, green extension	•24% average reduction in stops for TSP eligible buses •5-8% reduction in travel times •25-34% reduction in average intersection bus delay for TSP eligible buses • 40% reduction in critically late trips (trips not completed before next trip scheduled start) • Life cycle benefits are $15,000 service benefit per intersection and $40,000 passenger benefit per intersection (over 10 years life)
Toronto, Ontario	Street car, Bus	350	early green, green extension	• Up to 46% reduction in transit signal delay • 10 street cars removed from service • 4 buses removed from service in 2 initial corridors • Payback less than 5 years • Cross street traffic not significantly affected
Chicago, IL(Cermak RD)	bus	15	early green, green extension	• 7 to 20% reduction in transit travel time depending on time of day, travel direction •Transit schedule reliability improved • Reduced number of buses needed to operate the service • Passenger satisfaction level increased since TSP was implemented • 1.5 second/vehicle average decrease in vehicular delay (range: +1.1 to –7.8) • 8.2 second/vehicle average increase in cross-street delay (range: +0.4 to +37.9)
Minneapolis, MN (Louisiana Ave)	Bus	3	early green, green extension,	• 0 to 38% reduction in bus travel times depending on TSP strategy • 23% (4.4 seconds/vehicle) increase in traffic delay • Skipping signal phases caused some driver frustration
Los Angeles, CA (Wilshire & Ventura Blvd.)	Bus	211	early green, green extension,	• Introduced as part of Metro Rapid BRT • 8% reduction in average running time • 33-39% decrease in bus delay at signalized intersections • Minimal impacts to cross street traffic: average of 1 second per vehicle per cycle increase in delay • TSP did not change the traffic Level of Service
Pierce County, WA(Pacific Ave)	Bus	42	Signal coordination , early green, green extension, low priority pre-empt	• Initial deployment in two corridors involving both signal coordination and TSP • Signal coordination reduced total signal delay 18-70% for general purpose traffic, and 5-30% for transit • TSP reduced transit signal delay an additional 20-40% beyond signal coordination • TSP had little impact on traffic progression

Although active strategies are more flexible and more efficient than passive ones, they are much costlier than passive strategies. Communication technologies and bus detection system and their complexity in implementation (which may waste the investment with having no major effect as a system-wide point of view) can be stated as the major issue with these strategies.

Conditional granting of TSP requests

Granting priority to transit vehicles can be given as either unconditional or conditional methods. Unconditional methods provide priority to all transit vehicles that are equipped with detectors, regardless the status of the vehicle. Since the priority will be given to all transit vehicles, maximum saving in transit travel time can be achieved. On the other hand, there might be a set of constraints (e.g. being behind schedule, have a minimum number of passengers, etc.) in granting priority such that only the vehicles that met those constraints should benefit from TSP. Being behind schedule(schedule based) and having a minimum number of passengers(occupancy-based) are two common constraints that are mainly targeted in conditional priority schemes, despite the term "conditional priority" is occasionally narrowed to the systems that are seeking to grant priority using schedule based logics only (Furth and Muller, 2000). Conditional approaches are more sophisticated systems (like automated vehicle location (AVL) and other transmission and communication systems) than the unconditional ones(Baker et al., 2004). Nevertheless, their overall benefit (as a holistic view and not just for buses) is assessed to be higher. Over the past years, conditional priorities have become more popular than before, thanks to their proven performance and increasing developments of technologies.

Seeking to improve schedule and headway adherence of the transit services, the majority of conditional TSP strategies are granting priority to the buses that are behind their schedule. Furth and Muller (2000) reviewed a TSP method in which priority would be given only to the late buses. The TSP logic was such that if the bus was late and approached a red light, the signal quickly turned green to serve it. They studied a transit service in Eindhoven, Holland and an improvement in service quality by keeping buses on schedule via deploying conditional priority was reported. Limiting the negative impacts of the traffic was also observed. Besides, they claimed an easier operation to be achieved since the bus drivers are less concerned for adjusting their speed in order to stay on schedule.

Ma et al. (2010) approached the TSP strategy as a tool to make the delay of the buses close to a permitted delay which is defined by operators. Consequently, TSP for the early buses applies an additional delay to the bus. To make the bus delays as close to the defined threshold as possible, they proposed a method, named Coordinated and Conditional Bus Priority (CCBP) to generate optimal combination of priority strategies (i.e. decreasing or increasing of the bus delay). "Dramatic" decrease in bus delay and headway deviations and "much less" average delay of cars than unconditional priority was reported as the results.

Setting a minimum number of passengers is another constraints for conditional priorities. In this approach, the priority is given to the transit vehicle only if they have at least a pre-defined number of passengers. The communication system and source of data are the main elements of using this method. Letting the drivers trigger a TSP request (which may need recruiting as well as extra attention of the driver) is amongst the suggested approaches (Smith et al., 2005). Finally, the person-based delay approach (e.g. Christofa et al. (2013)) is another strategy in which the priority will be given using a capacity or number of passengers constraint.

As mentioned above, the major issue of conditional priority strategies is to establish a reliable while not costly communication system between vehicles and infrastructure. Over the past years, a remarkable progress in communication systems has happened. This growth can facilitate conditional TSP strategies since more real-time information is available and further details can be reflected. Availability of the number of passengers and demands, tracking the buses in their entire route, and having a central centre to make detailed decisions are amongst the improvements which may provide huge augmentation in application of conditional strategies.

2.2.2 ***TSP Logics***

In addition to the type of TSP strategies, different kinds of implementations can be seen in the literature. This variety is mainly due to the detection systems and arrival prediction models as well as the type of response to the requests. In this section, a review on different kinds of active TSP logics is presented in this section. A review on the methods of dealing with conflicting priorities (simultaneous TSP requests) is performed in section 2.2.6.

Liu et al. (2003) approached the problem using a weighting factor to the priority request. In their study, a bus with priority was converted to a set of vehicles by using a weighting factor (which is obtained from traffic demand and queuing conditions). Consequently, a passenger car equivalent rate for each approach would be obtained. The signal would then be timed using a new set of flow rates which normally is adjusted in favour of the approach with a TSP request. In this approach, setting appropriate weighing factors seems crucial.

Zlatkovic et al. (2012b) performed an analysis on a set of TSP strategies to find the optimum policy of a future bus rapid transit service. In their study, a heuristic TSP logic, called “Custom-TSP” was developed and compared with the common methods. The main feature of custom-TSP was that none of the phases could be omitted in this strategy. Besides, the proposed logic assures the traverse of the prioritized bus before the signal turns to red. A phase rotation strategy was also considered in their customized approach. They reported superior results than basic TSP strategy.

To improve the previously developed active TSP strategies, Ekeila et al. (2009) presented a dynamic traffic signal priority strategy which can provide priority in response to real-time traffic and transit conditions. Their method includes three major elements: virtual detection system, dynamic arrival prediction model, and dynamic TSP algorithm. The detection system is theoretically based on real-time data but is modelled by successive detectors (with 10m intervals) to track the location of the bus at each step. A linear model was also assimilated to predict arrival times. This arrival model is suggested to be enriched by refinement methods like Empirical Bayes (EB) and Kalman Filtering (KF). The algorithm recursively checks the predicted arrival time of bus till it reaches a time that a decision should be made. They defined a set of scenarios for the signal phase arrival times and their upper and lower bounds and suggested one of three types of defined TSP solutions (green extension, red truncation, and cycle extension) according to the situation. They used microsimulation method to evaluate their method and reported superior results than the Base (no TSP) and conventional TSP strategies.

Giving priority to the buses with near-side bus stops, Kim and Rilett (2005) presented an Improved Transit Signal Priority. They argued about the performance of common TSP logics for the buses with near-side bus stops in which the dwell time is a matter of uncertainty. They used a weighted-least-squares (WLS) regression model to estimate dwell time distributions thus predicting bus arrivals to the intersection. This prediction can help the algorithm to adjust the timings such that the bus can traverse the intersection without being stopped. Early green, green extension, phase insertion, and phase extension were the strategies that the algorithm implemented. Testing the model using microsimulation method, they reported less bus delay than the conventional TSP logics.

Customization of basic TSP strategies can be considered as a viable solution to improve the performance of the system. They can enrich system to more sophisticated decision making algorithms, reflecting different scenarios that can be observed in each intersection. Nevertheless, considering the ad hoc nature of the traffic state as well as the required level of accuracy in a macro level analysis, these approaches may incur extra computational cost to the evaluation process with no added benefit for strategic planning purposes.

2.2.3 *TSP Evaluation Methods*

Regardless the type of the developed and/or implemented strategy, evaluation of TSP performance is a matter of concern. In general, the following three approaches can be used to evaluate the impacts of TSP on traffic flow and transit performance (Abdy and Hellinga, 2011):

1. Microscopic Simulation
2. Analytical Methods
3. Field studies

In this section, a review on the available literature that used either of the aforementioned methods is presented.

Microsimulation Methods to Evaluate the Effect of TSP

The majority of the studies on TSP modelling and analysis have used microsimulation models (e.g. (Zlatkovic et al., 2012b, Zlatkovic et al., 2012a, Zlatkovic et al., 2013), (Stevanovic et al., 2011), (Kim and Rilett, 2005)). This is mainly due to the sensitivity of TSP efficiency to several parameters such as intersection layout, vehicular flow rates, bus headway, bus stop locations, and signal coordination (Ngan et al., 2004). Microsimulation models are able to consider a wide range of parameters and conditions which affect TSP effectiveness (Abdy and Hellinga, 2011).

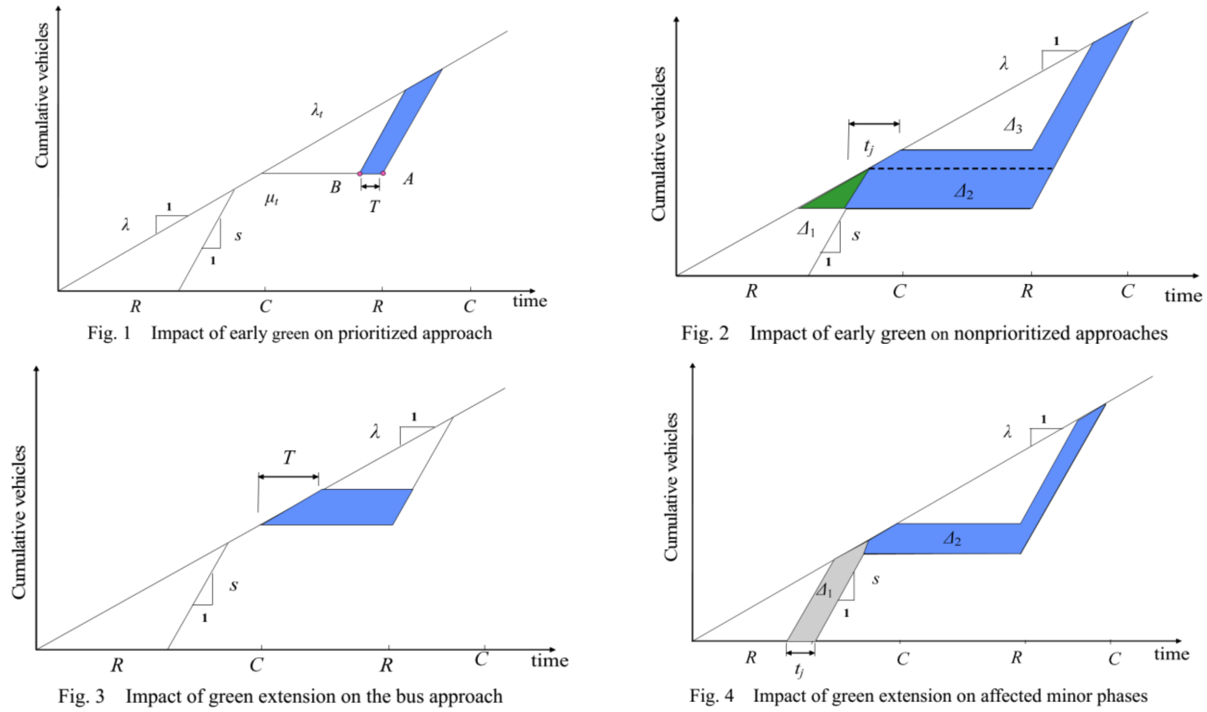
Sayed and Abdelfatah (2004) examined the impacts of a set of traffic parameters on the effectiveness of TSP application. Using VISSIM microsimulation method, they applied a set of TSP strategies on a corridor, and suggested some guidelines regarding TSP implementation. Ahn and Rakha (2006) investigated the system-wide effect of TSP operation on a corridor using INTEGRATION microscopic traffic simulation software.

Microsimulation analysis is known as the best method for the evaluation of TSP strategies. Numerous models for simulating cars and drivers behaviour as well as possibility of reflecting the network layout with maximum level of details all have made microsimulation models a popular approach. Nevertheless, there exist numerous drawbacks in their application. Having project-specific nature and calibration requirements, computational costs of their development and evaluation, and their commercial nature and limited license accessibility to undertake distributed/cloud processing has encouraged the researchers to consider other evaluation methods.

Analytical Methods to Evaluate the Effect of TSP

A number of studies developed an analytical approach to assess TSP strategies. Sunkari et al. (1995) was one of the first attempts to develop an analytical approach to evaluate the impact of TSP strategies at intersections. They used the basic delay equations of 1985 Highway Capacity Manual for signalized intersections. They reported an overall reasonable accuracy but overestimating delay at some circumstances. It was claimed to be a readily available tool to assess the feasibility of implementing priority strategies, although the method was oversimplified and was not appropriate for a practical application.

Using the fundamentals of queuing theories, Liu et al. (2008) presented a model to evaluate truncated red and extended green effects at an intersection. Their assumptions were that implementation of TSP does not significantly change the randomness of traffic stream and the impact of TSP can be captured assuming deterministic arrival and service rates. Focusing on early green and extended green as the most common TSP strategies, they calculated the increased delay for both bus approach and the opposing movements. Figure 2-3 shows the diagrams used to calculate extension effect on delays. The delay was calculated for just one cycle and their effect beyond the first cycle was ignored.



T: green interval for the prioritized approach
S: saturation flow rate of lane group iin vehicle/s.
R: red interval of phase i
C: cycle length in second
λ,s: arrival and service rate of the intersection, respectively
Δ_1: *initial queue delay caused by the residual queue because of the truncation of the phase*
Δ_2: *additional delay caused by the increased traffic arrivals during the prolonged red interval in the subsequent cycle*
Δ_3: *delay under normal operation when there is no truncation*

Figure 2-3 Analytical evaluation of impact of TSP strategies on bus and cars (source Liu et al. (2008))

Abdy and Hellinga (2011) argued the prior studies on analytical evaluation of TSP impacts for a number of shortages: Calculation of the delays for only one cycle and thus ignoring TSP impacts that may extend beyond the first cycle, deficiency in estimating the delay when TSP causes an oversaturated flow in the opposing movement, and ignoring bus frequency effect on TSP performance were issues they addressed and presented a model to tackle them. In their proposed model, depending on the TSP type (Early green or green extension) and queue dissipation cases, a set of scenarios were defined and mathematical formulation for calculation of the total vehicle delay and time of dissipation of the queue were presented. The results calculated from the model was compared with the ones obtained using microsimulation analysis and a close match, especially for the flows with v/c <0.8 was reported. Similar to many other analytical models, this research was yet based on queuing theory and deterministic arrival and service rates (i.e. D/D/1). Figure 2-4 shows their developed diagram to calculate delay of non-prioritized approach with red truncation control type for a set of defined scenarios.

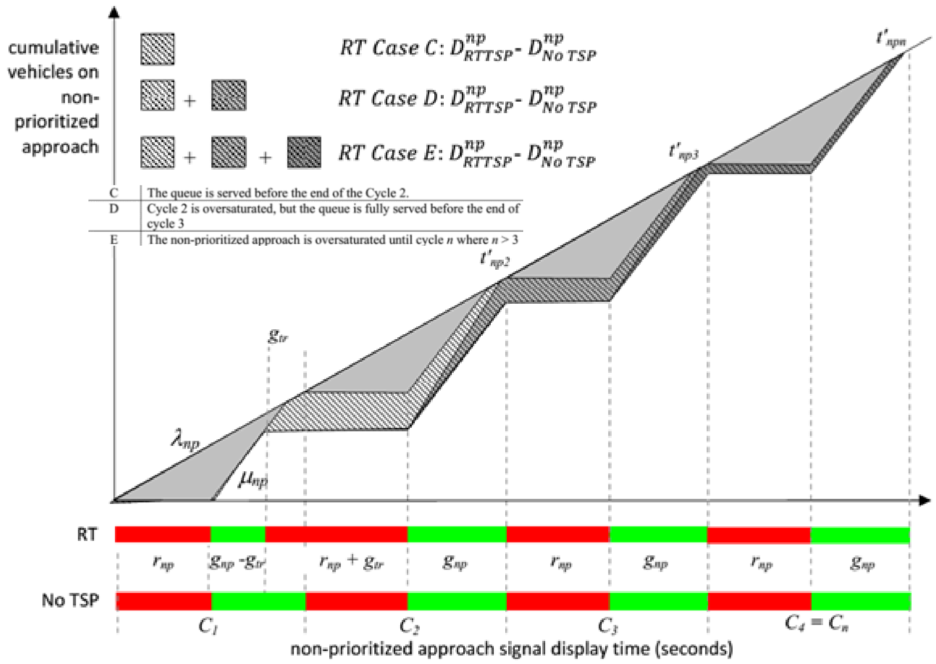


Figure 2-4 Calculation method of signal delay in different scenarios-source: Abdy (2010)

In a recent study, Skabardonis and Christofa (2011) presented a new method to estimate the effect of TSP on control delay and the level of service of an intersection. They assumed that the probability of receiving priority equals the probability of arriving within extended green and calculated average delay and level of service for different modes. Their analysis model relied on the Highway Capacity Manual (National Research Council . Transportation Research, 2010) method for intersection delay estimation. Adjustment factors for intersections with TSP were suggested for each approach. In their study, it was assumed that the delay is only a function of the degree of saturation (volume to capacity ratio) and green time to cycle length ratio. GE and RT were two strategies which were implemented as the TSP strategies.

Analytical approaches can be considered as a viable solution for analysis of TSP performance at a network level study. Thanks to a set of simplifications assumptions, the evaluation process is much faster than simulation methods and results matches the ones obtained by microsimulation methods. Nevertheless, to our best of knowledge, the literature shows the delay and travel time values as the only implemented measures of performance of these approaches. One seminal measure is the reliability index that can be extracted from the data obtained from "individual" vehicles while such disaggregated data cannot be seen in analytical approaches. Indeed, Current studies cannot reflect the stochastic nature of the traffic and the characteristics like variability which are bond to them.

Field Studies

Evaluation of the effect of TSP by comparing the data of before and after TSP deployment is another method to estimate TSP impacts. This method is usually utilized after applying a strategy and in pursuit of evaluating its performance in the field. In this section, an overview on two empirical studies on the performance of TSP strategies is presented. Further details and studies can be found in references such as Smith et al. (2005).

Using observed data, Wang and Northwest (2007) performed a comprehensive study on an implemented TSP strategy in Snohomish County, Washington State. They evaluation of TSP deployment was performed for a set of effectiveness measures (Transit time match, transit travel time, traffic queue length, signal failures, frequency of TSP calls, average person delay, and vehicle delays) for data before and after deployment. The data were obtained from TSP logs, GPS data of the vehicles, traffic controller logs, traffic video data, and log forms made by bus driver (in case of unusual transit vehicle delays). Their evaluation confirmed the positive effect of TSP for transit vehicles and insignificant negative impacts on traffic delay. They recommended considering the importance of TSP control strategies and signal coordination modules before implementation.

Kimpel et al. (2005) studied the effect of TSP implementation on both operators and passengers. They evaluated the performance of the TSP in different perspectives and measures of performance but reached atypical conclusions. They showed that on the contrary of the improvements in bus running times, the adherence of the buses to their headway was decreased. Table 2-2 summarizes the performance measures of their study in different times and segments of the study corridor.

Table 2-2 Percentage of segments showing improvements by route (source: Kimpel et al. (2005))

Segment	No. Segs.	Mean Actual Run Time (%)	Var. Actual Run Time (%)	Sched. Run Time Savings (%)	Recov./Lay. Time Savings (%)	OTP (%)	Mean Hwy. (%)	Var. Hwy. (%)	Excess Wait (%)
12	4	50.0	50.0	50.0	50.0	75.0	50.0	0.0	0.0
14	4	50.0	50.0	50.0	0.0	25.0	0.0	25.0	25.0
72	6	33.3	33.3	33.3	50.0	33.3	0.0	0.0	33.3
94X	2	50.0	100.0	50.0	100.0	0.0	100.0	50.0	50.0
109	4	50.0	25.0	50.0	25.0	50.0	25.0	0.0	25.0
112	4	50.0	50.0	50.0	50.0	50.0	100.0	50.0	50.0
Total	24	45.8	45.8	45.8	41.7	41.7	37.5	16.7	29.2

Since these approaches are only limited to before-after studies, field measurements cannot be applied for a decision making process in a network-wide level. They can be used for either having a prediction of TSP performance in similar sites or evaluation of the developed strategy after its application. Considering the latter, these observations can provide a filter to limit the number of intersections with the potential of TSP deployment. In other words, a set of guidelines can be extracted from these observations to be applied in future studies. These guidelines can be considered in the objective function as constraints thus narrowing the searching process to the better solutions.

2.2.4 *TSP Measures of Performance and Objective Functions*

In this section, a review of the adopted methods for evaluation of TSP strategies is presented. Among the goals for applying TSP strategies, the followings can be stated (Smith et al., 2005):

1. The impacts of TSP implementation on bus and car travel times.
2. TSP Impacts of the variability of the transit system (e.g. schedule adherence or preserving headways)
3. The effect of TSP on decreasing air pollution, and modal shifts
4. Reducing excessive transit delay at a specific intersection or a corridor as the corollary of TSP
5. Possible savings in transit operational costs (e.g. savings by reducing fleet size)
6. The impacts of TSP on total person-based throughput of the study area

Stevanovic et al. (2011) considered private vehicle delay, delay per person (assuming private and transit vehicle occupancies), and transit vehicle delay as three performance measures to assess different TSP scenarios and sought to optimize basic signal timings (cycle length, offset, splits and phase sequence) along with TSP parameters. Similarly, Ekeila et al. (2009) developed a dynamic transit signal priority strategy and compared it with the traditional strategies. Average travel time of the buses and the cross street delays were two criteria they used to compare strategies.

Ahn and Rakha (2006) studied the system-wide benefits of applying a green extension priority policy. They stated that there is no guarantee of system-wide benefits of TSP systems although a transit vehicle will generally benefit from that. Total and average vehicle delays for bus and private cars, average stops per vehicle, queue length of the crossing-streets, fuel consumption, and emissions (HC, CO and NOx) were compared for different TSP scenarios. Zhou et al. (2007) presented a mathematic formulation to optimize TSP parameter settings. They introduced minimization of average delay of the buses in intersection as the objective function.

While the majority of studies on the performance of the TSP strategies used travel time (or delay) as the measure of effectiveness, there exists few research that used other criteria.Chang et al. (2003), for instance, evaluated the effect of TSP on service reliability and compared it with the results obtained from delay measurements. In Kimpel et al. (2005), adherence to schedule and preserving the headway was evaluated.

Over the past years, it has extensively shown that travel time reliability is as important as (if not more important than) the value of travel times. Depending on the socio-economic parameters, different suggestions are presented to compare reliability measures with the value of reliability. Regardless, not only no attempt has been made considering reliability as the objective of an optimization module, there exist no research in which travel times and reliabilities are considered simultaneously as a unique objective function. This approach can reflect the impacts of TSP implementation more than traditional single-objective measures. Following this approach, a simulation based model is required to capture the randomness of the traffic state and current analytical approaches are unable to handle it.

2.2.5 *Optimization of TSP Characteristics*

While numerous signal timing optimization packages and models are available in the literature (e.g. Park et al. (1999), Sun et al. (2006), Stevanovic et al. (2007), Cui et al. (2013)), few studies differentiated between traffic and transit vehicles. This is surprising when there are numerous studies that can be found working on TSP implementation and evaluations. This is mainly due to limitations in incorporating TSP settings and applications with optimization tools in commercial packages (Stevanovic et al., 2011). In this section, a review on the available literature related to optimization of the TSP characteristics is presented. The searching methodologies and a set of techniques for improving searching performance is introduced in section 2.4.

Stevanovic et al. (2008) presented a model to optimize basic signal timings and transit priority settings of the intersections using microsimulation method. This optimization tool was introduces as VISSIM based Genetic Algorithm Optimization of Signal Timings (VISGAOST) and was claimed to be the only package for optimization of all four signal timing parameters (Cycle length, green splits, offsets, and phase sequence). Besides, they implemented an emulator in VISSIM called “LMD 9200-peak” to integrate TSP capabilities in the optimization model. Limits for early green strategies, maximum value for green extension strategy, and settings for new walking times if a TSP request was granted were three parameters optimized in this study.

Stevanovic et al. (2011) developed an optimization method considering auto delays, transit delays, and person delays as the performance measures. They used their VISGAOST package to evaluate the quality of signal timings and adjust their settings in each signal. They optimized the values of green extension (green extension and early green values). To optimize signal characteristics of a corridor with 70 intersections, they employed 20 dual-processor machines and performed 3 months of continuous runs.

In general, research on developing an optimization module for TSP settings can be seen to be limited to one research group (Stevanovic et al (2007-2013)) where a GA based microsimulation tool is developed to convey different facets of TSP strategies. However, application of the modules is limited to the corridors only and no effort has been done to consider TSP effects on a network with conflicting TSP requests). Besides, as reported by Stevanovic et al. (2011), integration of microsimulation tools and repetitive-based optimization tools imposes significant computational costs and it might be necessary to work on efficacy of this process.

2.2.6 *Conflicting Priorities*

Increasing the popularity of preferential strategies by transit agencies has caused an increase in the number of TSP requests in a network. This situation leads to an augmentation in the probability of having concurrent request for TSP by two or more buses approaching an intersection. Handling conflicting TSP requests is an emerging topic in the realm of TSP application and a handful of methods are suggested to tackle them. In this section, a review on the strategies for managing conflicting transit signal priority is reviewed.

First-In-First-Serve (FIFS) strategies are the most common and simplest version of multiple-TSP strategies. In these strategies, the first bus that requests priority will be granted and all the other requests will be ignored until the system is restored to its normal condition. Head et al. (2006) and Zlatkovic et al. (2012a) showed that this method is not an efficient TSP strategy and even may occasionally perform worse than a Non-TSP strategy.

Head et al. (2006) presented a decision model for bus priority handling of traffic signals. Relying on the precedence graphs, they proposed a mixed-integer mathematical model and formulation that considers the arrival time of all the buses in a conflicting scenario and makes a decision such that minimum total delay can be achieved. They minimized total priority delay while considering precedent, phase duration, and service phase selection constraints. The model was applied on a simple scenario and their model can serve multiple priorities efficiently, although the complexity of the problem was stated as a noticeable drawback. Keeping on this research, He et al. (2011) presented a heuristic algorithm for TSP with multiple priority requests. They assumed some simplifications in the prior formulations and made it a “solver-free” problem. Assuming phase sequences to be fixed, a FIFS rule for the requests in the same phase, and ability of serving all requests in two cycles were three assumptions that made the algorithm applicable on an isolated intersection. Evaluation of the model using a microsimulation method confirmed its ability to perform better (in terms of minimizing total bus delays) than the prior methods.

Zlatkovic et al. (2012a) presented a new method to deal with conflicting Transit Signal Priority strategies at the intersection. The major difference between their presented method and the FIFS approach was that in their model once the first arrived bus left the intersection, granting priority for the second bus would be checked. In other words, multiple-TSP algorithm will not ignore the second arrived bus, as is the case in basic FIFS models. This model was defined as an unconditional priority and the moment in which a TSP call is placed as well as the signal status at that moment are two important parameters of the algorithm.

In a recent study, a person-based traffic responsive signal control system for transit signal priority was presented by (Christofa et al., 2012). This paper is relying on a set of research they performed on person-based traffic signal optimization (Christofa and Skabardonis, Christofa and Skabardonis, 2011a, Liu et al., 2012, Christofa, 2012, Christofa et al., 2013) They formulated a mixed integer linear mathematical model in which the objective is to minimize the total person delay at the intersection. Assuming that the system has real-time data of the traffic stream (both cars and buses) along with the passenger occupancy of them, they presented the following formulation:

$$min \sum_{a=1}^{A} o_a\, d_a + \sum_{b=1}^{B} o_b\, d_b \qquad 2\text{-}1$$

$S.T.$

$$\sum_{i \in I_j} G_i < G_{j\,min} \qquad 2\text{-}2$$

$$\sum_{i=1}^{P} G_i = \mathrm{C} \qquad 2\text{-}3$$

Where:

o_a	passenger occupancy of auto a(*pax/veh*),
o_b	passenger occupancy of transit vehicle b(*pax/veh*),
d_a	control delay for auto *a(s)*,
d_b	control delay for transit vehicle *b*(*s*),
A	Total number of private cars(P) and buses(*B*) in the network
B	The unit cost of the TSP facilities
I_i	set of phases that can serve lane group *j*,
G_i	green time allocated to phase *i*(*s*),
$G_{j\,min}$	minimum green time allocated to lane group *j*(*s*),
P	number of phases in a cycle, and
C	cycle length (*s*).

A number of simplifying assumptions were considered in their work. First, the model is valid for an under-saturated traffic condition. Furthermore, a deterministic regime was assumed for both vehicle arrivals and service times. In addition, the arrivals of transit vehicle at the intersections were assumed to be known in real-time. Although for a set of performance measures (i.e. Speed, number of stops per vehicle, and emissions) the results of the mode were shown to be consistent with microsimulation results, there exist some limitations in this model. Capability of reflecting different traffic states (regardless their level of congestion) as well as the random delay of the vehicles can make the model more applicable to real world problems.

2.2.7 *TSP Deficiencies*

TSP is a widely accepted operational strategy that changes intersection signal timing in favour of buses and thus may reduce overall bus delay (and consequently fuel consumption) at intersections. Nevertheless, despite the increasing implementation of TSP strategies, these strategies still face a number of drawbacks.

It is acknowledged in the literature that TSP may not efficiently serve transit services with nearside stops due to the existing uncertainty in the duration of dwell time (Ngan et al., 2004, Kim and Rilett, 2005). Since nearside bus stops are a common sight in big cities, TSP implementation may not be well argued for a significant number of intersections. Although the available model to address this issue showed overall success in coordinating TSP with the dwell time Kim and Rilett (2005), an extra delay for non-prioritized movements was reported. Negative impact on non-prioritized movements is another concern of TSP application. This problem is addressed in the literature as the main issue of TSP implementation (e.g. Li et al., 2008, Christofa and Skabardonis, 2011b) where prioritizing buses may incur extra delay to competent modes and movements. Consequently, applying such preferential transit strategies at intersections is normally limited to moderate congestion and an appropriate network layout. The idea of minimization of person delay was recently introduced to give a fair share of delay to each movement, depending on the number of individuals experiencing delay at intersections(Christofa, 2012). Relying on their person-based framework, Khalighi and Christofa (2015) presented an emission-based optimization signal timing method for an isolated intersection. In this model, the aim was to decrease the number of vehicle stops and thus accelerations and decelerations and consequently reach a reduction in fuel consumption. They reported that the total bus emission (which is correlated with fuel consumption) had no significant improvement, mainly due to the prevailing share of autos making emissions in an intersection. In other words, the major benefit in minimizing intersection fuel consumption is in favour of passenger cars and there is modest (if any) benefit for the transit operators in this regard(Sobh, 2015).

2.2.8 *Using Vehicle to Infrastructure and Vehicle to Vehicle Communications*

With the advent of connected vehicle (CV) technology which is classified as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, new opportunities for intelligent transportation systems have been provided. In this regard, V2I communication has been attracting much attention and has been developed to improve transportation operations over the past few years. General examples include their implementation in signal pre-emption (Jordan and Cetin, 2015), integration of V2I to Macroscopic Fundamental Diagrams(Xu et al., 2015), and improving the performance of Transit Signal Priority tools (Hu, 2014, Hu et al., 2015, He et al., 2014).

Using V2I technology, data are transmitted between the signal control systems and approaching buses. This is opposite to the common signal controllers which only receive data from the vehicle using equipment such as loop detectors. Such flexibilities are harnessed in signal controlling systems in a number of studies. Hu et al. (2015) developed an integration of TSP and CV technology (called TPCSV) in which a person-based optimization method was implemented as the signal controller logic. In that study, bus speeds as well as signal timings were optimized, aimed at minimizing total person delay. The potential interruptions due to dwell times were relaxed in their study. Using a similar approach, Ubiergo and Jin (2015) proposed a method to adjust vehicles' speed thus directing them to reach the intersection when the signal phase was green and showed around 8% reduction in fuel consumption. The effect of bus stops, especially the ones behind the intersections that not only make the arrival times uncertain (due to dwell time), but also constrain a bus to reach its required speed (due to the short distance to the intersection), were not considered in their study.

2.3. Using Passengers Information to Identify Transit Network Issues

One of the seminal tasks of deploying priority strategies is to have a tool to observe the network and identify problematic routes, corridors, intersections and zones in terms of the experienced unexpected delays for the passengers. Over the past few years, as the corollary of using smart card Automated Fare Collection (AFC) to collect revenues, the availability of massive and disaggregated passenger's transactions data for transit planning and operational purposes has significantly increased. Depending on the fare collection scheme, invaluable source of travellers' data such as departure and arrival times, passenger's origins and destinations, selected transit routes, and transfers information are available or can be inferred by applying a series of assumptions. As a result, AFC data has attracted a lot of attention by transit agencies and researchers in the last several years. Pelletier et al. (2011) performed a comprehensive literature review on smart card data and showed their range of application, from strategic to tactical and operational levels. Amongst the studies that relied on smart card data, origin-destination demand estimation (e.g.Chan, 2007), travel patterns identification (Ma et al., 2013), ridership prediction (Van Oort et al., 2015), activity detection (Nassir et al., 2015) and reliability measures (Morency et al., 2007, Uniman et al., 2010, Zhao et al., 2013, van Oort, 2014, Hendren et al., 2015, Wood, 2015, Diab et al., 2015) can be mentioned. In the case of the latter, AFC data can not only provide a better and more accurate measure of the existing indicators, but new reliability metrics can also be defined for a better representation of service performance for its users. Implementation of passenger-oriented delay reliability metrics is amongst the new possibilities AFC data has provided for transit agencies.

An increasing trend to shift from service-based reliability metrics to passenger-oriented ones can be seen in the literature (e.g. Wood, 2015, Hendren et al., 2015, Chakrabarti and Giuliano, 2015, Cats, 2014). This is mainly due to the supply-oriented nature of traditional measures of variability and their potential discrepancy from the reliability when accounting for passengers' travel patterns. Consequently, policies and strategies designed to improve service reliability may not necessarily result with the envisaged effects when considered from passenger's perspective. Such shift toward passenger-oriented metrics thus seems crucial to reach a higher ridership and increasing agencies revenues.

Numerous measures of travel time reliability are developed and implemented in practice. Diab et al. (2015) performed a comprehensive literature review on bus service reliability and classified these measures into passengers' and transit agencies' perspective. In another study, Gittens and Shalaby (2015) performed a review on the existing user-based reliability indicators and presented them through five different classes (travel time, schedule adherence, headway regularity, wait time, and composite indicators). They identified travel time and waiting time variabilities as the chief indicators of a transit service reliability. In another study, van Oort (2014) conducted a survey to see how transit agencies measure their service reliability in practice and reported that the existing measures are mainly based on vehicle data. He observed the lack of a passenger-oriented measure of transit reliability in practice and accredited its necessity for a transit agency, suggesting AFC implementation as a viable dataset to develop and utilize reliability metrics in practice. To consider passenger impacts, Van Oort (2016) suggested two metrics focusing on the extension of passenger travel time and its distribution. Similarly, Lee et al. (2014) dealt with one of the shortcomings of supply oriented metrics, being transfers. They performed analyses of service reliability of multi-leg journeys.

A couple of studies proposed reliability metrics based on passenger's travel time experience. These metrics reflect the predictability of the service for the passengers based on their experienced travel times. Uniman et al. (2010) defined the Reliability Buffer Time (RBT) measure as the time a passenger should allocate as buffer time to secure on time arrival to their destination with a pre-specified degree of uncertainty. They suggested the difference between 95th and 50th percentile travel time values as the representative of typical and acceptable levels, respectively. They extended this work by classifying the performance into recurrent and incident-affected ones. Then they introduced Excess Reliability Buffer Time (ERBT) metric as the difference between 95th percentile travel time values in overall (i.e. including incident affected records) and typical dataset. These measures are appropriate in the context of high frequency services where passenger arrival pattern can be considered to be uniform.

In conjunction with predictability metrics, transit service punctuality (i.e. adherence to the timetables) ones are the second category of the transit travel time variability, reflecting how close the service is to the promised (i.e. scheduled) one. London Underground defined Excess Journey Time (EJT) as the difference between the scheduled and experienced arrival time to the destination. It can be presented as the additional time that may be added to the scheduled travel time due to incidents, queuing and crowding delays (Hendren et al., 2015). Zhao et al. (2013) developed this measure and performed a reliability measurement on the London rail network (Overground) using Oyster smart card data. Oyster users tap their card upon entries and exits of the system thus an assignment module was used to find passenger route choices, including transfer locations. In addition, as the tap incidents were happening before entering the platform, the data reflect not only the in-vehicle time, but a combination of waiting time, queuing delays, in vehicle delays and egress times.

One common feature of the regularity (e.g. RBT) and punctuality (e.g. EJT) metric is that both have been established for the case where smart card data validation is performed at stations. In other words, transaction records provide information about the location and time of passenger entrance to the system and their exit at destination. Consequently, chosen routes cannot be directly observed and models such as assignment tools are used to estimate them. Besides, the available travel time data include walking and waiting times. Therefore, as acknowledged by Hendren et al. (2015), such reliability metrics do not provide actionable information for the transit agencies to apply priority strategies. Providing a framework for delivering a practical reliability measure for transit agencies and operators for buses and trams that can reflect the sources of delay for passengers seems legitimate.

2.4. Optimization Tools

Optimization algorithms can be divided into two categories: Deterministic algorithms, and stochastic algorithms (Reklaitis et al., 2006). Deterministic algorithms follow a rigorous procedure to reach the exact solution of a problem. On the other hand, stochastic algorithms seek to find the optimal solutions using a directed random search and the found solutions are not necessarily exact global optimum. Due to the complexity of transportation problems, solving a real-world problem via exact method is almost infeasible (due to significant computational costs and effort requirements). As the results, metaheuristic algorithms are known as viable searching algorithms for solving real world problems. Genetic Algorithm (Goldberg and Holland, 1988) is the most common metaheuristic method that has been applied on a plenty of transportation problems. Nevertheless, over the past years, numerous research has been presented (e.g.Teodorović (2008), Mazloumi et al. (2012), He and Hou (2012), Shafahi and Bagherian (2013)) New stochastic optimization tools which are shown to work better than GA-based tools (in terms of computational costs and precision of the found solutions). These algorithms can be enriched by optional tools such as niching methods (Mahfoud, 1995) or heuristic innovations to improve an algorithm performance. In this section, a review on the swarm intelligence, one of the new searching methods is discussed. To follow these subjects, a reader can refer to the cited references or resources such as Kennedy et al. (2001) and Reklaitis et al. (2006).

2.4.1 *Swarm Intelligence*

Swarm intelligence is a branch of artificial intelligence which is based on study of individuals' behaviour in various decentralized systems (Teodorović, 2008). In this realm, a swarm is defined as a group of agents which communicate with each other in a defined region (searching space) to find the optimal solution. Different interaction methodologies have resulted in the emergence of a variety of problem-solving approaches over the past years. Particle Swarm Optimization (Kennedy et al., 2001), Ant Colony Optimization (Dorigo et al., 2006), Stochastic Diffusion Search (Bishop, 2007), and Bee Colony Optimization (Teodorović, 2008) can be mentioned as the most known swarm based algorithms. Among the stochastic optimization tools, Ant Colony Optimization has absorbed researcher's attention for tackling complex transportation problems (Teodorović, 2008). Particle Swarm Optimization, on the other hand, in spite of its robust potential upon complex engineering problems, is rarely applied to transportation problems (e.g. Babazadeh et al. (2011) and Shafahi and Bagherian (2013)). In this section, a review on particle swarm optimization algorithm is presented.

2.4.2 *Particle Swarm Optimization*

Inspired by the social behavior of bird flocking and fish schooling, particle swarm optimization is an evolutionary computation model. First proposed by Kennedy and Eberhart (1997), PSO performs a swarm-based search using particles to represent potential solutions within the search space. Each particle is characterized by its position, velocity, and a record of its past performance.

In the basic PSO algorithm, using the following equations, the position (x) and velocity (v) of each particle in the swarm can be updated upon each iteration.

$$x(t+1) = x(t) + v(t+1) \qquad 2\text{-}4$$

$$v(t+1) = v(t) + C_1 r_1(t)[g(t) - x(t)] + C_2 r_2(t)[p(t) - x(t)] \qquad 2\text{-}5$$

Where C_1 and C_2 are the accelerator constants, r_1 and r_2 are randomly generated numbers that are distributed uniformly in the [0, 1] interval, $g(t)$ is the best answer found by the population to that point, and $p(t)$ is the best answer found by each particle.

There are many extensions of basic PSO to improve its convergence behavior. (Shi and Eberhart, 1998) introduced the "inertia weight model" in which the inertia of the particle (the $v(t)$ term) would be multiplied by a w parameter. This parameter plays an important role in trading off the exploration and exploitation of the algorithm. Large amounts of inertia weight will improve the exploration, but the diversity may also increase. In contrast, small values of w increase the possibility of searching in a specific area to obtain better solutions but may also increase the probability of trapping in local optimums (Parsopoulos, 2010). Consequently, Equation 2-6 can be rewritten as:

$$v(t+1) = \boldsymbol{w}v(t) + C_1r_1(t)[g(t) - x(t)] + C_2r_2(t)[p(t) - x(t)] \qquad 2\text{-}6$$

In this equation, the inertia weight can either stay constant or decrease during the iterations of the algorithm. A dynamic value for the inertia weight is utilized in this study.

Another modification is velocity clamping (Eberhart et al., 1996). In each iteration, if the calculated displacement of a particle exceeds the specified maximum velocity, it is set to the maximum value. Let $V_{max,j}$ denote the maximum velocity allowed in dimension j. The particle velocity is then adjusted before the position update using.

$$v_{ij}(t+1) = \begin{cases} v'_{ij}(t+1) & if\ v'_{ij}(t+1) \le V_{max,j} \\ V_{max,j} & if\ v'_{ij}(t+1) \ge V_{max,j} \end{cases} \qquad 2\text{-}7$$

Since the basic PSO is developed for tackling problems with continuous domain, it should be modified for solving discrete problems. This modifications is performed using a simple conversion from real values to integer ones, applied on each single term of the Equation 2-7. In other words, the velocity updating equation is modified as follows:

$$v(t+1) = \boldsymbol{int}(wv(t)) + \boldsymbol{int}(C_1r_1(t))\,[g(t) - x(t)] + \boldsymbol{int}(C_2r_2(t))[p(t) - x(t)] \qquad 2\text{-}8$$

Once the terms were converted to integer values, the velocity of the particles in each step would be integer as well. Consequently, PSO is forced to search only the integer values (i.e. the index of each candidate path) as the variables. Figure 2-5 exhibits the flowchart of the PSO algorithm which was utilized by the author for tackling the transit network design problem(Kermanshahi et al., 2015, Bagherian et al., 2013)

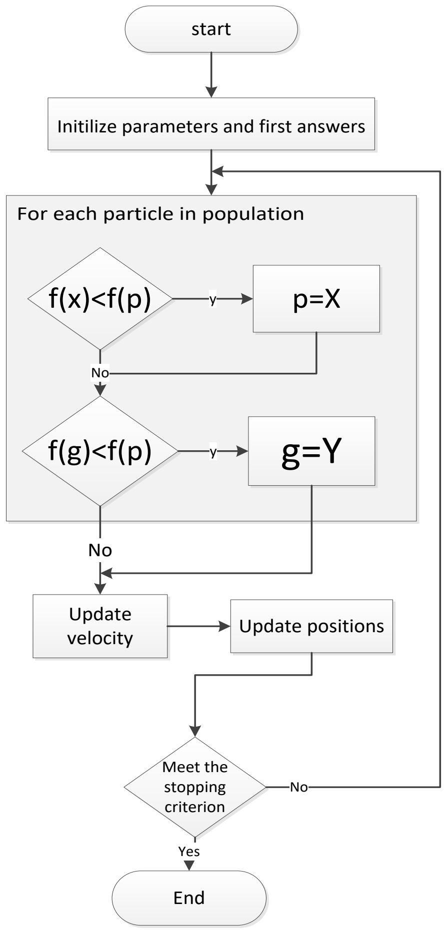


Figure 2-5 Flow chart of the PSO algorithm

2.5. Research Gaps

Having a comprehensive literature review on the defined realm, we identified the following gaps:

1. Numerous research efforts are recently performed on integration of signal systems with transit service using V2I communication system. Nevertheless, the effect of dwell times on bus trajectories is not considered in the developed models. This dwell time is crucial for consideration, especially in near-side bus stops where such dwell times can increase uncertainty of predicted bus arrival times to intersections. In addition, the location of bus stops may also affect buses reaching their desired speed (due to the short distance to the intersection), yet no research conducted to address this issue.
2. To evaluate the performance of the TSP strategies, different measures of performance are introduced. Nevertheless, no attempt has been made to consider reliability and values of travel times simultaneously.

3. The existing approaches in practice to measure the performance of transit service are relying on vehicle information only. This research introduces and implements two passenger-oriented measures of transit travel time reliability using smart card data. These measures correspond to user experience of punctuality (deviation from the schedule) and predictability (day to day variation) of the service for any spatio-temporal level of interest.
4. The deployed traffic signal priority strategies are mainly developed for isolated or corridor level studies. In this level of evaluation, transit services are all along the corridor and multiple requests for granting TSP would not encounter. Evaluation of TSP impacts on a grid network with conflicting TSP request is not performed so far. These impact can range from adjusted route choice by passenger cars drivers to the effect of TSP on the entire transit route, thus reflecting multiple requests from crossing movements.
5. Optimization of different characteristics of TSP strategies is another area which has rarely been focused in the literature. Although a few of the studies are presented in which an optimization method is applied on microsimulation model, this area still needs further research. Application of different optimization algorithms, especially the newly introduced stochastic ones on TSP settings and optimum TSP equipment's' locations, development of searching algorithms customized for the TSP problems itself (instead of generic optimization tools), introducing contexts like multi-objective optimization (considering different objective functions) and niching algorithms (finding a set of optimum solutions) , and general strategies to improve the precision and efficacy of stochastic based optimization algorithms are all examples of the areas which are not comprehensively addressed in the literature.
6. Finally, integration of different preferential strategies to improve the transit operation and overall performance of the network is the other gap found in the literature. Although the performance of some preferential combinations (e.g. Queue Jumpers and TSP) has been evaluated in some studies, still multi-policy strategies (e.g. integration of route allocation and transit signal priority strategies) still need further research and development.

To address these gaps, Chapter 3 of this thesis presents the developed TSP logics, including the V2I based TSP along an intersection (gap 1). In chapter 4 the proposed measures of performance to evaluate the performance of priority strategies in terms of delay, variability, and fuel consumption are introduced (gap 2). The passenger oriented measures of delay and reliability (gap 3) that were developed for network evaluation are presented in chapter 5. Chapters 6 and 7 are allocated to developed analytical and simulation based evaluation of priority strategies in the network (gap 4). Finally, optimization of preferential strategies is presented in chapter 8 where TSP location as well as integrated TSP and Transit Priority Lanes (TPS) ones (gaps 5 and 6) are optimized throughout a grid network.

2.6. Chapter Summary

This chapter was dedicated to describe a review on the existing related literature on transit preferential strategies (with main focus on TSP) and their implementations and designs. Firstly, an overview on these strategies was presented and different strategies were compared together. In section 2.2 TSP strategies were comprehensively reviewed. Existing TSP logics, evaluation methods, the developed metrics to measure their performance, optimization of TSP strategies, their deficiencies, and integration of emerging technologies such as V2I communications were discussed. Furthermore, the current practices in utilizing smart card data for different operational purposes were explored, from a perspective of gaining insight through the network status and areas that should be prioritized. A review on metaheuristic algorithms that was implemented as the optimization tool was also presented in section 2.4. This chapter was concluded by identifying the gaps in the literature and the structure of this thesis to address them.

3. Developing New TSP Logics

This Chapter explains the preferential strategies and logics that have been developed and utilized in this study. The TSP logics discussed here can be categorized into two groups, namely microsimulation and analytical. The majority of the implemented logics in the literature are developed in a microsimulation model, whereas a number of them are analytically developed. These logics are a seminal component of the upcoming chapters where TSP evaluation and optimization models are introduced.

Firstly, a review on the approach to develop different TSP logics in microsimulation models is presented then developing the typical TSP logics is discussed. Next, a set of proposed TSP logics are introduced, where Vehicle to Infrastructure modules are integrated with the existing priority strategies. The section is finalized with recommendations and a summary. Figure 3-1 depicts the relationship of this section to the entire study.

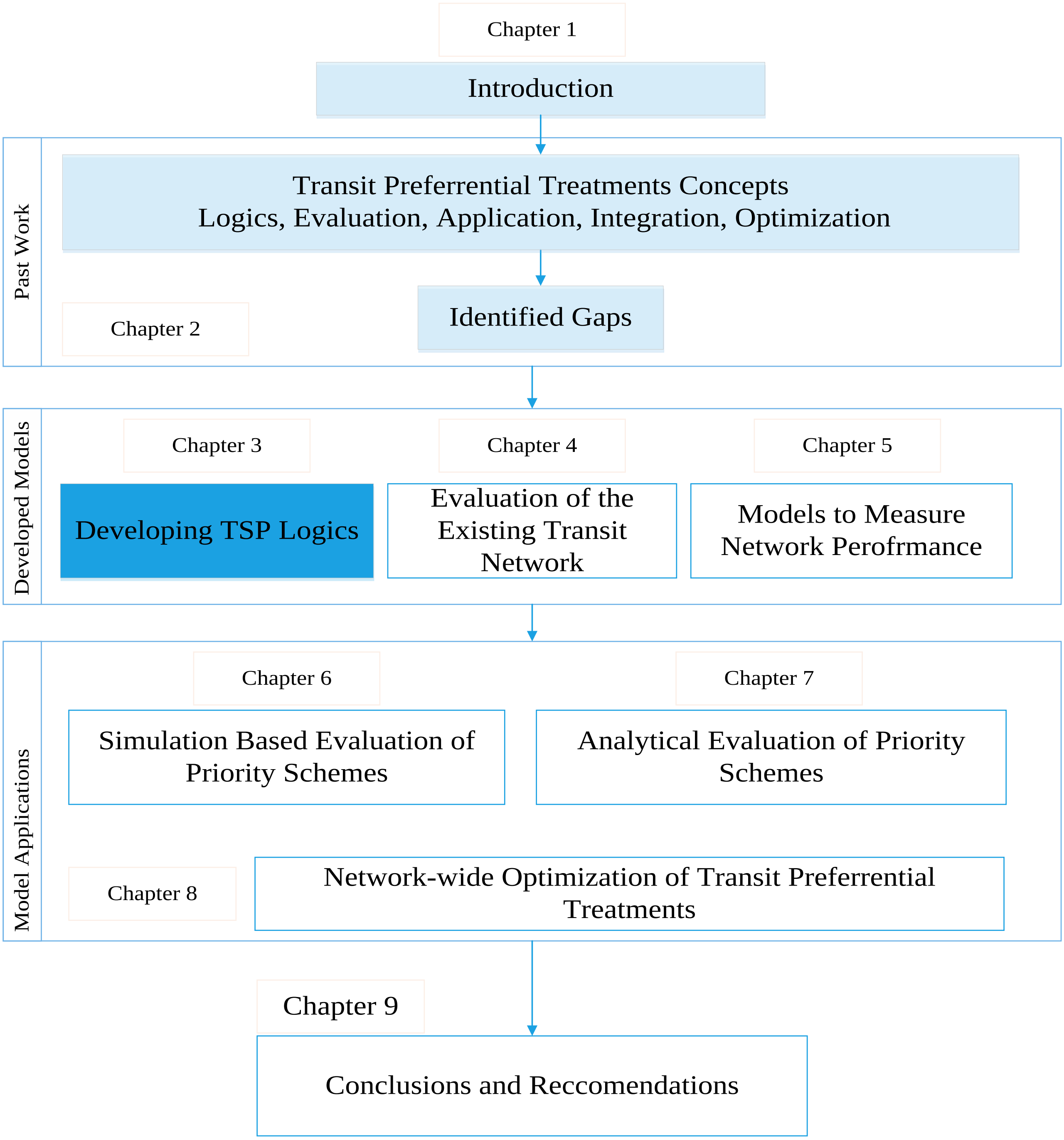


Figure 3-1 Thesis outline and highlighted current chapter

3.1. VAP: an Environment for TSP Logic Development

In order to evaluate different signal settings in microsimulation studies, firstly those settings need to be defined. Depending on the simulation environment, a number of interfaces signal setting development interfaces are available for developing TSP strategies into the models. Using the VISSIM microsimulation package to perform experiments, Vissig, VisVAP, text editors and programming tools are developed to define the desired logics. In this regard, the Vissig package is firstly implemented to define the structure of the signal. Number of phases, definition of stages, interstage times, and possible updates can be initialized using Vissig graphical interface. Forming the signal timing layout (stored as *.PUA text file), a Vehicle Actuated Programing (*.VAP) file is required to define signal controller's logic and customizations. VAP is an add-on to allow user define their signal timing logic in this microsimulation model. VISSIM takes the coded VAP logic as one of the inputs and processes it in each simulation step. VisVAP, the tool developed to create the logics as flowcharts, was used to initialize a VAP file. Both *.vap and *.pua files can be edited programmatically, letting automated adjustment of signal timings parameters. Figure 3-2 shows the requirements to use the VISSIM microsimulation model to evaluate different signal timing scenarios, including TSP strategies. Note that *.sig and *.vv are the default format of Vissig and VisVAP interfaces, respectively. Despite the flexibility of VAP to develop customized signal controlling logics, it was necessary to occasionally develop models using VISSIM COM libraries in C# programming language, as will be explained in this section.

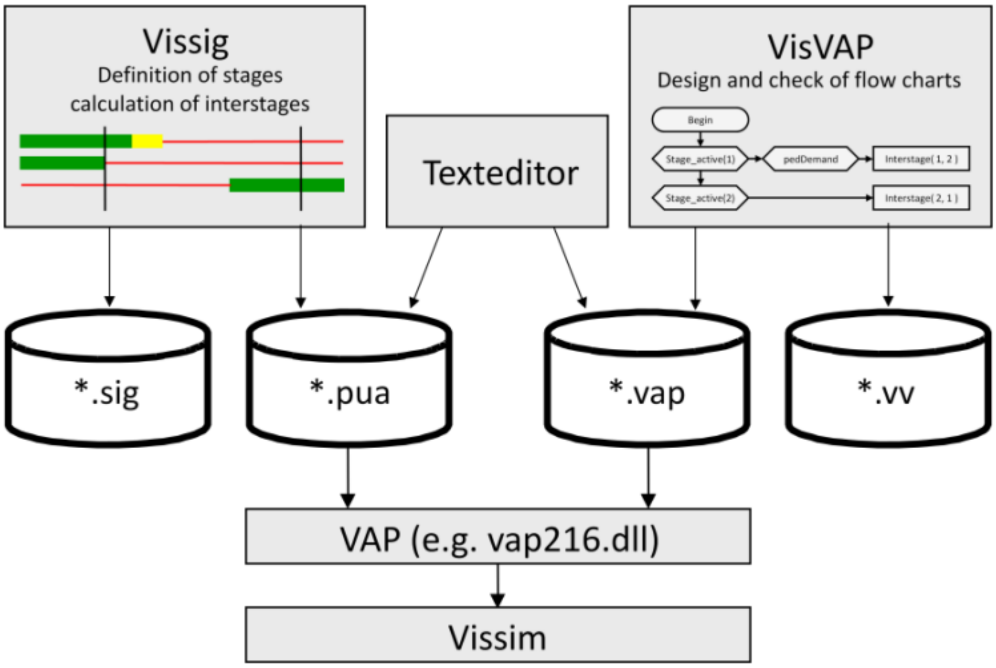


Figure 3-2 Developing a signal controller logic in VISSIM

3.2. Signal Timing Optimization

In order to optimize the location of implementing TSP strategies at the network level, pre-determined signal timings are assumed. These values should be justified based on the changes in network so as to have a fair comparison before and after TSP deployment. Consequently, one integral part of this framework would be finding optimum signal timings for all the intersections of the network. This is a large task because of the number of intersections in a network. Moreover, it might be interesting to explore the impacts of applying TSP on the vehicles route choice, thus having dynamic flows at each link, depending on the TSP locations. In such circumstance, signal timings should be updated for each scenario. However, due to iterative nature of route choice algorithms, it's cumbersome to perform this task manually. Having a tool to get the layout and to be able to optimize signal timings for different flow rates in an automated way is preferred.

The SIDRA package is a well-known solution to optimize signal timings of an intersection. However, during an optimization process or even for setting signal timings of the network, it is practically infeasible to manually change the variables. To tackle this issue, SIDRA application programming interface (API) was used to develop a module to perform the timing task automatically. This module programmatically gets the flow rates of each single movement of the intersection, updates its layout, and returns timings of each intersection. The results would be used to update the VAP logic initialization values for each single intersection. In other words, the module gets SIDRA layout and an array of flow rates of each movement and returns the optimum signal timings.

3.3. Typical TSP Logics

3.3.1 *Green Extension and Red Truncation with a Fixed Extension Value*

Green Extension (GE) and Red Truncation (RT) scenarios are the most common TSP logics in practice and in the literature. These two strategies were considered as the initial implemented prioritization tools. To implement GE and RT strategies, a set of assumptions were made:

1. Pre-computed signal timing is utilized when no bus is approaching the intersection. In other words, a fixed signal timing was formed for the intersection using the network layout and the flow rate of each approaching link. When no bus is identified to be granted TSP, signal timing is based on default settings.
2. GE is granted when a bus is detected on an approach, the signal is green, and the bus can pass the stop-line with this extension. A bus arrival time prediction model is required to check whether GE can allow the bus to clear the intersection.
3. The amount of extension is pre-determined (e.g. 10 seconds). This value can be fixed or considered as the maximum extension value so as to turn the signal to red once the bus crossed the intersection. In this case, once the bus crosses the stop line, transition to the next phase is triggered.
4. RT is granted when a bus is detected on an approach and the signal is red.
5. A priority request in the current cycle is ignored if a priority request was granted in the previous cycle.

6. Communication of the transit vehicles and signals is formed using two vehicle detectors, one deployed at 100m from the intersections and the other immediately after the stopping lines.

Figure 3-3 shows the achievable savings and changes in signal timing when the standard GE and RT strategies are implemented in an intersection and compares the phase durations and achievable savings together. As can be seen, depending on the status of the signal upon predicted bus arrival time to the intersection, either GE or RT can be activated. While RT can shorten the amount of red in prioritized movement to a certain value, its probability to be triggered is higher than GE. On the other hand, GE can be granted to a less portion of services but the amount of saving is more than red truncation strategy.

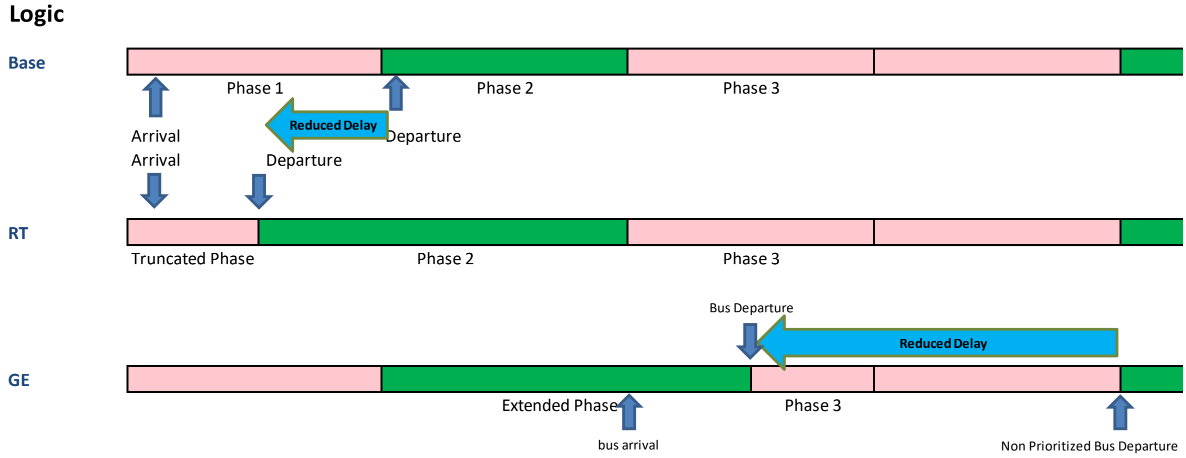


Figure 3-3 Green Extension(GE) and Red Truncation(RT) application

3.3.2 *TSP Cycle Recovery Module*

The adverse effects on the non-prioritized movements are reported as the seminal concern of TSP implementation. Indeed, TSP can shorten the amount of green time and thus capacity of the opposing movements, making an extra delay for the cars approaching on them. To address this issue, a signal recovery module is developed and integrated to the existing TSP logic. Using this logic, if a non-prioritized approach is affected by TSP by t seconds additional red time it will be given an additional t seconds green time in the next cycle, so as to mitigate the potential incremental delays on that approach.

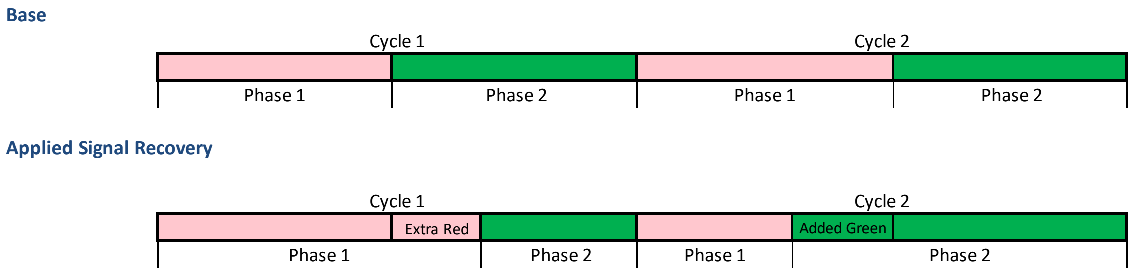


Figure 3-4 TSP cycle recovery on non-prioritized approach

A cycle recovery module can be integrated with any of the developed methods, depending on the basic TSP logic the congestion level. It will be demonstrated through the upcoming chapters how a cycle recovery module can mitigate the non-prioritized delays with no effect on bus delay reduction.

3.4. Coping with Multiple TSP Requests

Multiple TSP requests can be a common scene in urban areas where the frequency of buses in two crossing corridors is relatively high. Considering the effect of TSP strategies at the network level, multiple TSP requests are probable. Consequently, there is a need to adjust the developed TSP logic such that an appropriate response can be made. To fulfil this task, the VAP logic file is modified. The multiple-TSP model has been adopted based on Ma et al. (2011). At this stage, the developed strategy is a First-Request-First-Serve strategy which follows the assumptions and conditions that was presented before. Once a TSP priority request was granted and signal times were adjusted in a cycle, they cannot be changed during that cycle and the succeeding one. Although this logic can have potential extra delays for a non-prioritized bus, the overall benefit for transit service is still positive.

3.5. Conditional TSP Logics

It was shown in Literature Review (chapter 2), that many studies have suggested conditional TSP strategies to mitigate the negative impacts on the competent modes and approaches and potentially minimize total passengers delay. In this study, conditional TSP scenarios were defined base on two key criteria. Firstly, a conditional TSP grants priority to buses that are behind the schedule and TSP can help to improve the service punctuality. Once a TSP request is made by a bus, a comparison between the bus schedule and its current location will be made. For the buses with near-side bus stop, the checking point is the moment of departure from the stop where the scheduled departure time would be the benchmark of service punctuality. In addition, a service with far-side stop will be evaluated on the detectors by estimating the arrival time to them and comparing to the current bus time-location profile. The second condition to be checked is the vehicle’s passenger load. In this regard, the bus will be granted priority if its number of passengers are higher than a pre-defined threshold. These two conditions were integrated to the existing TSP modules to form conditional TSP. Figure 3-5 shows a review on conditional TSP logic chart.

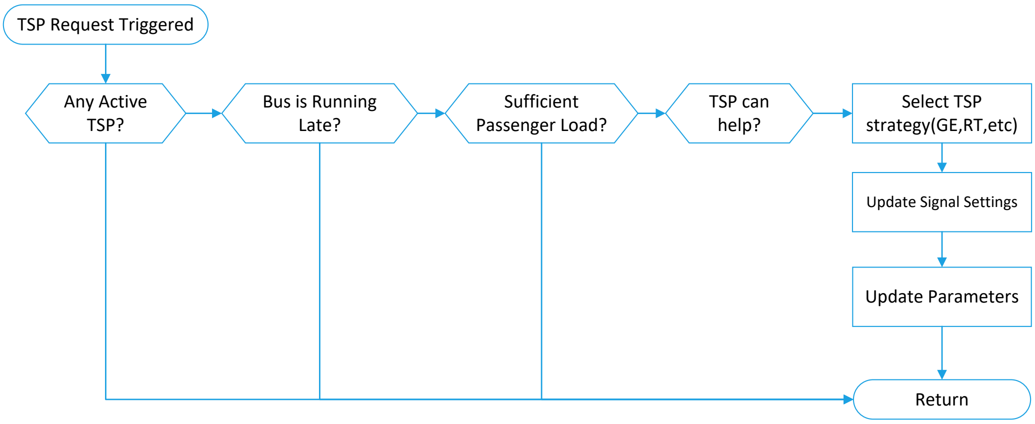


Figure 3-5 The sequence of criteria in conditional TSP

In the first case study the developed TSP strategy was applied to an intersection which has three pre-timed fixed phases. To evaluate the performance of conditional TSP, it was tested for an isolated intersection (Sir Fred Schonell Dr- Gailey Rd intersection) in three levels of congestion. The model was developed to see the effect of TSP deployment on route 412, heading toward Brisbane City from the University of Queensland. Route 412 information. Intersection characteristics (including geometric layout and phasing) and the prioritized bus route are presented in Fig 2. The cycle length was fixed at 90 seconds. A set of scenarios were then defined to model a delay function for each approach of the intersection.

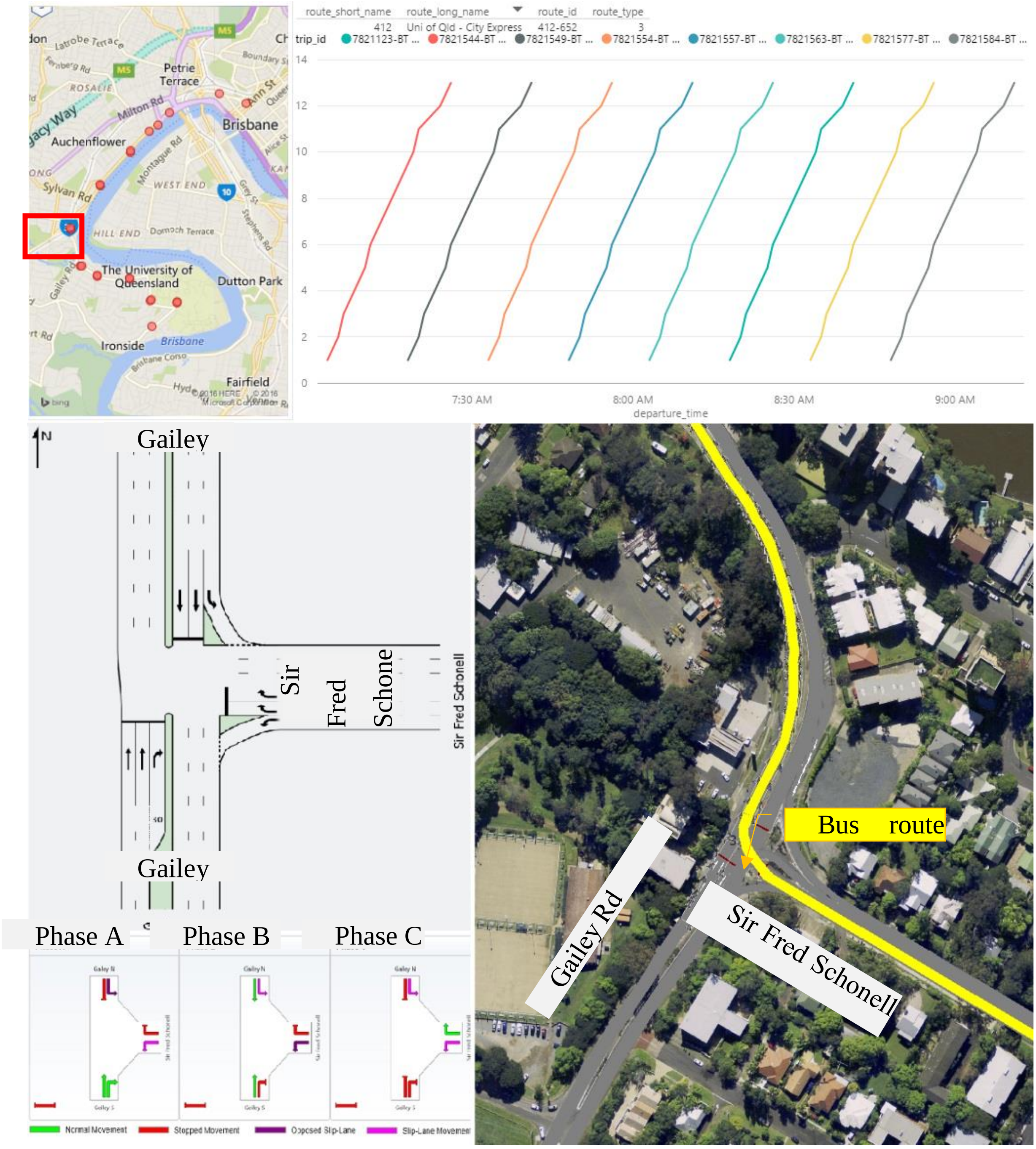


Figure 3-6 Sir Fred Schonell Dr- Gailey Rd intersection: layout, phasing, VISSIM model and prioritized bus route.

Figure 3-7 shows how conditional TSP can change the performance of the TSP logic. It can be seen that conditional TSP has an overall lower negative impacts on competing modes than basic TSP. It can be seen that with the increase of the traffic flow rate, the effect of basic TSP on car delay is exponentially increased while conditional TSP is moderating these delays. For example, in near-saturation condition (Flow Rate=1200vph), conditional TSP caused 46% less delay than basic TSP implementation. Such improvement acknowledges the performance of conditional TSP on improving bus service punctuality and delay with minimum negative impacts on private cars of the crossing movements.

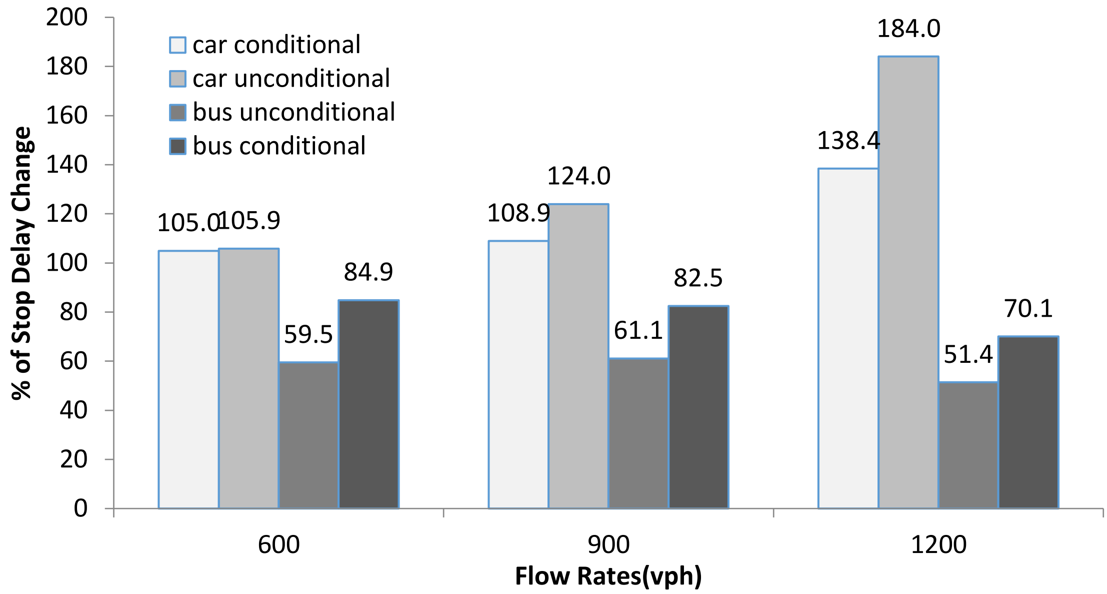


Figure 3-7 The effect of conditional priority on vehicles delay

3.6. Proposed TSP Logic

The basic TSP logic developed sets the amount of priority (for both GE and RT) based on a defined maximum extension value. This value can be considered as one of the inputs of the model that can be set by the user. As long as the extension value is smaller than the signal phases durations, it can be used in the TSP logic. The amount of extension would be taken from the phase before (RT) or after (GE) the prioritized movement's phase. This approach is a common strategy in developing TSP logics. Nevertheless, two issues may be raised in the implementation phase. Firstly, taking the required from only one phase limits the amount of extension that can be given. In other words, to extend the amount of green time of a phase, only one phase would be affected. This can be a significant concern when applying TSP to signals with more than two phases, causing the applicable extension value to be quite small. Secondly, adding or removing the extension value to/from a phase can have significant impact on the movement permitted in that phase. This is especially the case for phases with short durations. Consequently, the basic TSP logic was updated to address these issues.

The basic assumption in the proposed TSP logic is to give maximum amount of priority to the buses by adjusting all other phases to their assigned minimum values. Many signal timing models suggest a minimum green time for each phase in addition to the practical ones.

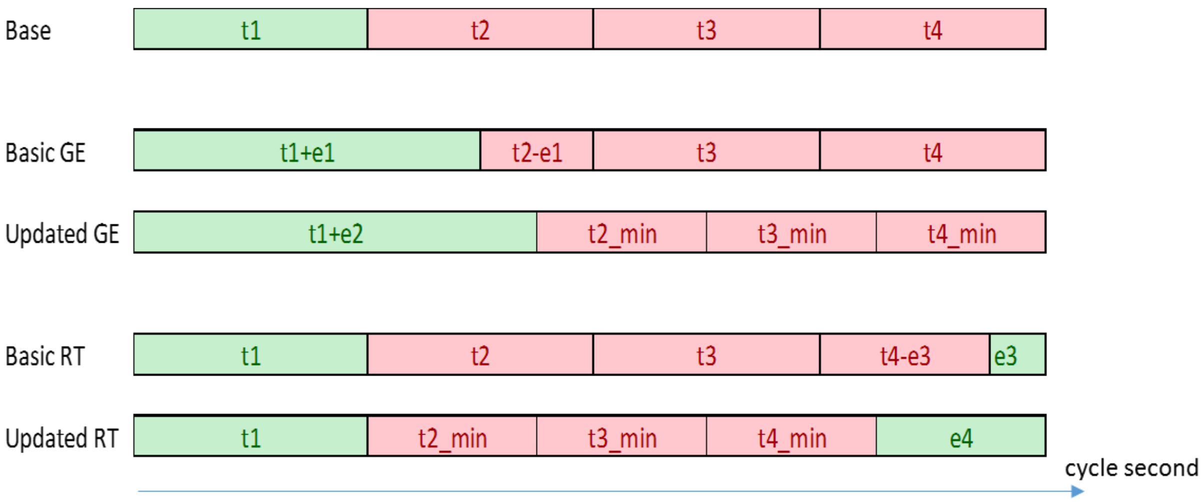


Figure 3-8 Comparison of the developed TSP logics

Figure 3-9 shows the pseudo-code of the updated TSP logic for microsimulation model analysis. In this logic, once an eligible bus (i.e. the bus that meets the load and delay conditions) requests TSP, all phase times except the prioritized one will be set to their minimum time. The gained additional time would be added to prioritized phase, providing more green time for the signal. The developed procedure grants both GE and RT with the same logic which can ease its implementation in signals with more than two phases. Note that in none of the developed TSP logics, cycle length is manipulated, as suggested in literature (Christofa and Skabardonis, 2011a).

Procedure1: Updated TSP Logic
Initialization
Set Signal Settings(Cycle Length, Phase Sequences)
Set Typical and Minimum Green Times
Set Conditional Parameters (If applicable)
Set Passenger load and Delay Threshold of each bus route
Set status=Base
For each Simulation Second:
If eligible bus exists in any approach
If (Status=Base)
$e^{max} = \sum_{i=1}^{n_p} (t_i{}^{max} - t_i^{min})$
$t_i \;\; = t_i^{min} \; \forall \, i \, \in \, n_p$
$t_{pr} \;\; = t_i^{min} + e^{max}$
$set \ status = TSP$
Else
If (status=TSP)
Initialize settings
Finalize Simulation

Figure 3-9 Algorithm of applying uUpdated TSP logic in microsimulation

3.7. Signal and Dwell Time Coordination Using V2I

With the expansion of public transportation networks in urban areas, transit operational costs are sharply increasing. In addition, a rapid increase in traffic congestion on urban roads and limitations in developing infrastructure urge transit agencies to seek better operation of available facilities. Consequently, it seems logical for transit agencies and operators to aim at minimizing their operational costs.

Fuel consumption is one of the seminal components of transit operating costs(Heaslip et al., 2014, Soltani-Sobh et al., 2015, Khalilikhah et al., 2016). Bus fuel consumption is highly dependent on engine performance, driving speed, number of passengers, and the number of interruptions and stops in the vehicle's routes (Stevanovic et al., 2009). Maintaining moderate speeds throughout the trip, as well as a reduction in the number of interruptions, are identified as the main traffic controls to reduce bus fuel consumption (Zarkadoula et al., 2007). Regarding the latter, it is widely accepted that reducing the number of stops during a trip can significantly lessen the amount of fuel consumption of buses in urban areas (Ozkan et al., 2012, Rakha and Ding, 2003). Such stop-and-go elements can be formed as the result of traffic congestion along the links in oversaturated conditions, stopping at bus stops, and stops at intersections. One way to remedy the latter is to implement Transit Signal Priority (TSP) strategies which are a common approach in transit operations (Danaher et al., 2007). TSP is a widely accepted operational strategy that changes intersection signal timing in favour of buses and thus may reduce overall bus delay (and consequently fuel consumption) at intersections. Nevertheless, despite the increasing implementation of TSP strategies, these strategies face a number of drawbacks in both implementation and achieving reduced bus fuel consumption.

It is widely accepted that TSP may not efficiently serve transit services with nearside stops due to the existing uncertainty in the duration of dwell time (Ngan et al., 2004, Kim and Rilett, 2005). Since nearside bus stops are a common sight in big cities, TSP implementation may be argued for the vast majority of intersections. To cope with this issue, Kim and Rilett (2005) developed a dwell time estimation model which was integrated with TSP strategy to reduce the probability of buses experiencing red signals at intersections. Although the model showed overall success in coordinating TSP with the dwell time, the inherit uncertainty in dwell time prevents developing a precise estimation model.

Negative impact on non-prioritized movements is another concern of TSP application. This problem is addressed in the literature as the main issue of TSP implementation (e.g. Li et al., 2008, Christofa and Skabardonis, 2011b) where prioritizing buses may incur extra delay to competent modes and movements. Consequently, applying such preferential transit strategies at intersections is normally limited to moderate congestion and appropriate network layout. Thus, the idea of minimization of person delay was recently introduced to give a fair share of delay to each movement, depending on the number of individuals experiencing delay at intersections (Christofa, 2012). Relying on their person-based framework, Khalighi and Christofa (2015) presented an emission-based optimization signal timing method for an isolated intersection. In this model, the aim was to decrease the number of vehicle stops and thus accelerations and decelerations and consequently reach a reduction in fuel consumption. They reported that the total bus emission (which is correlated with fuel consumption) had no significant improvement, mainly due to the prevailing share of autos making emissions in an intersection. In other words, the major benefit in minimizing intersection fuel consumption is in favour of passenger cars and there is modest (if any) benefit for the transit operators in this regard.

With the advent of connected vehicle (CV) technology which is classified as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, new opportunities for intelligent transportation systems have been provided. In this regard, V2I communication has been attracting much attention and has been developed to improve transportation operations over the past few years. General examples include their implementation in signal pre-emption (Jordan and Cetin, 2015), integration of V2I to Macroscopic Fundamental Diagrams (Xu et al., 2015), and improving the performance of Transit Signal Priority tools (Hu, 2014, Hu et al., 2015, He et al., 2014).

In this part of the dissertation, a Vehicle to Infrastructure (V2I) communication module was formed to minimize the number of bus stops at intersections thus reduce the amount of transit fuel consumption in urban areas and save operation costs. The module forms a real-time data exchange between the signal system and the buses. In this interaction, the transit service transmits its location and schedule to the signal controller. With the aim of directing the bus so it has a smooth movement through the intersection, two possible actions are proposed, namely speed adjustment and dwell time extension. The proposed method was tests on a set of scenarios through a model developed in the VISSIM microsimulation package. It was observed that using the proposed method resulted in up to 15% saving on bus fuel consumption at intersections. The importance of this module to transit agencies is that contrary to basic transit preferential tools, such as transit signal priority or route space allocation, savings can be achieved with no manipulation in the competent modes or opposing transit movements. Integration of this module and preferential tools can maximize the logic’s efficacy.

3.7.1 *Signal and Dwell Times Coordination Methodology*

The main objective of this module is to minimize the number of bus stops at an intersection thus reducing bus fuel consumption without manipulating the signal settings. Two main components were developed to fulfil this task, namely speed adjustment and dwell time extension. The speed adjustment module changes bus cruising speed to direct it to arrive at an intersection when the signal phase status is green. This module shows its effect when the bus is in a relatively long distance from the signal and where no near-side bus stop exists. Secondly, a dwell time extension method is proposed that can keep the bus at the bus stop by extending its dwell time so as to skip an expected stop at the intersection. This module moves the stopped time from the red signal to the bus stop, thus reduces the total number of stops and required bus decelerations and accelerations associated with them. Figure 3-10 shows how these two modules may change a bus space-time profile. Note that it is assumed that buses only receive signal information and no adjustment in signal timing can be made.

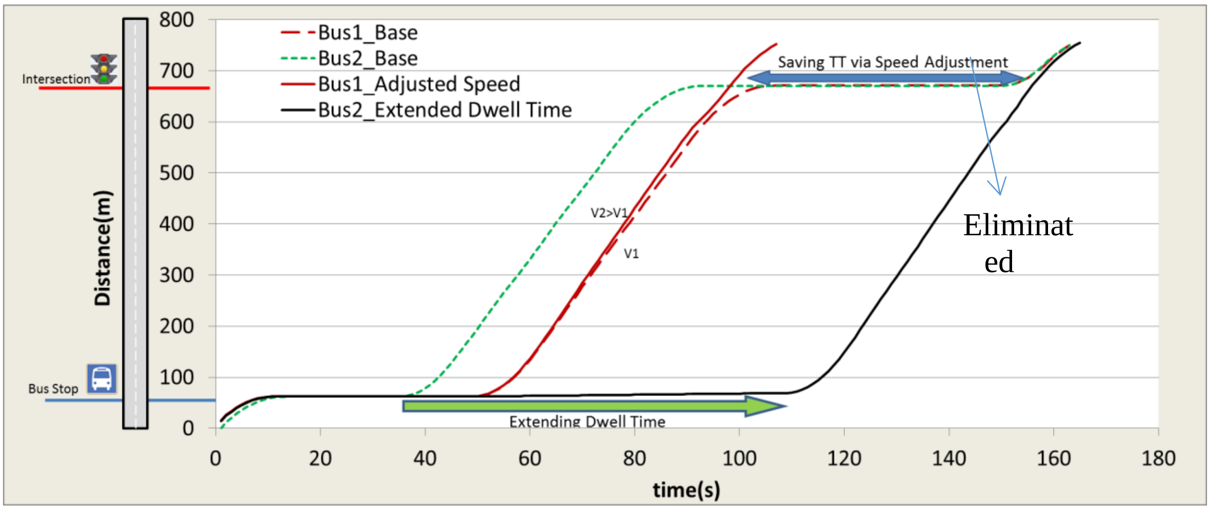


Figure 3-10 The effect of dwell time extension and speed adjustment on bus time-position profile

The initial version of the proposed method of coordinating signal and dwell times relies on the following assumptions:

- The bus has full information about the signal settings, thereby it is able to know its phase status at any time before reaching the intersection.
- Bus dwell time is unknown. Adjustments will be applied either at the end of dwell time (dwell time extension) or afterwards (speed adjustments)
- Market penetration of connected vehicles technology for the private vehicles is zero thus no information of the level of congestion is available for buses. Any information on traffic congestion will improve the efficacy of the proposed method
- Buses are directed to arrive at the intersection with a predefined offset value from the interstage second (the time the signal turns to green). This is to ensure the intersection queue is discharged.
- Cycle length and phasing sequence of signals are fixed. This assumption can be disregarded if the alternative option (such as actuated method) is still able to provide the signal timings for an approaching bus.

Figure 3-11 shows the general method proposed for adjusting bus arrival at an intersection. At each simulation step, a check is made to ascertain whether the bus is ready to depart from a stop. If this is the case, the arrival time to the intersection is predicted and thus the signal status at that moment will be identified. If the signal at that moment is not green, a test for speed adjustment will be performed. In this regard, it will be determined whether increasing the cruise speed can help the bus to pass non-stop through the intersection. If the bus can pass the intersection with increasing speed, it would be given permission to depart the bus stop and increase its speed to its upper speed limit. Otherwise the bus stays at the bus stop until the time is right for it to depart so as to evade having another stop at the intersection. In addition, at each simulation step the cruising speed of the bus approaching the intersection would be adjusted if required. This extra process can improve the performance of the method by adjusting the estimated arrival time and the associated speed.

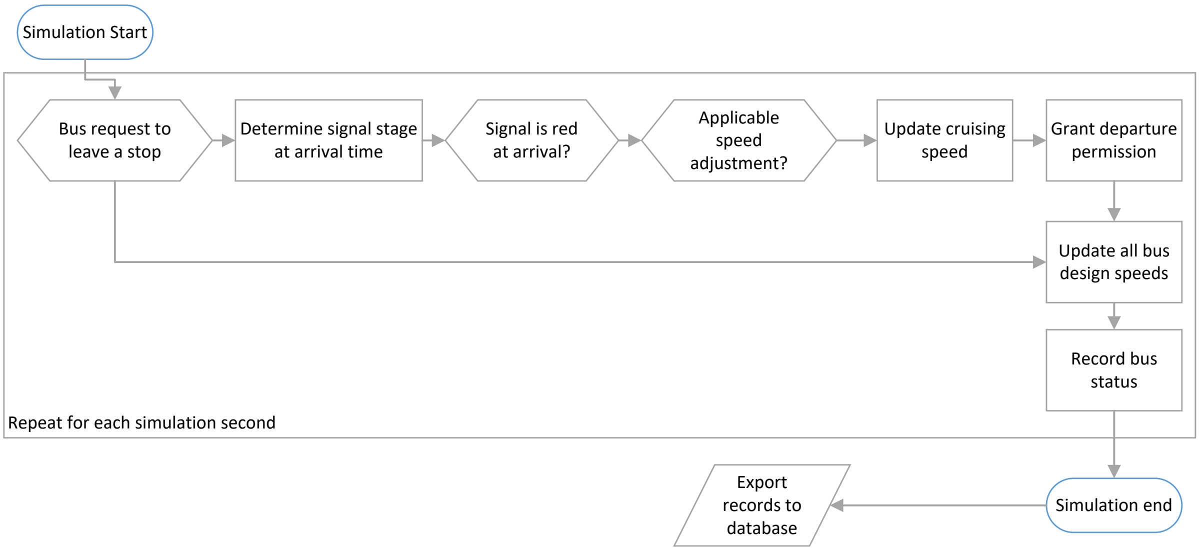


Figure 3-11 Flowchart of the proposed V2I based method in a microsimulation model

The proposed method is not supposed to be an alternative for preferential strategies such as TSP strategies but an optional feature to reduce fuel consumption by receiving and acting on signal timing information. As a result, as far as the signal timings can be provided, the method can be implemented on any traffic signal controller.

3.7.2 *Integration of TSP and V2I Based method*

As discussed in former section, to reduce the amount of bus fuel consumption, two components were developed, namely speed adjustment and dwell time extension. The speed adjustment module changes bus cruising speed to direct it to arrive at an intersection when the signal phase status is green. This module shows its effect when the bus is in a relatively long distance from the signal heads and has no bus stop close to the intersection. Secondly, a dwell time extension method is proposed that can keep the bus at the bus stop by extending its dwell time so as to skip an expected stop at the intersection. This module moves the stopped time from the red signal to the bus stop, thus reduces the total number of stops and required bus decelerations and accelerations associated with them. Dwell time extension was showed to be a superior strategy to reduce fuel consumption, especially in nearside bus stops where there is no enough length for the bus to reach its cruising speed. Nevertheless, due to the inherent errors in arrival time predictions, extended dwell time was caused an excess delay at intersection. Consequently, without changing signal timings, fuel cost consumption reduction may result in increasing travel time component. To address this issue, a TSP strategy is proposed to compensate this excess delay.

Figure 3-12 shows how TSP strategy and bus dwell time extension can change the trajectory of a bus thus improve its operation. Indeed, while TSP shortens the delay at intersections, Dwell time extension shift this delay component thus reduce the number of stops during a trip. In this section, the simplifying assumptions and integrated modules are presented and then the proposed logic is outlined.

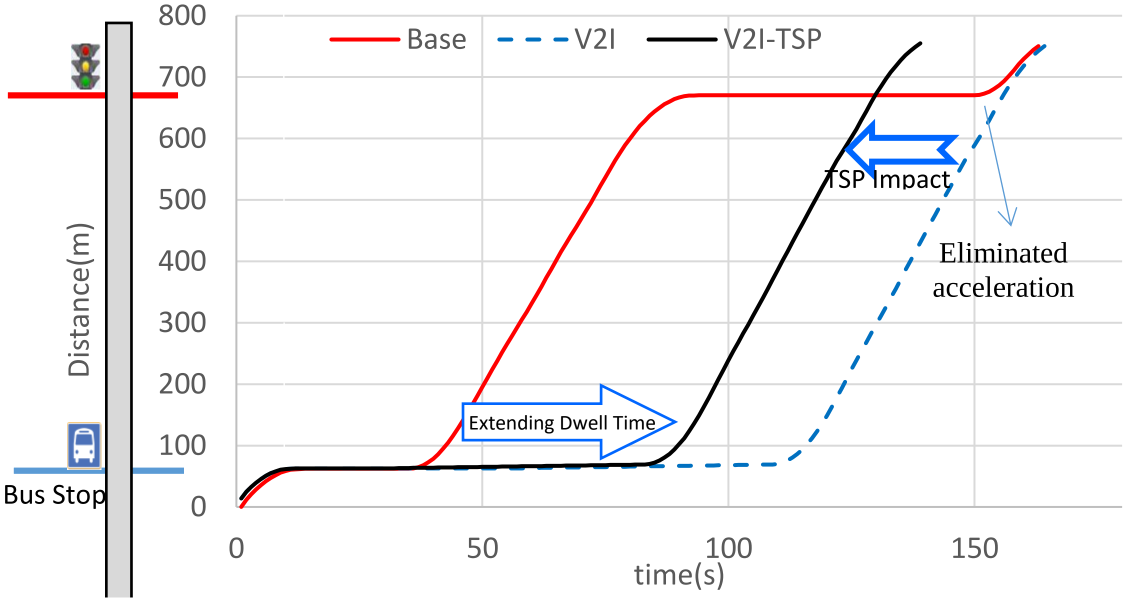


Figure 3-12 The effect of dwell time extension and speed adjustment on bus time-position profile

The coordination module can be integrated with other signal timings, including TSP strategies. Figure 3-13 shows the modified V2I based method to integrate TSP with dwell time extension. At each simulation step, firstly a check was made to see if any bus is approaching the intersection. If this is the case, signal program would be changed to a prioritized one thus a bus can gain a higher share of green time. Using the updated signal timing, the bus arrival time to the intersection would be calculated afterwards. Then, a check is made to ascertain whether the bus is ready to depart from a stop. If this is the case, the arrival time to the intersection is predicted and thus the signal status at that moment will be identified. The bus can be granted for a departure only if it is predicted to face green time on arrival. In other words, the bus stays at the bus stop until the time is right for its departure to avoid having another stop at the intersection. Once the bus passed the intersection, default signal timings would be applied again. Application of the proposed method is shown through a numerical example in section 6.3.

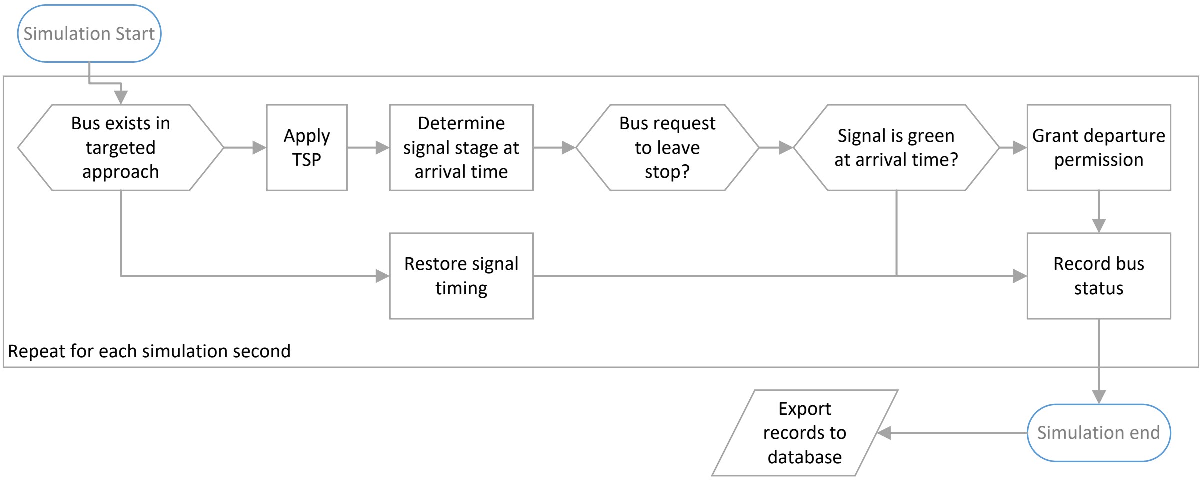


Figure 3-13 Flowchart of V2I-TSP integration in a microsimulation model

3.8. Chapter Summary

In this chapter, the developed and implemented preferential strategies at intersections were introduced and validated. In this regard, firstly a review on the method to develop TSP logics were made and then a set of TSP strategies were elaborated and validated. Targeting the bus fuel consumption reduction, a V2I based logic was also developed to reduce fuel consumption by coordinating bus dwell time and signal timings.

The developed TSP logics have been implemented throughout this study to evaluate different scenarios. Chapter 6 is dedicate to the simulation based evaluation of these priority strategies where the logics are implemented to the selected intersections in local, corridor, and network level studies. In addition, the application of the developed V2I based models are shown through a numerical example.

4. Priority Strategies and Associated Performance Measures

This chapter presents measures developed to evaluate the performance of different transit priority strategies. In order to evaluate, design, and optimize preferential strategies, it is necessary firstly to develop a mathematical formulation to measure the performance of a given scenario. Depending on the analysis level (intersection, corridor, or network level) and availability of the data (e.g. aggregated or individual vehicles), a variation in the evaluation tool can be considered. The measures of performance should represent both operator and user costs of a given scenario.

In this chapter, firstly a generic objective function to reflect different cost items (user, operator, and community) is proposed. Derived from this generic function, a mathematical formulation for simulation based evaluations is then developed. A method to estimate the amount of bus fuel consumption (as an integral component of both operators and community costs) is then elaborated and finally the section is concluded with the recommendations and summary of the developed measures. Figure 4-1 shows the relation of this section to whole the study. As can be seen in the figure, This chapter along with Chapters 3 and 5 form the base of the models and will be applied through the next chapters.

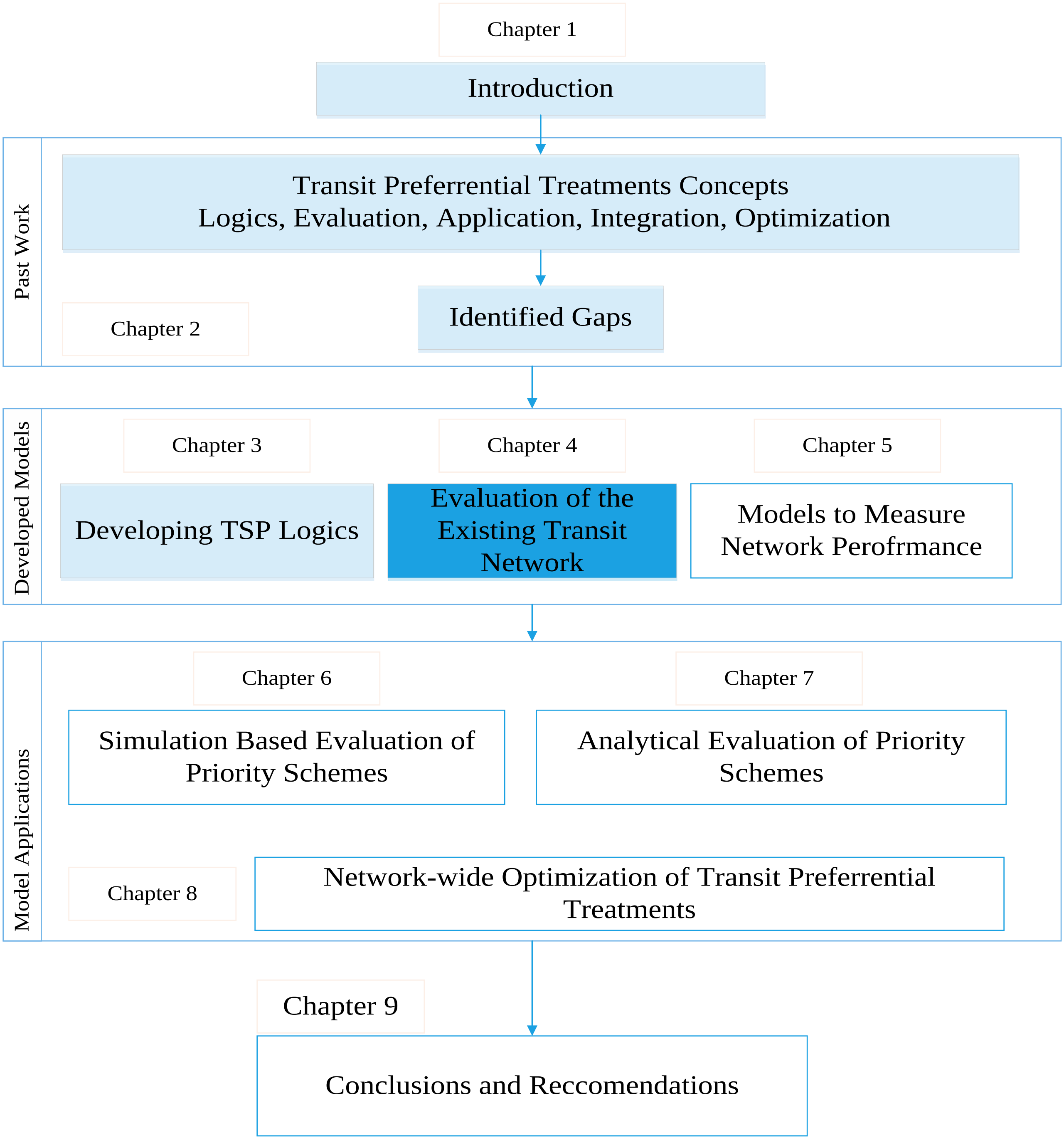


Figure 4-1 Thesis outline and highlighted current chapter

4.1. Measuring Transit Performance at the Network Level

To develop a procedure for the design and analysis of priority strategies, it should be identified how such strategies can affect the users and operators as well as to estimate their potential effects on the community (e.g. emissions, noises, etc.) at the network level. Considering user costs, changes in the amount of travel time value and reliability of both prioritized and non-prioritized modes and movements is expected before and after deploying a priority strategy. Indeed, such policies are basically aimed at decreasing bus in-vehicle delays and thus achieving a reduction in transit travel time. Nevertheless, such improvement is achievable at the expense of additional delays on the competing modes. Safety concerns are another factor that is crucial to be considered in addressing such priority strategies and especially for pedestrians and cyclists (which are not the scope of this study). In terms of operator costs, construction and maintenance costs for different types of treatment can be considered. Regarding TSP, implementation costs include both equipping signals with the hardware and possible maintenance costs. The recent signals systems mainly embed the standard prioritizing policies and the main concern is to maximize their operational performance in an intersection. However, there might exist intersections with no embedded TSP hardware thus TSP implementation cost should be considered in potential capital costs. The capital costs of introducing dedicated bus lanes is another operator cost. For a network-wide analysis, the effect of TSP on the network can be formulated as:

$$Z(X) = \sum_{i=1}^{I}(\alpha\, O^c\ t^c_{X,i} f^c_{X,i}\ + \beta\, t^b_{X,i} p^b_{X,i}) + \gamma \sum_{s=1}^{S} var^b_{X,s}\, p^b_{X,s} + \sum_{j=1}^{J} \delta c_{X,j} + \varphi Imp_{X,j} \qquad 4\text{-}1$$

Where:

$Z(X)$	Defined Cost function to evaluate prioritizing scenario *X* in the network
X	*A j* sized vector representing the setting in each movement $j \in J$
$i \in I$	*Set of Links in the network*
O^c	Occupancy of the passenger cars
$t^c_{X,i}$, $t^b_{X,i}$	Travel time of bus (*b*) or car(*c*) along link *i* for TSP setting *X*
$f^c_{X,i}$	Car flow rate of link *i* in the analysis period for TSP setting *X*
$p^b_{X,i}$	Average passenger flow of the buses traversing link *i* during the analysis period with TSP network settings *X*
$s \in S$	Set of stops in the network
$var^b_{X,s}$	Variability measure of buses traversing the segment between stop s and *s-1* during the analysis period with TSP network settings *X*
$p^b_{X,s}$	Average passenger load of the buses crossing segment between stop s and s-1 during the analysis period with TSP network settings *X*
$j \in J$	Set of movements considered for evaluation
$c_{X,j}$	Cost of updating priority strategy in movement j with TSP network settings *X*
$Imp_{X,j}$	Community costs of network setting x for movement *j*
$\alpha, \beta, \gamma, \delta, \varphi$	Weighting parameters

The first term of Equation 4-1 estimate bus and car passengers travel times along the links of the network. The second term measures the experienced passenger travel time variability for PT users. The last term reflects the capital and community (e.g. air pollution, noise, etc) costs of a priority setting. Equation 4-1 can be implemented to measure the performance of the transport system at any level of study. Depending on the level of study, transit service performance and impacts of different preferential strategies can be measured at any intersection, links between intersections, and the segments (the leg between two successive stops), or for the whole network. This formulation can be applied to the existing observation or a set of scenarios that can be simulated or analytically evaluated. The analysis method and the level of detail of the available data dictate the level of details that can be considered for evaluation. For example, while a microsimulation method provides data to measure the service reliability elements(e.g. schedule adherence), macro level tools may only give rough estimation of the experienced delays in each mode. It will be shown over the next chapters of this section how simplified versions of Equation 4-1 are presented and utilized for different levels of analysis.

To measure the service performance, transit information (passenger load and travel times) can be extracted from available datasets (e.g. AVL and AFC data) or simulation methods. Variability measures can be estimated using the approaches presented in next section. These measures along with the community cost depend on the implemented strategy. In planning level transport modelling studies, numerous models are presented to estimate the required parameters that are discussed in the following section. Such approaches are especially useful to evaluate different scenarios and design TSP strategies (e.g. identifying the best intersections to be equipped with TSP) in the network. Next two chapters elaborate the simulation based as well as analytical tools to measure TSP strategies' and other preferential strategies' performance.

4.2. Simulation Based Evaluation of TSP Scenarios

To reflect the impact of TSP deployment, a generalized cost function is proposed. This model considers both travel time and reliability indexes as measures of performance. For each travel mode (either private car or bus), a measure of travel time reliability index is defined which is calculated for each mode as the deviation from average travel time. These measures can be replaced by other reliability indexes such as passenger-based reliability ones that are introduced in the next chapter of this thesis. These indexes along with the travel time measurements are then combined using a set of weighting parameters. With exclusion of community costs and further developing the Equation 4-1, Mathematical formulation of the model can be stated as follows:

$$\boldsymbol{Z}(\boldsymbol{x}) = \sum_{p=1}^{P} O^{p}(\alpha\, \boldsymbol{t_p} + \beta\, \boldsymbol{var_p}) + \sum_{b=1}^{B} O^{b}(\gamma\, \boldsymbol{t_b} + \delta\, \boldsymbol{var_b}) \qquad 4\text{-}2$$

$S.T.$

$$\sum_{s=1}^{S}\sum_{m=1}^{M_s} Y_m^s < N \qquad 4\text{-}3$$

$$D^s < \sigma\, D_0^s \;\forall\, s \in S \qquad 4\text{-}4$$

$$G_{min} \leq e \leq G_{min}^{s} \; \forall\, s \in S \qquad \text{4-5}$$

$$t_p, var_p, t_b, var_b \rightarrow Simulation\ results \qquad \text{4-6}$$

Where:

Z(x)	Defined Cost function to evaluate prioritizing scenario *X* in the network
$p \in P$	Set of cars *P* entering and exiting the network during the simulation period
$b \in B$	Set of buses *B* entering and exiting the network during the simulation period
t_p , t_b	Travel time of private car *p* and bus *b* (from origin to destination), respectively
var_p , var_b	The measure of travel time variability of the private car *p* and bus *b*, respectively
O^p, O^b	Occupancy of car *p* and bus *b*, respectively
Y_m^s	Binary variable of TSP deployment which is 1 if movement *m* of junction *s* is selected for TSP implementation and 0 otherwise
D^s	Average car delay at intersection *s*
D_0^s	Average car delay when no TSP strategy is implemented
σ	Parameter to control the threshold of giving priority to buses
$s \in S$	Total number of intersections in the network that are candidates for TSP installation
$m \in M_s$	The number of movements of intersection *s* with the possibility of sending TSP request
N	Total number of TSP equipment
e	Maximum amount of extension time of a signal phase
C	Cycle length of the intersections in the network (fixed)
G_{min}	Minimum green time of the intersections
G_{min}^{s}	Minimum green time of the intersection s
$\alpha, \beta, \gamma, \delta$	Weighting factors to convert values to a monetary measure

Equation 4-2 is the objective function, incorporating travel time value and variability (i.e. unreliability) for both private and public systems. Constraint 4-3 guarantees the total number of implemented TSP strategies to be less than (or equal to) the total amount of available equipment. This constraint is important in considering issues such as budget or equipment limitations. Constraint 4-4 limits the level of priority and the maximum amount of permitted adverse effect on the cars at each intersection. Finally, Constraint 4-5 controls the amount of priority (extension value) that can be given to an intersection. Travel time value and variability (for both buses and cars) are the parameters that should be obtained for each TSP scenario, as mentioned implicitly in Equation 4-6, a microsimulation model was implemented to obtain the required values. This model is comprehensively explained in the next chapter of this thesis.

4.3. Fuel Consumption Calculation

In addition to the measures of travel time and reliability, a module to decrease the amount of bus fuel consumption is also developed in this thesis. To measure the amount of fuel consumption, the model suggested by Frey (2007) is used to calculate the amount of fuel consumption in each scenario. This model relies on Vehicle Specific Power (VSP) (Zhai et al., 2008) of the bus during every second of its trip to calculate total fuel consumption. VSP is a variable that reflects the engine load and is correlated with vehicle fuel consumption and emissions. Aerodynamic drag, tire rolling resistance, and road grade are the parameters that VSP takes into account. This value can be calculated as below (Zhai et al., 2008):

$$VSP = v \times (a + g\sin(\varphi) + \beta) + \gamma\, v^3 \qquad 4\text{-}7$$

Where VSP is measured in kW/ton, v is vehicle speed (m/s), a is vehicle acceleration (m/s2), g is the gravity magnitude (9.81 m/s2), φ is road grade value, β is rolling resistance coefficient (0.092) and γ is drag term coefficient (0.00021).

VSP can be calculated using the instantaneous speed and acceleration which can be derived from a microsimulation model. Indeed, VSP can be obtained for each vehicle at each simulation second. Zhai et al. (2008) classified VSP modes into eight discrete modes, each representing a certain fuel consumption. Once the VSP modes are calculated, the amount of fuel can be estimated as:

$$TE = \sum_{i}^{I} TVSP_i \times FR_i \qquad 4\text{-}8$$

Where *TE* is total fuel consumption of a bus, *i* is the VSP mode, $TVSP_i$ is the total time a vehicle spent in VSP mode *i*, and FR_i is the fuel consumption rate for *VSP* mode *i*. Fuel consumption rate for the buses is a function of parameters such as bus type, and the bus passenger load. In this study, the rates suggested by Frey (2007) are used to calculate the fuel consumption of each bus. In the numerical example (Chapter 6), an analysis is also performed to reflect the sensitivity of model output to the level of passenger load.

4.4. Chapter Summary

In this chapter, metrics to measure the performance of different preferential were presented. Firstly, a generalized cost function was proposed, reflecting all the parameters that may be affected by deploying transit priority strategies. This function reflects the travel time and reliability of all modes as well as the community cost of deploying each scenario. In section 4.2, a simulation based measure of performance was developed that can be estimated using the vehicles trajectories. These inputs can be obtained from real data or simulated ones. Finally, in section 4.3 the suggested method to calculate the amount of bus fuel consumption using their trajectories and second-by-second vehicle information was presented.

As a key component of evaluation and design of transit priority strategies, the developed measures of performance are extensively used throughout this study. Depending on the targeted objective, available data, and the level of study, an appropriate measure of performance can be implemented. For example, to reflect the effect of preferential strategies on the variability of a service, an agent based approach can be implemented, whereas for planning level studies where only a rough estimation of the priority impacts is sufficient, one may opt to use pre-existing parameters. Application of the developed metrics is presented through several example studies through the next chapters.

5. Measuring Network Performance Using Smart Card Data

One of the seminal tasks of deploying priority strategies is to identify the services that experience unexpected delays and the segments along their route that such delays occur. As discussed in chapter 2, in a network-wide perspective, using smart card data is a viable approach to obtain a passenger-oriented insight of the experienced delays and variabilities in different spatio-temporal areas of interest.

This section is elaborating the proposed methodology to analyse the network and identify the areas for possible priority strategy deployment using smart card data. Following a literature review in Chapter 2, in this chapter firstly an overview of the method and contributions of this approach are presented. Then a methodology, including the proposed passenger oriented metrics is introduced and the required data preparation and processing procedures are elaborated. An example study shows the implementation of this method in a transit priority context. This part of the study is concluded with a summary of this chapter. Figure 5-1 depicts the relation of this chapter to whole this study.

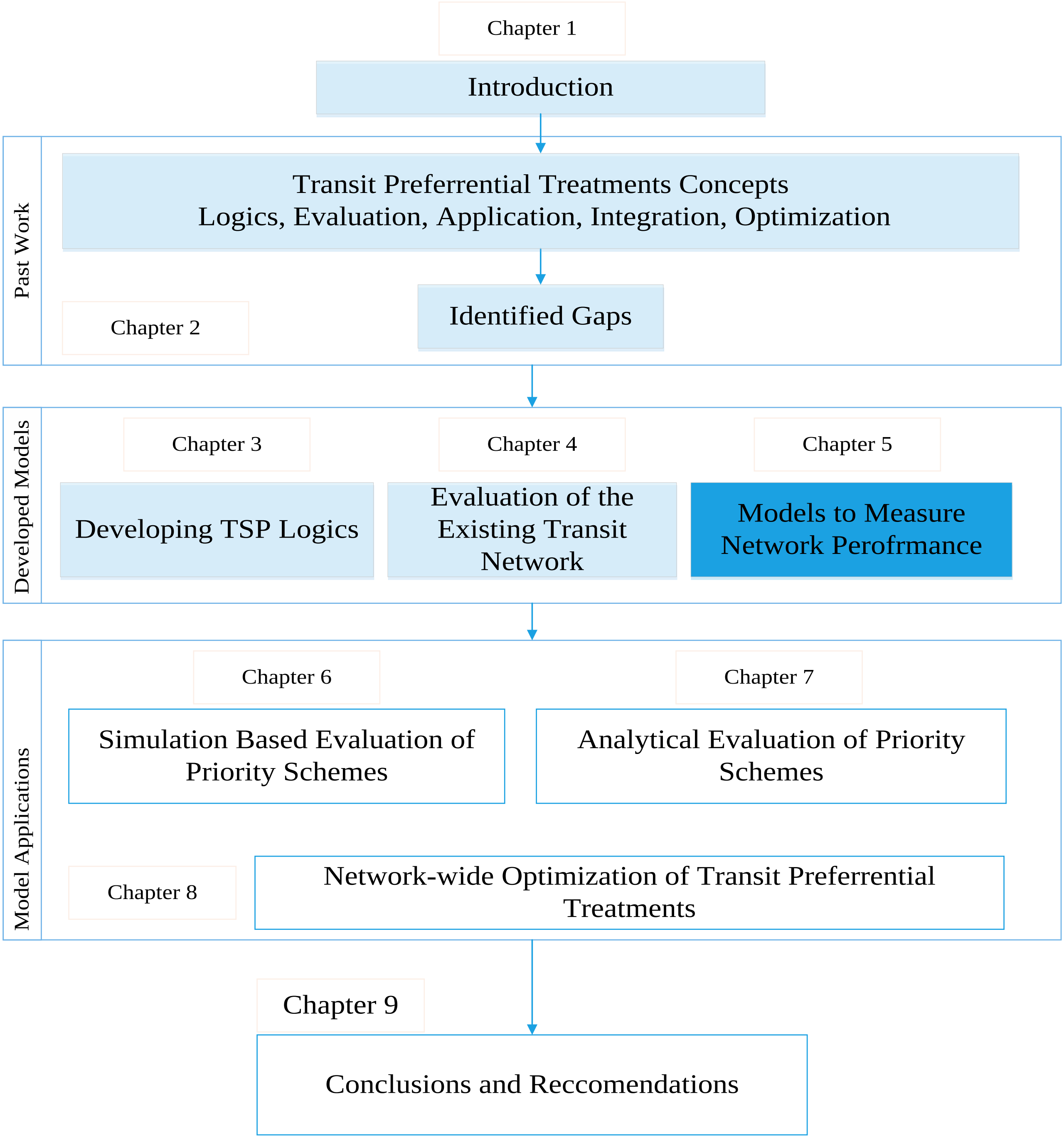


Figure 5-1 Thesis outline and highlighted current chapter

5.1. Introduction

Nowadays, surface transit service is a common scene in the majority of the metropolitan areas. Indeed, depending on the urban structure of a city and the importance of public transport to the decision makers and planners, the network is extended to maximize a combination of coverage and ridership. In order for preferential strategies to be analysed and designed in such networks, it seems crucial to achieve an elaborate insight into the whole transit network at the first step. The patterns of transit demand, corridors and areas with higher defined routes and transit vehicles, spots (either road segments or an intersection) where the vehicles experience unexpected delays, the location of bus and stops (e.g. bus stops are near-side or far-side of the intersections), and relative layout of transit lines (points of intersection, transfer points, etc.) are amongst the knowledge a network-wide analysis of the transit network can provide.

This research introduces two passenger-oriented measures of transit travel time reliability using smart card data. These measures reflects user experience of punctuality (deviation from the schedule) and predictability (day to day variation) of the service for any spatio-temporal level of interest. The main contributions of this chapter are:

- Developing a passenger-oriented transit reliability metric in terms of both punctuality and predictability
- A method for measuring the defined indicators from a raw smart card transactions dataset
- A tool to measure service variability for any targeted time period, mode, line, and area of interest

The rest of the chapter is organized as follows. In Section 5.2, firstly the proposed reliability measures and mathematical formulations are presented. Then, the analysis framework and data preparations are described. Section 3 presents the application of the developed tool and reliability metrics to measure the reliability of the public transport network in the Hague, the Netherlands, followed by a discussion on the results. The chapter is concluded by summarizing the findings and suggesting directions for future research.

5.2. Methodology

This Section elaborates the proposed passenger-oriented reliability metric and the steps required to derive them from AFC data. Firstly, two reliability measures, reflecting regularity and punctuality of the service as a passenger point of view are introduced. Mathematical formulation of these metrics as well as their scalability to have aggregated measures (e.g. reliability of a specific line or mode) are then provided. Then, the developed tool to measure the reliability metrics is introduced and key data processing and inference challenges and remedies to tackle them are explained.

5.2.1 *Passenger Oriented Measure of Reliability*

The approach in this study is to directly calculate two service reliability measures from observed passenger trajectories. The two proposed reliability indicators of this paper target passenger-oriented predictability (day to day variation) and punctuality (deviation from the schedule). The former considers day-to-day variations in travel experience, whilst the latter refers to the discrepancy from scheduled travel times. The measures are calculated at origin-destination level and can then be scaled to measure the travel time reliability of a stop or terminal, a set of selected stops (e.g. bus stops along a route), or the whole network. The latter is particularly relevant for monitoring and assessing service performance by comparing how network performance evolves and benchmark the performance by comparing different networks.

The measures are formulated and implemented for a fare collection strategy where passengers validate their card upon boarding and before alighting each vehicle. The metrics account thus for service arrival time variability as well as transfer coordination. The time interval between the first in-vehicle tap-in to the last in-vehicle tap-out is therefore considered, including transfer times. However, the initial passenger waiting time as well as access and egress times from and to origin and destination stops cannot be captured from the dataset. The approach taken in this study is to analyse passenger travel time reliability in terms of extreme events which were found to have a disproportional effect on traveller perception and future choices (Friman et al., 2001)

The following notations were used throughout this paper to refer to the aforementioned attributes:

$n \in N$	Recorded smart card transaction n in smart card set *N*
$s \in S$	The stop where either check in or check out is recorded there
$l \in L$	Set of defined transit routes in the network
$t^{o}_{n,i}$	Tap out time passenger *n* at stop *i*
$t^{c}_{\mathrm{n},i}$	Tap in time passenger n at stop *i*
$l_{n,i}$	Transit route that passenger n is boarded at stop *i*
$r^{l}_{t,i}$	Trip id of scheduled line *l* service to arrive at stop i at time t

Daily Variability of Passenger Travel Time

The first metric measures the daily variability of trip travel time for a given time of the day. From passenger point of view, it is important that trip travel times are predictable (i.e. past experiences are indicative of future ones) and demonstrate little day to day variation so that expectations concerning arrival times at the destination are met. Similar to the Reliability Buffer Time (RBT measure) introduced by Uniman et al. (2010) to evaluate rail service regularity, a Daily Variation(DV) reliability metric was developed based on on-board tapping strategy to reflect the effect of vehicle's operation on passenger travel time reliability. In addition to the in-vehicle travel time variability, DV measure reflects the effect of coordinating services for possible transfers.

The DV metric reflects the regularity of a service based on the experience of the passenger over a period of time. It measures the ratio of an upper percentile (ς) and the travel time in typical conditions as the indicator of trip travel time variability. For a given OD-Pair *i* and *j*, the daily variation measure during a targeted period of the day (τ) is formulated as follows:

$$R^{DV}_{i,j}(\tau) = \frac{k^{\varsigma}\left(tt_{i,j}\right) - k^{t}\left(tt_{i,j}\right)}{k^{t}\left(tt_{i,j}\right)} \qquad 5\text{-}1$$

$$tt_{i,j} = \{t^{o}_{n,j} - t^{c}_{n,i} | t^{c}_{n,i} \in \tau, n \in R_{i,j}(D)\} \qquad 5\text{-}2$$

Where

$R^{DV}_{i,j}(\tau)$	Passenger oriented regularity index for OD pair *i,j* during time period τ
$k^{\varsigma}\left(tt_{i,j}\right)$	Upper percentile ς of travel time sets between OD pairs *i* and *j*
$k^{t}\left(tt_{i,j}\right)$	Representative percentile of the typical travel time between OD pairs *i* and *j*
$R_{i,j}(D)$	All the available journeys between OD pairs *i* and *j* in analysis days *D*

The 95th percentile and the median (i.e. 50^{th} percentile) were suggested by Uniman et al. (2010) as the upper (ς) and typical (t) percentile of travel times, respectively. Wood (2015) also used the 95th percentile threshold, suggesting that passengers find a once a month chance of late arrival acceptable. This metric therefore measures the extent to which abnormal unusual travel time experiences deviate from the central value of the travel time distribution for which there is the same number of longer travel times as there are shorter travel times. In order to enable the scalability of the metric for different OD pairs, time periods, modes and systems, the DV measure is presented as a dimensionless indicator. Consequently, 1 minute variability in a 5 minute service and 10 minutes variability in trips that has a median value of 50 minutes are identical.

Deviation from Scheduled Travel Time

The second reliability metric reflects the punctuality of the service within a defined time period. This measure, defined as passengers based Schedule Deviation (SD) measure, reflects the deviation of individuals' actual travel time from the scheduled one. Having a sufficient sample size for each OD pair, the SD measure is defined as the ratio of the excess delay to travel time at a targeted percentile (e.g. median or 95th). For a given origin-destination pair, travel time punctuality is measured using the following formulation:

$$\boldsymbol{R^{SD}_{i,j}(\tau) = \overline{f_{sd}}\left(t^{c}_{n,i}, t^{o}_{n,j}, t^{p}_{n,i}, t^{p}_{n,j}\right) \qquad \forall\, t^{a}_{n,i} \in \tau, n \in R_{i,j}} \qquad \mathbf{5\text{-}3}$$

$$f_{sd}\left(t^{c}_{i}, t^{o}_{j}, t^{p}_{i}, t^{p}_{j}\right) = \frac{k^{\varsigma}\left(tt_{i,j} - tt^{p}_{i,j}\right)}{k^{\varsigma}\left(tt_{i,j}\right)} \qquad 5\text{-}4$$

$$tt_{i,j} = \{t^{o}_{n,j} - t^{c}_{n,i} | t^{c}_{n,i} \in \tau, n \in R_{i,j}\} \qquad 5\text{-}5$$

$$tt^{p}_{i,j} = \{t^{p}_{n,j} - t^{p}_{n,i} | t^{a}_{n,i} \in \tau, n \in R_{i,j}\} \qquad 5\text{-}6$$

Where:

$R_{i,j}^{SD}(\tau)$	Passenger oriented punctuality index of OD pair *i*,*j* during time period τ
$tt_{i,j}$	Observed travel times between OD pair *i*,*j*
$tt_{i,j}^{p}$	Scheduled travel times between OD pair *i*,*j*
$t_{n,j}^{p}$	scheduled arrival time of passenger n to stop *j*

The SD measure needs more parameters and calculations than DV to be calculated as a connection between passenger trajectories and service timetables has to be formed. For a transferred trip, in addition to origin and destination stops, considering transfer points, routes, and walking times are also imperative and calculations are costlier. In this study, SD measures were calculated for $\varsigma = 50$ and $\varsigma = 95$, representing the median ratio of variability and the one that passengers may experience 5% of their time, respectively. Section 5.2.3 shows the details of the procedure to extract scheduled travel time for each journey.

Scaling the Measures

The measures that were introduced in previous section estimate the reliability of the service for each origin-destination pair. These values can be aggregated to represent the variability of any set of trips. In this study, three levels of aggregation, namely bus stop level, transit lines level and network level are studied using the following formulations:

$$\mathrm{R}_s\,(\tau) = \frac{\sum_{j\in S} R_{s,j}(\tau)\cdot q_{s,j}(\tau)}{\sum_{j\in S} q_{s,j}(\tau)} \qquad \text{5-7}$$

$$\mathrm{R}_l\,(\tau) = \frac{\sum_{i\in S_l}\sum_{j\in S_l}\left(R_{i,j}(\tau)\cdot q_{i,j}(\tau)\right)}{\sum_{i\in S}\sum_{j\in S} q_{i,j}(\tau)} \qquad \text{5-8}$$

$$\mathrm{R}_M(\tau) = \frac{\sum_{i\in S}\sum_{j\in S}\left(R_{i,j}(\tau)\cdot q_{i,j}(\tau)\right)}{\sum_{i\in S}\sum_{j\in S} q_{i,j}(\tau)} \qquad \text{5-9}$$

Where:

$\mathrm{R}_s\,(\tau)$	Measures of reliability(either DV or SD) for stop *s*
$q_{i,j}(\tau)$	Number of passengers travelling from stop *i* to *j* at time period τ
$\mathrm{R}_l\,(\tau)$	Measures of reliability(either DV or SD) for line *l*
$\mathrm{R}_M(\tau)$	Network level measure of reliability(either DV or SD)
S_l	The set of stops of line *l*

5.2.2 *A Tool for Analysing Passenger-Oriented Reliability*

A set of input data and preliminary tasks, metrics, and post-calculations are required in order to obtain the proposed reliability indicators. Figure 5-2 illustrates the analysis framework, consisting of the required input data and data preparation and analysis steps in yielding passenger-oriented measures of transit service reliability. In this section we elaborate the components of this framework. An application of this framework is presented in section 5-3. to demonstrate how the tool can be used to evaluate network performance.

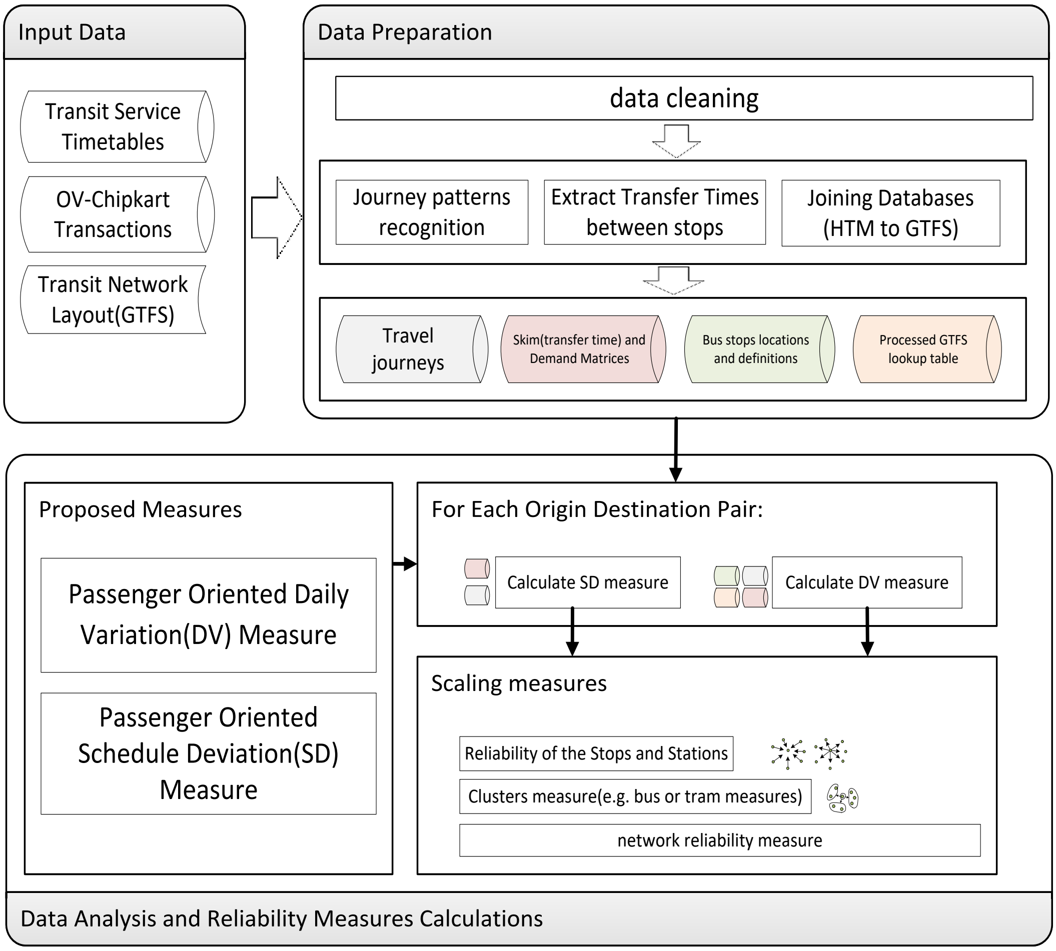


Figure 5-2 Proposed method to calculate passenger-oriented reliability

Input Data

The presented methodology relies on three datasets: (1) recorded passenger transactions; (2) transit service timetables, and; (3) network layout including the stops locations and transit lines.

The main dataset is the Smart Card Transaction (SCT) data, recorded for each leg of the trip. Excluding cases with missing data, the raw data includes the time and location of passenger boarding and alighting, the transit line of the respective vehicle, and the passenger encrypted ID. In order to deduce information about passenger travel time reliability, passengers' journeys need to be systematically inferred from single leg transactions.

General Transit Feed Specification (GTFS) (Catala et al., 2011) provides all the required data on network layout and service timetables as a set of standard CSV files. This data is processed to infer the scheduled service that is considered in SD when contrasting the planned and provisioned trip travel time. In contrast, the DV measure relies solely on transaction data.

Transaction datasets need to be pre-processed to extract the reliability metrics. Data preparation serves four main goals: removing outliers from missing values and incorrect records, forming journeys, linking transaction data with other datasets, and optimizing database structures to enable fast queries. These procedures are discussed in the following sub-sections.

From Smartcard Validations to Passenger Journeys

The very first step in data preparation process is to derive journeys from the tap-in-tap-out transactions. To do so, it is necessary to cope with data outliers. A series of filters was applied to handle outliers. After excluding data that contains missing values (e.g. missing tap-in or tap-out, no line identifier), Procedure 1 (Figure 5-3) is applied to construct the journey database. This procedure involves the specification of three parameters. Firstly, a minimum value of leg duration time (γ_{min}^{leg}) was defined to exclude transactions with short durations that are prone to fallacious records. The second parameter is the maximum duration of a single leg (γ_{max}^{leg}) to filter the trips that are abnormally long, mainly due to systematic error in recording the tapping timestamp. Finally, $\gamma^{transfer}$ is defined as the time interval between two successive legs with same card ID to classify the set of trips an individual performs on a given day into journeys. The output of this procedure is a database of the identified journeys, including an ID, date, number of transfers, and a list of details (line id, tap-in time and location, tap-out time and location) for each leg.

Procedure 1: Forming Journeys Database
Remove transactions with same location of tap-in and tap-out
Remove transactions between stops i,j with $\boldsymbol{t_{n,i}^{o}} - \boldsymbol{t_{n,j}^{c}} < \gamma_{min}^{leg}$
Remove transactions with abnormally long durations $\boldsymbol{t_{n,i}^{o}} - \boldsymbol{t_{n,j}^{c}} > \gamma_{max}^{leg}$
For each day in analysis period:
Group transactions using card ID
For each group:
  Sort transactions using check-in timestamp
  For each transaction rn in Rn :
    Form journey if $\boldsymbol{t_{r_n}^{c}} - \boldsymbol{t_{r-1_n}^{o}} < \gamma^{transfer}$
    For each journey:
      Calculate transfer times using walking distance
      Calculate the number of transfers
      Add journey to database

Figure 5-3 Developed Procedure to form journeys from transaction dataset

5.2.3 *From Passenger Journey to Reliability Metrics*

After the journey database has been generated, it is possible to obtain the DV metric for any given time window-location. However, to calculate the SD metric, journeys need to be matched to the timetable dataset. This section first presents the approach adopted for linking the two datasets. Then, the algorithm for deriving the scheduled arrival time for each journey is described. Finally, a heuristic approach for restructuring the dataset in order to speed the processing time is presented.

Matching Passenger Journeys and Service Timetables

One of the necessary tasks of this study was to form a link between definitions of stops and lines and similar attributes in smart card transactions as these two databases were not consistently related to each other. To address this issue, a one-to-many line matching procedure was adopted so that a set of candidate GTFS lines was identified for each service line identified in the smartcard data. In each iteration the corresponding line is selected by considering the time discrepancy between the line recorded in the smartcard data and the scheduled arrival time of each of the candidate lines.

A similar approach was used in matching the stops in the two databases. *The stops included in the SCT database refer often to both directions of the same line or a number of platforms.* In this procedure, using stop coordinates, for each stop in the SCT database a set of GTFS stops was selected. The elements of this set were selected by applying two basic rules:

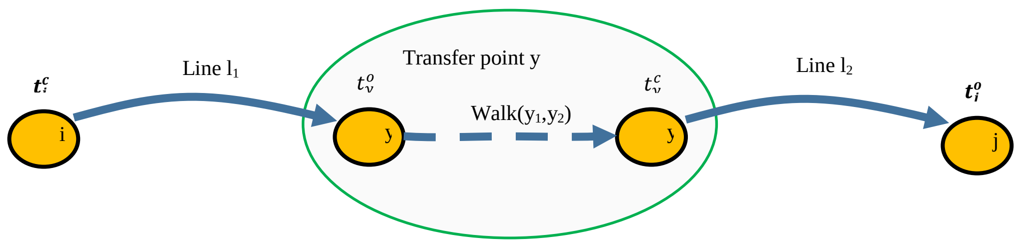
1. A GTFS stop is within an acceptable distance (e^{d}) from the SCT stop
2. There is at least one common line that serves both stops

For each transaction, the corresponding stop for each leg (tap-in or tap-out) was identified by checking if a corresponding trip can be made from the origin stop to the destination one using the recorded transit line. In the unlikely event that more than one GTFS stop qualifies, the closest one (i.e. the stop that cause the minimum additional delay) is selected. The walking distances are then calculated between the stops introduced into the SCT database. Consequently, walking distances between the stops with same "parent-station" are uniformly assigned with a minimum value, γ^{w}_{min}, representing the minimum required time to perform a transfer.

Path Finding Algorithm

A path-finding algorithm is required for estimating the scheduled time of the service corresponding to each transaction. Using the boarding and alighting stops, service timetable, and the transit line of each leg of a journey, walking distance between the stops, and the timestamp of the first check-in, the corresponding scheduled journey can be inferred. A procedure was developed for obtaining the scheduled boarding and arrival times ($t^{p}_{n,i}, t^{p}_{n,j}$) for a direct (i.e. single leg) journey. For a given leg, firstly the corresponding candidate stops was determined. For each candidate stop pair, the connectivity via the recorded route name was checked. Then, the provided services that could potentially serve the passenger n were extracted. Finally, the service with minimum buffer from $t_{n,i}^{c}$ were identified and its timetable was used as $t_{n,i}^{p}$ and $t_{n,j}^{p}$ values. For a given tap-in time, the corresponding scheduled trip arrival time is determined by minimizing the discrepency from passenger boarding time. This inference rule relaxes the assumption that the order in which buses arrive at stops corresponds to the order indicated in the timetable, reflecting the possibility of overtakings.

A method to calculate the scheduled travel time was also developed for non-direct journeys. In this regard, given a first tap-in time and a trajectory (lines and stops) as the arguments, a sequential procedure was designed for determining the scheduled arrival time at the destination. The transfer walking time is estimated based on the adjusted aerial distance between transfer points where a square root of 2 was multiplied by the walking distances to convert aerial distances to distances on the network. Figure 5-4 illustrates a journey with one transfer and the procedure used for determining scheduled arrival times.



Procedure 2: scheduled arrival time calculation procedure
For each journey in analysis period:
If (n_transfers=0)

$t_{n,i}^{p} = t_{i}^{r_{n,i}}$

$r_{n,j} = r_{i}^{l_j}\ (t_{n,i}^{p})$

$\boldsymbol{t_{n,j}^{p}} = t_{j}^{r_{n,j}}$

Else:
For each transfer y in Y:
Calculate transfer distance $t_{y_i}^{w}$

$t_{n,i}^{p} = t_{i}^{r_{n,i}}$

Set $t_{n}^{cur} = t_{n,i}^{p}$

for each stop s_n *in* S_n

$r_{n,s_n} = r_{s_n-1}^{l_s}(t_{n}^{cur})$

$t_{n}^{cur} = t_{s_n}^{r_{n,s}} + t_{s_n}^{w}$

next

$\boldsymbol{t_{n,j}^{p}} = t_{n}^{cur}$

Figure 5-4 Generic method to calculate the scheduled arrival time of the journeys

Once the scheduled arrival times of each journey are calculated, the measure of reliability for each OD pair for a given time period can be obtained. Unlike the DV measure that is derived from travel time distribution and thus requires a set of data for different days, the SD measure can be calculated for any individual journey since the timetable is used as the benchmark.

Restructuring Datasets

The computational costs and feasibility of query and metrics calculation within a reasonable amount of time can become prohibitive for large datasets such as SCT. In the initial implementation of the proposed method, using the existing SCT database (transformed and optimized using SQL Server) and GTFS data files (loaded into memory once the software is initialized), the elapsed time for each query was noticeably high, refraining the evaluation of the simplest queries. For instance, running the program for two hours resulted with SD measures for around 2500 records, less than 0.05 percent of the monthly number of records. To improve the querying speed, two indexed look-up tables were formed to load journeys and timetables into memory and achieve a significant saving in computational cost of each query. Since the date and stop id are the two essential arguments for all queries, a two dimensional array with the size of D and S was formed and timetable and transactions were loaded into this array in the initialization phase. Consequently, instead of searching over all days and all the stops for a corresponding line and time period, the search is conducted over the line and time period only. This improvement allows in the case study application to perform queries in a fraction of the time initially required (almost 30000 times faster). This made it possible to attain SD metrics for a typical AM peak period in a fraction of a second.

5.2.4 *Passenger Reliability Tool Interface*

The developed tool and metrics to evaluate passenger-oriented reliability of the transit service is available as a standalone executable application. The tool offers analysts, planners and decision makers an interface to obtain the results at the spatio-temporal level of interest. Figure 5-5 shows a screenshot of the interface. The application is using the Language Integrated Query (LINQ) component, allowing users to dynamically filter the target days, stops (origin and/or destination), mode sequence (e.g. bus, tram, first bus and then tram, etc.), analysis period (e.g. time of day, day of the week, specific dates), and transit line. Such flexibility along with the instant generation of passenger reliability metrics empowers transit operators and agencies by having a direct insight into the performance of the whole the network and individual network elements.

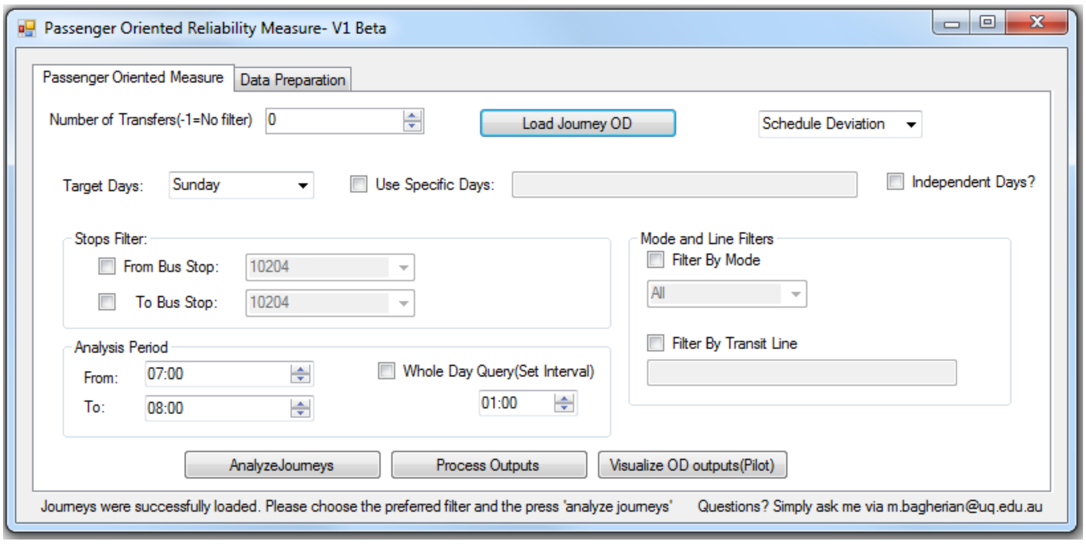


Figure 5-5 Main interface of the developed passenger-oriented reliability measurement tool

5.3. Application

This section shows the procedure and results of applying the suggested framework (including reliability metrics) on the Hague transit agency's (HTM) services. This network consists of 12 tram and 8 bus lines and 923 stops (Figure 5-6). Transaction data from a single month (March 2015) period containing 8,177,434 records were analysed in this study. More details on the utilized smartcard data may be found in Van Oort et al. (2015). A representation of the network including the stops and defined routes can be found in http://gtfs.ovapi.nl/htm/gtfs-kv1htm-20150227.kmz. Using the developed tool, a study was performed using a top-down approach, to find out the sources of variability in the network during the analysis period.

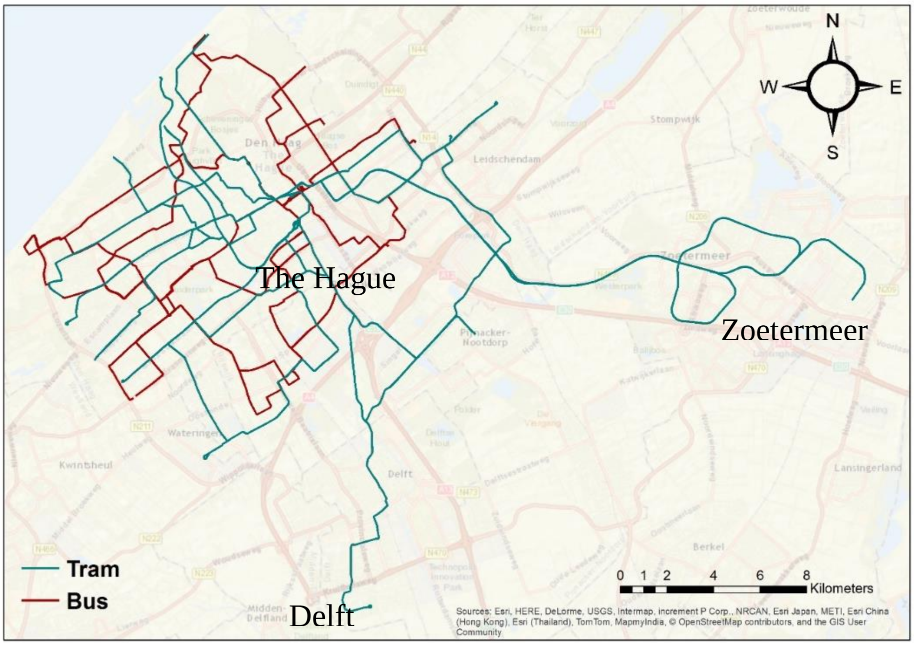


Figure 5-6 the public transport network of The Hague

In this section, firstly a review on the data preparation process is shown. Then, the descriptive statistic of the passenger trips, transferring behaviours, and spatial distribution of the demands are presented. The results of using daily variation and schedule deviation metrics to estimate passenger-oriented reliability of the service is then discussed.

5.3.1 *Descriptive Analysis of Transfer Patterns*

The method to form passenger journeys database from transactions records (Figure 5-2) was applied to HTM database in March 2015. To remove the outliers, the incomplete transactions, the taps in same stop, and the ones outside the defined range of 60 seconds to 60 minutes (i.e. $\gamma_{min}^{leg} = 1min, \gamma_{\max}^{leg} = 60min$, respectively) were excluded from the database. As a result, less than 1% of the records were discarded in the analysis. To compose the journeys, the definition established by the local public transport operator - identifying transfer for transactions within a time interval of up to 35 minutes (as $\gamma^{transfer}$) between two successive check-out and check-in - was adopted. Consequently, the procedure resulted with 6,265,185 journeys in the analysis period.

Figure 5-7 shows how the tap-in and tap-out times as well as average travel times vary over the day. The AM peak period is characterized by a short and well-defined peak a in passenger load, whereas the PM peak period builds up over a long period and peaks at a level similar to the AM peak followed by a moderate decline. This pattern can be presuambly attributed to the high share of part-time workers in the Netherlands. Journey duration (from first boarding time to last leg alighting time) is within the range of 15 to 20 minutes during most of the day.

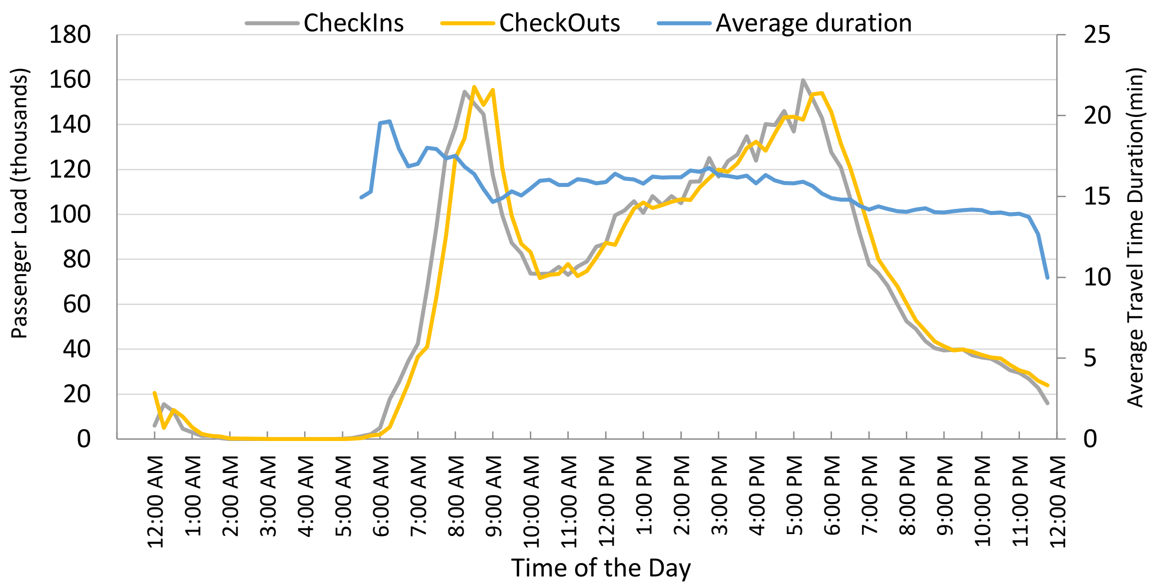


Figure 5-7 Daily pattern of check-in, check-out and journey duration

Figure 5-8 shows the distribution of the observed transfer times. A pronounced peak can be observed at 3-4 minutes interval and 50% of the journey include transfer times that exceed 6:47 minutes. The average transfer time per journey is 9:35 minutes due to the long tail of the distribution which is sensitive to the transfer threshold parameter($\gamma^{transfer}$). Note that the transfer times is calculated as the difference between two successive tap-out and tap-in in all the trips with transfer. Consequently, the transfer time includes the walking time between the stops as well as waiting fort he downstream leg.

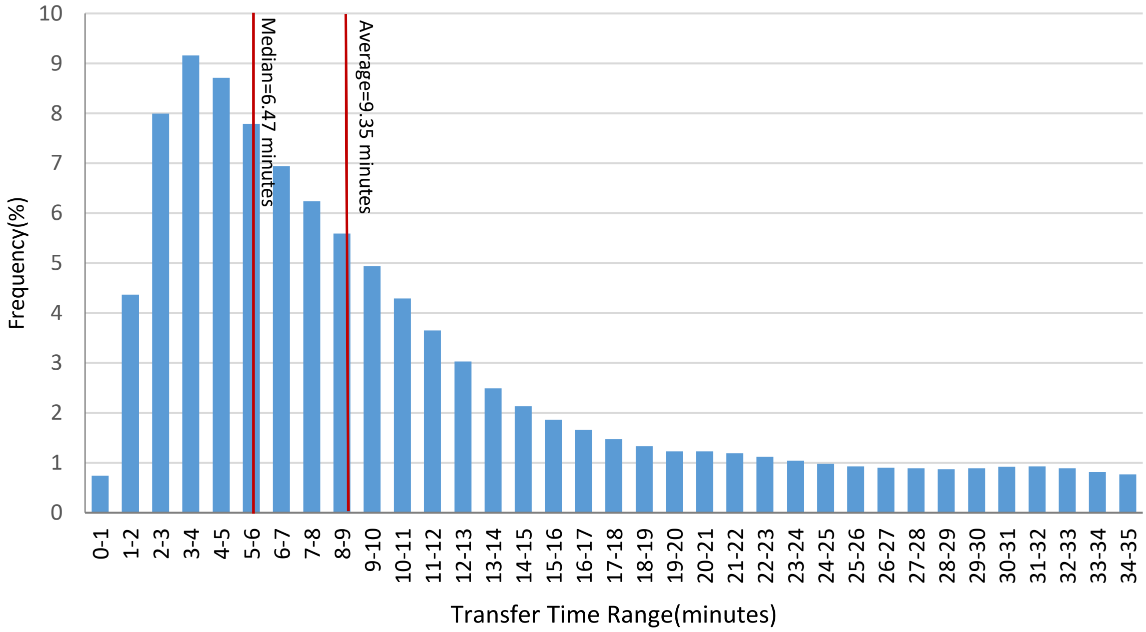


Figure 5-8 Distribution of transfer time durations

Journeys were classified based on their number of transfer. Figure 5-9 shows the share and the travel time distributions of each class. It can be seen that around 80.5% of the trips are identified as direct journey that do not involve any transfer and journeys with one and two transfers have 17.1% and 1.8% of total number of journeys, respectively. Only 0.6% of the journeys were found to comprise of more than two transfers.

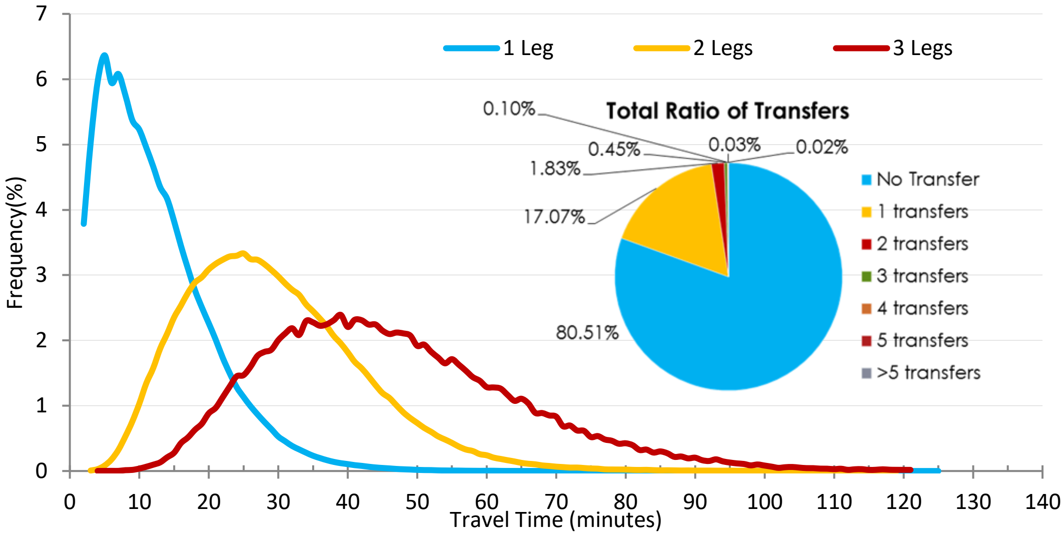


Figure 5-9 Travel time by number of transfers and a break-down of the journeys by number of transfers

Demand spatial distribution was also investigated using the origin and destination of the trips and their corresponding coordinates. Figure 5-10 shows the schematic map of the trip generation on an average weekday. As can be seen, a significant ratio of the demand is originated at few stops. In fact, 20% of the bus stops accounted for the generation of more than 70% of the trips. An analysis of the demand matrix indicates that all the journeys recorded during the analysis period were associated with merely 18% of the possible OD pairs in the case study area. This uneven demand distribution stresses the importance of using passenger-oriented measures in evaluating service performance rather than targeting vehicle-based measures.

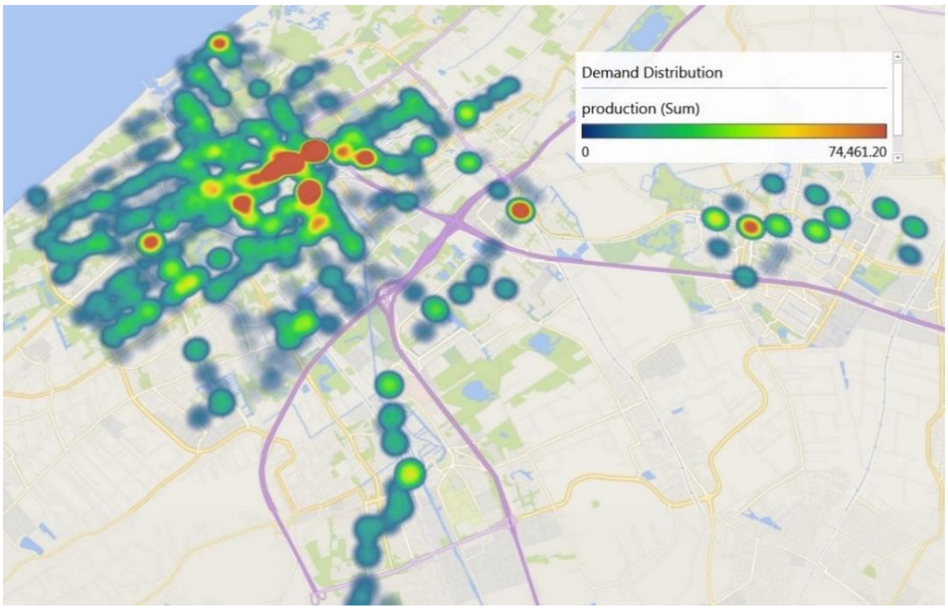


Figure 5-10 Schematic view of demand distribution across the case study network (based on smart card data)

The main output of the data preparation module is the journey database that can be used to measure reliability for various spatio-temporal levels, as illustrated and discussed in the following section.

5.3.2 *Results*

The proposed framework along with the passenger-oriented reliability metrics was applied to the HTM dataset. According to the operator's records, no major incident or failure occurred during the analysis period and services generally operated as planned". In the following, we present the results of our analysis at a network-wide level for the entire month of March 2015 as well as an illustration for a specific instance which is used to illuminate the potential insights that can be gained by further investigating the spatial and temporal variations in service performance.

The DV metric was first calculated for different days and time periods. For each OD pair, the DV measure was calculated if the sample size exceeds a pre-defined value (10 observations here). The values were then scaled to the network level. Figure 5-11 shows the results of calculating the network level DV for different time periods. It can be seen that during the analysis period, AM peak travellers experienced more reliable services than during other periods as far as the total journey time experienced on former trips on the same day of the week are considered. For example, extremely long travel times on weekdays are 25% longer than the median travel time during the afternoon peak period. It can also be observed that travellers have the highest level of variability on Monday morning and afternoon as well as Friday PM peak compared with the corresponding time periods on other days of the week, suggesting that the start and end of the working week are subject to more unusual travel conditions.

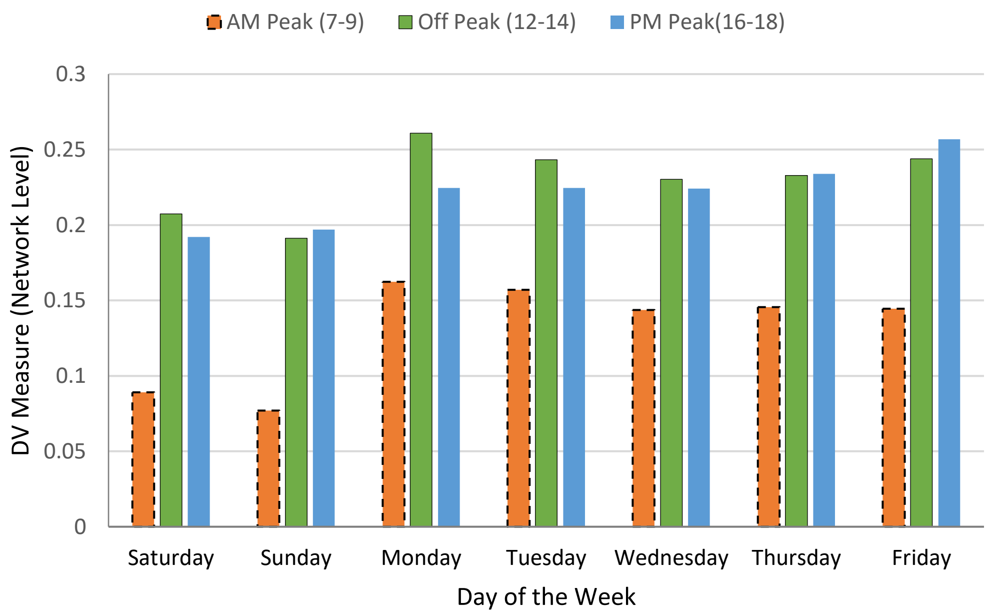


Figure 5-11 Comparison of travel time predictability measure (DV) for different days of the week

To gain a better insight into the daily variation patterns, the SD of the AM peak period was calculated for each day of the month and is displayed in

Figure 5-12. In addition, the corresponding passenger load across the network is depicted. Most weekdays are characterized by a SD value in the range of 0.25-0.35. This implies that 5% of the passengers experience a travel time that is 25 to 35% longer than the scheduled journey travel time. In other words, an average commuter will experience once in two weeks a travel time that exceed by more than 25% the travel time expected based on the schedule. It can be observed that weekends are characterized by lower demand levels and higher service reliability. Notwithstanding, lower service reliability does not necessarily occur when higher passenger loads are observed. For example, March 25 has a highest level of SD, although it is not the day that experienced the highest demand level. This day, along with March 18 which can be considered a representative of a typical day for comparison purposes, were selected for further investigation.

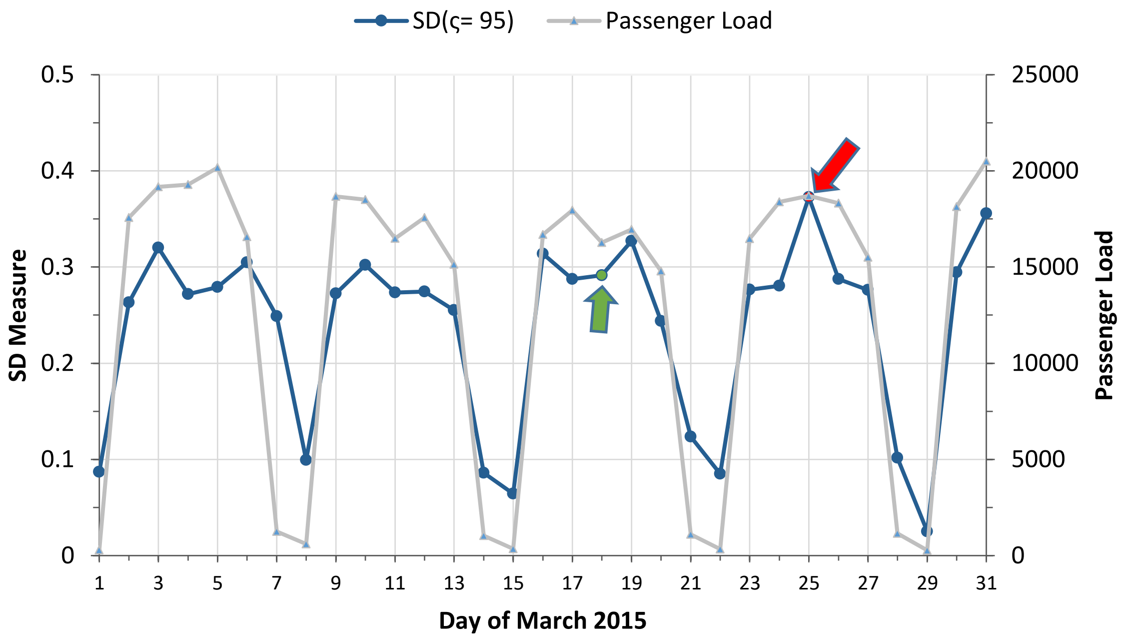


Figure 5-12 Passenger load and network level reliability measure in different days (AM peak period)

Passenger Reliability by Mode

The HTM transit network consists of 12 tram and 8 bus lines. Reliability was analysed for each mode separately to compare their performance and the results are presented in Table 5-1. In addition to the higher passenger load, it can be seen that the reliability of buses and trams was worse on March 25 than on March 18. Comparing buses and trams, it can be seen that for passengers, trams were consistently less reliable than buses during the AM peak period of the selected days. To find out the reason of experiencing such variability in tram lines, further analysis was performed.

Table 5-1 Reliability measures of buses and trams in AM peak period(7:30-8:30AM)

Measure		**March 18th**		**March 25th**	
		Tram	Bus	Tram	Bus
Passenger Load		13839	2030	15577	2665
Travel time [sec]		803	823	822	816
Absolute deviation [sec]	$\varsigma = 50$	61	35	96	65
	$\varsigma = 95$	206	135	305	176
Schedule deviation	$\varsigma = 50$	0.09	0.04	0.16	0.08
	$\varsigma = 95$	0.31	0.17	0.40	0.22

Passenger Reliability Per Line

Schedule deviation was analysed for each specific tram line of the network using Eq. 8. Figure 5-13 shows the comparison of SD measure for different tram lines for March 18 and March 25. It can be seen that two lines (Line 3 and 4) experienced the greatest deterioration in reliability when comparing these two days. Tram Line 4 was selected for a more detailed analysis.

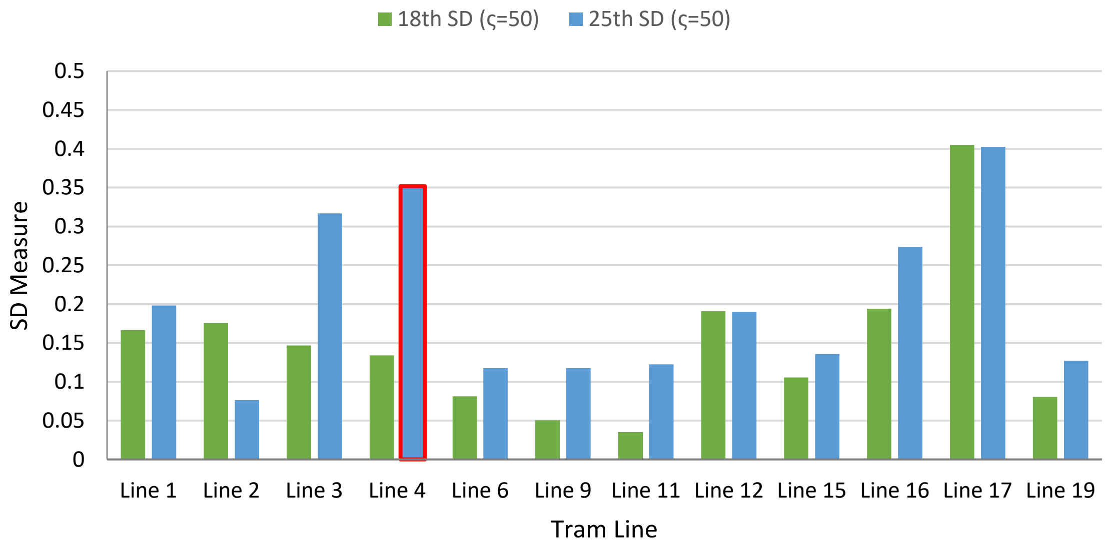


Figure 5-13 Comparison of tram lines reliability measure in two selected days (line 4 is highlighted as the critical one)

Passenger Reliability for a Given Line

The SD measure was calculated for the selected line for the whole analysis period of March 2015. As can be seen in Figure 5-14, line 4 had a SD measure below 0.15 (indicating 15% delay in arrival time) for the vast majority of days, with the exceptions of March 25 and March 28. This sudden change coincides with a noticeable increase in passenger load on this line.

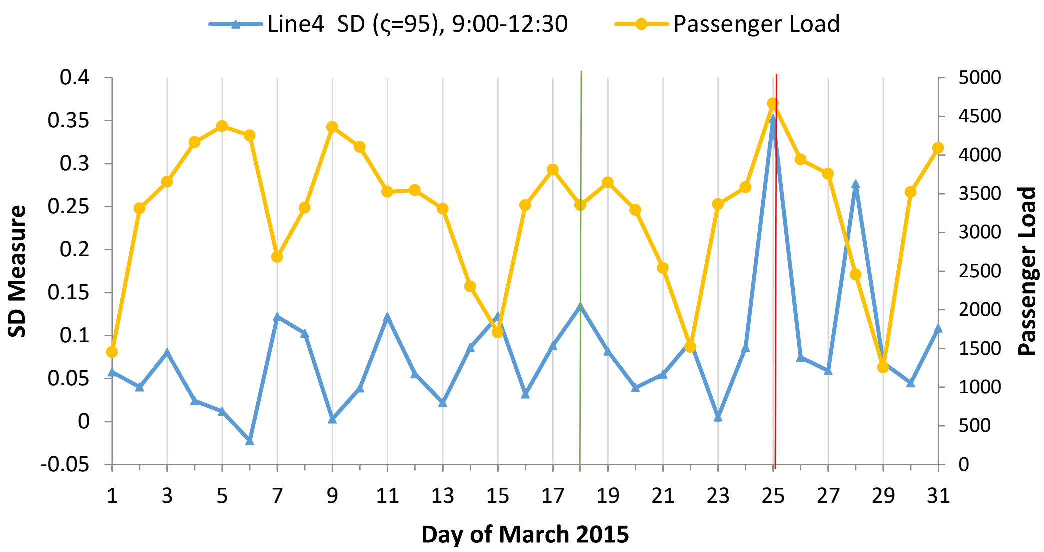


Figure 5-14 Passenger load and reliability measure of tram line 4 in different days of the analysis period

The daily trend of Line 4 was compared in one hour intervals for both March 18 and March 25 (Figure 5-15). The SD measure does not follow the AM and PM demand peaks. On March 25, the most noticeable change in service reliability of line 4 occurred directly after the AM peak (9 AM- 1 PM) and PM peak (6-7 PM).

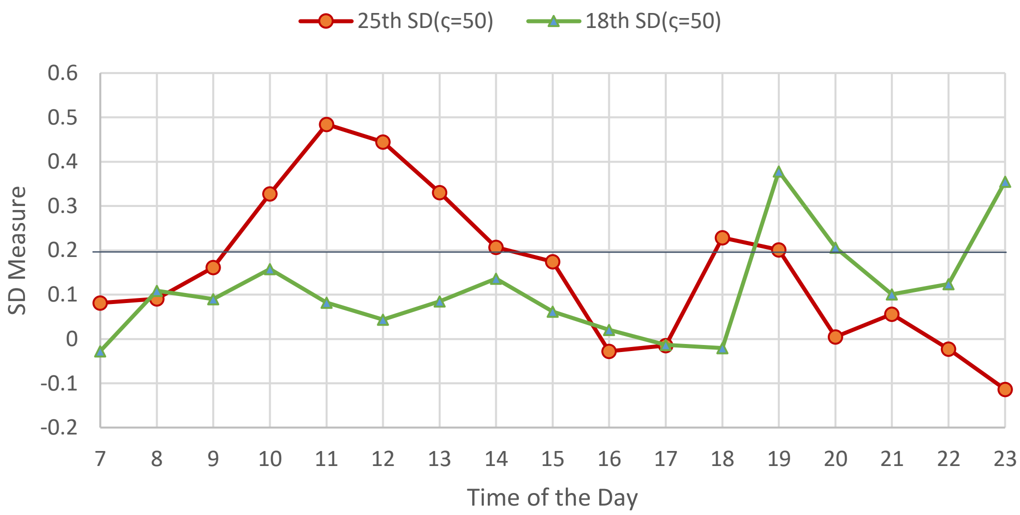


Figure 5-15 Comparison of tram line 4 reliability measure between 18th and 25th March2015

Considering the variability changes in different times of the day in smaller intervals (15min), 9:45-10:15am was identified as the interval where a noticeable increase in service variability of tram line 4 occurs. For This period, the SD measure at stop levels was generated for each stop along the line. Figure 5-16 shows a schematic comparison of the person delay changes along the line on a typical day (March 18) and the abnormal day (March 25). While service reliability worsened for almost all stops during the time period selected for analysis, certain locations experienced a particularly extreme increase in passenger delay (denoted by red colour). Such a fine interval-scale insight can help transit agencies to precisely identify the variability sources and potentially design measures to mitigate them.

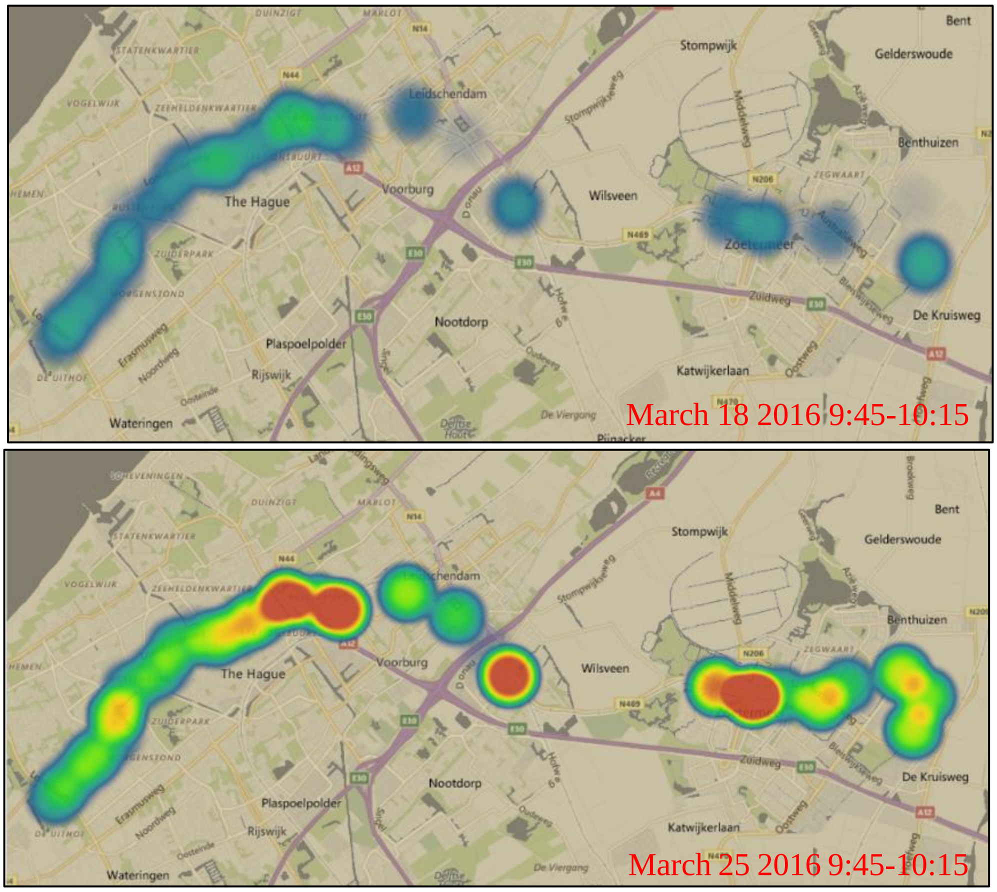


Figure 5-16 Person-delay visualization of tram line 4 for the targeted abnormal period

5.4. Chapter Summary

In this chapter, a practical approach to observe the network situation and identify prone areas for transit priority deployment was presented. In this regard, a comprehensive tool to estimate the passenger-oriented measure of transit service reliability was presented. This method included two novel metrics to reflect both predictability and punctuality of the network in the selected spatio-temporal window, measured at the passenger journey level. The methodology was presented along with the data analytics procedures. With the availability of reliability measure at origin-destination level, the method for measuring the reliability at stops, lines, transit modes, and for the network as a while was developed as a tool with a user friendly interface. While the aggregated level of punctuality and regularity can be derived at the network level, disaggregate measures can aid agencies and operators in identifying the locations and times where maximum person-delay may occur so as to deploy transit priority strategies in that areas.

Passenger-oriented reliability metrics can lead to a paradigm shift in managing transit services from planning to operations. The introduction of incentive strategies based on passenger reliability metrics rather than vehicle-based performance measures will assist service providers in focusing on remedies such as preferential strategies, rescheduling the services, and transfer points coordination where and when most needed in terms of their consequences for passengers. Monitoring passenger reliability in real-time can facilitate steering operations towards passengers' experience. Research into passengers' perception of service reliability will enable differentiating between different journey components and account for their contribution to the overall passenger experience.

6. Using Microsimulation to Evaluate Transit Priority Strategies

As discussed in chapter 2, using microsimulation method is the most common strategy in performance evaluation of TSP strategies. This chapter presents the simulation based implementation methods and application results that were introduced in former chapters. All the simulation models were developed in VISSIM microsimulation package(PTV, 2013). Information on either implementation or core algorithms of the software can be found from the software manuals or references such as Barceló (2010). Through the following sections, major modules that are related to modelling TSP logics and detections are briefly presented.

In this chapter, application of the developed TSP logics and measures of performance for different levels of analysis (a single intersection, a corridor, or a network) is firstly presented. For each level of analysis, a case study example demonstrates the model performance and the challenges of deploying TSP strategies. Then, the developed V2I based models that were introduced in section 3.7 are then applied to an intersection and the results are comprehensively discussed. The section is finalized by recommendations and summary of this section. Figure 6-1 depicts the relation of this section to the entire study.

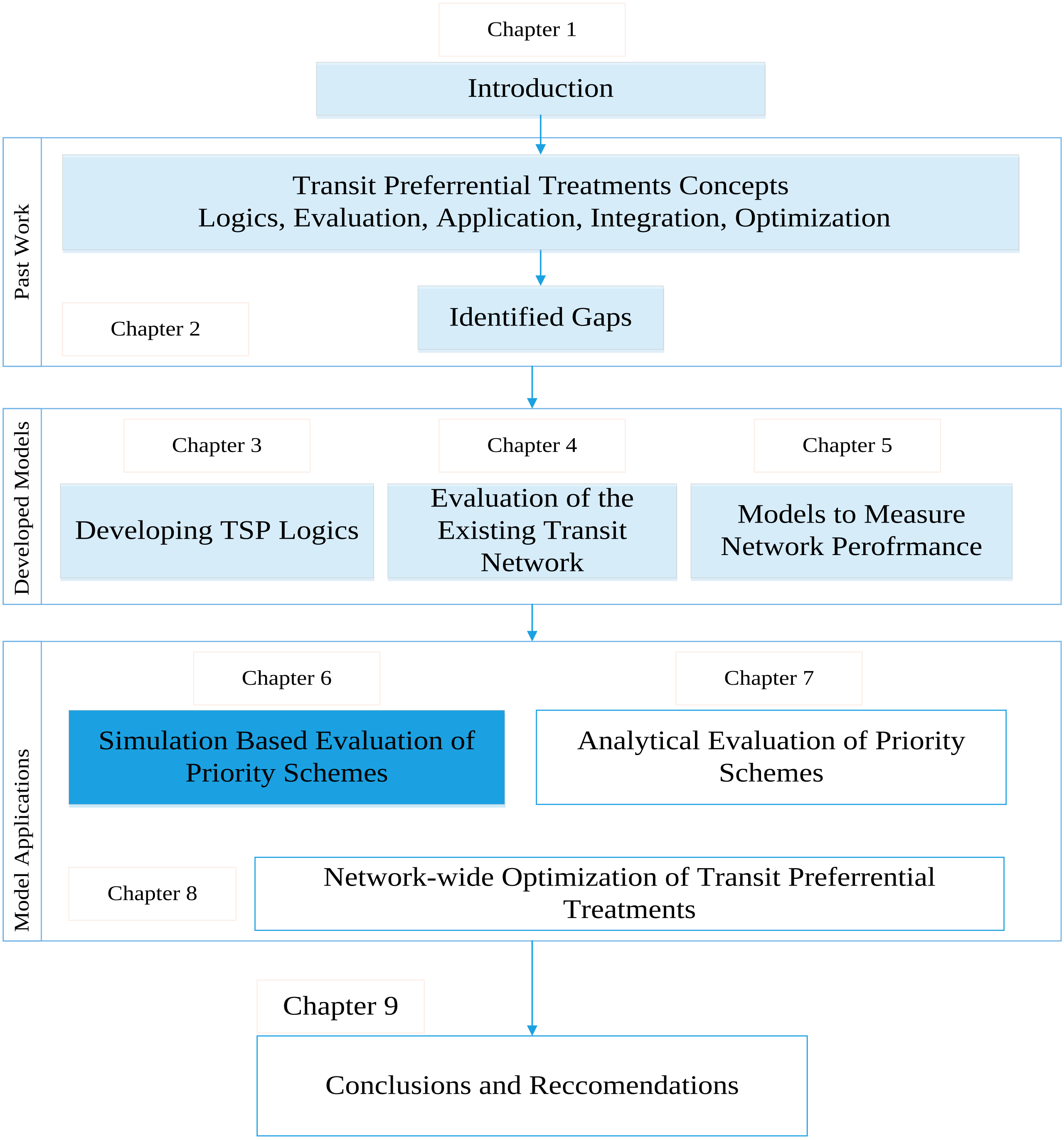


Figure 6-1 Thesis outline and highlighted current chapter

6.1. Initialization of the Simulation Model

In this section the developed TSP logics and performance measures were implemented through three examples in different levels to show the performance of the developed TSP models. The simulation models were all developed in VISSIM microsimulation package (PTV, 2013). Through the next sections, major modules that are related to modelling TSP logics and detections are briefly presented. A Vehicle Actuated Program (VAP) was also used to model TSP Logics in VISSIM software. As introduced in chapter 3, VAP is an add-on to allow users to define their signal timing logic in microsimulation model. In the present work, the developed Green Extension (GE), Red

Truncation (RT), and Cycle recovery modules were evaluated in a set of scenarios. The simulation models of this study have a set of common modules that are presented first.

6.1.1 *Arrival Prediction Model*

One of the main requirements of the proposed model is a reliable estimation of bus arrival time to the intersection's stop line. To be able to suggest any changes in dwell time or bus speed, one should answer the question, 'how long does it take to reach the intersection?' A predictor of travel time is meant to answer this question. Considering intersections and bus stops as the main reason for variation of arrival times, estimation of bus arrival time at a destination like a bus stop has attracted much attention from researchers (e.g. Zheng and Van Zuylen, 2013, Yu et al., 2011). Nevertheless, here the problem can be simplified as estimating the travel time between a bus stop and its closest downstream intersection. Consequently, the congestion of that segment is the only source of uncertainty in bus arrival time. The proposed method to estimate the bus arrival time from a bus stop to an intersection can be formulated as follows:

$$\begin{cases} t_a^i = t_0^i + \dfrac{v_c^i}{a^i} + \mathrm{d(f)} & if \quad d = \dfrac{(v_c^i)^2}{2a} \leq D \\ t_a^i = t_0^i + \dfrac{v_c^i}{a^i} + \dfrac{\left(D - \dfrac{(v_c^i)^2}{2a}\right)}{v_c^i} + \mathrm{d(f)} & otherwise \end{cases} \qquad \text{6-1}$$

Where t_a^i is the time bus *i* arrives at the intersection, t_0^i is the time bus *i* requests to leave the bus stop, v_c is the cruising speed, a is the bus preferred acceleration rate, d is the distance the bus requires to reach cruising speed (acceleration length), *D* is the distance from the bus stop to the intersection, and *d(f)* is the bus delay due to a congestion with flow rate *f* on a link variable. *d(f)* was intuitively considered by introducing an offset value for bus arrival time. Once the arrival time is estimated, the status of the signal at predicted bus arrival moment is calculated and adjustments for the bus speed or an extra dwell time is provided. In this regard, if the bus is able to avoid the red signal phase by only increasing its speed within the limits, the bus will be granted permission for departure and the speed value will be adjusted. Otherwise a dwell time extension will be triggered to shift the bus arrival time to the time the signal turns green.

6.1.2 *Detecting Buses at an Intersection*

Detection systems can be classified as either Automatic Vehicle Location (AVL) or Selective Vehicle Detections (SVD). AVL provides continuous monitoring of bus location, and can be considered as a viable solution for gathering TSP triggering data. However, in practice, SVD systems are mostly applied for TSP strategies due to their simplicity and availability in simulation models. This is the method which is implemented in the developed microsimulation models. Liu et al. (2004) performed an analysis on the optimal location of bus detectors and suggested placing detectors between 150-300 m upstream (i.e. distance from the stopping line). This variability is mainly due to the variability of the traffic patterns from time to time. In this study, a distance of 200m is assumed as the default distance. However, in some circumstances when the length of the segment is not long enough, shorter distances were assumed.

6.2. Transit Signal Priority Deployment: Numerical Examples

In this section the developed logics and models were evaluated through three numerical examples. Firstly, the developed TSP logic was applied to a single intersection to evaluate the effect of TSP and test its efficacy. The effect of each variable was addressed at this stage. TSP performance in different levels of congestion, signal settings and logics were examined through a set of sensitivity analyses of the deployment results. In the second case study, the proposed method was used to evaluate the effect of TSP deployment on a corridor located in South-East Queensland, Australia. To this end, a set of scenarios were defined to assess applicability of the model to larger problems. A corridor level model can reflect the effect of signals at upstream and provides a better insight on the TSP performance in practice. Finally, TSP strategies were applied to a small grid network to gain ultimate insight about the TSP performance in the network. The effect of multiple TSP requests on the observed delays, shift in routes choice by car travellers due to priority strategies, and the travel time reliability measures are discussed in this section.

6.2.1 *Case Study I: An Isolated Intersection*

In the first case study the developed TSP strategy was applied to an intersection which has three pre-timed fixed phases. Intersection characteristics (including geometric layout and phasing) and the prioritized bus route are presented in Figure 6-2. The cycle length was fixed at 90 seconds. A set of scenarios were then defined to model a delay function for each approach of the intersection.

Figure 6-2 Sir Fred Schonell Dr- Gailey Rd intersection: layout, phasing, VISSIM model and prioritized bus route.

27 scenarios were defined assuming three GE values of 0, 5 or 10 seconds, and nine green time values (ranging between 15 and 55 seconds). For each scenario 15 levels of flow rate (ranging between 100 and 1500 vph) were considered. Five different microsimulation runs (i.e., different random seed numbers) were performed for each scenario.

Impact of Signal Parameters on Delay

The efficiency of the TSP strategy depends on its parameters. In this case they were maximum GE allowed (e), saturation and traffic flow rates, and signal timings for the delay function. The effect of other parameters is considered implicitly (through calibration parameters. For each of the variables a comparison between different signal timing scenarios was made. Figure 6-3 shows the intersection delay for different values of green time and maximum allowed GE (e). With an increase in the green time value, a decrease in intersection delay can be observed. In addition, it can be seen that higher GE values result in shorter delays for the buses. Using the TSP compensation module, the effect of TSP on car delay is negligible for different levels of GE. In this example, a saturation flow rate of 3840 vph was obtained from microsimulation.

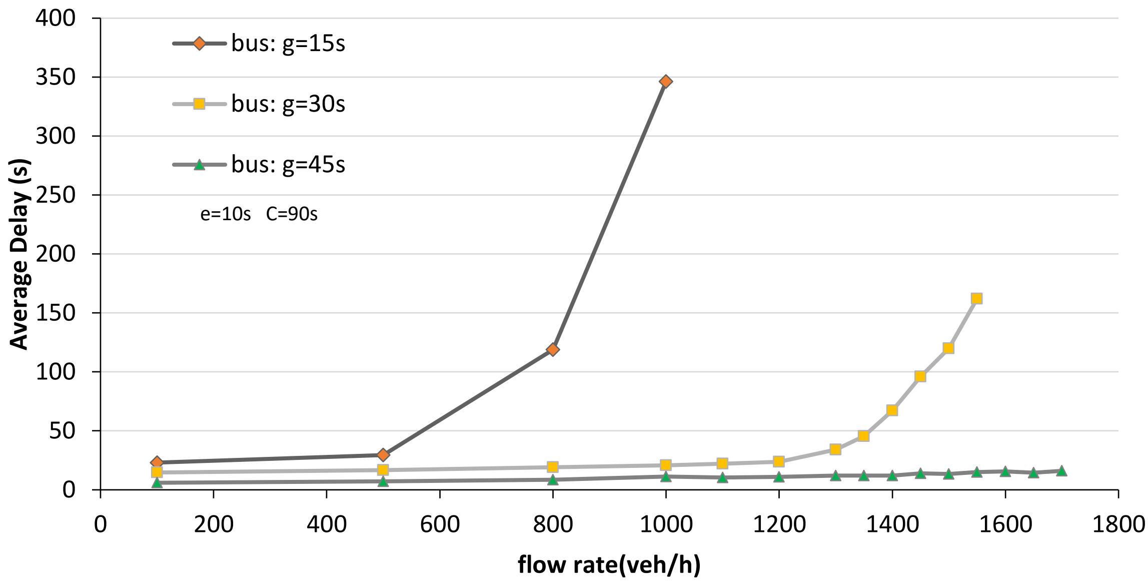


Figure 6-3 The effect of green time ratio on bus experienced delay

The effect of granting priority to buses was also measured for different levels of congestion. Figure 6-4 shows how TSP can reduce bus delay in an intersection in whole range of congestion. Indeed, it was observed that for an isolated intersection, TSP can significantly reduce bus travel time in undersaturated conditions. Nevertheless, the main concern in congested conditions is the additional delays that non-prioritized movement may be incurred due to TSP implementation.

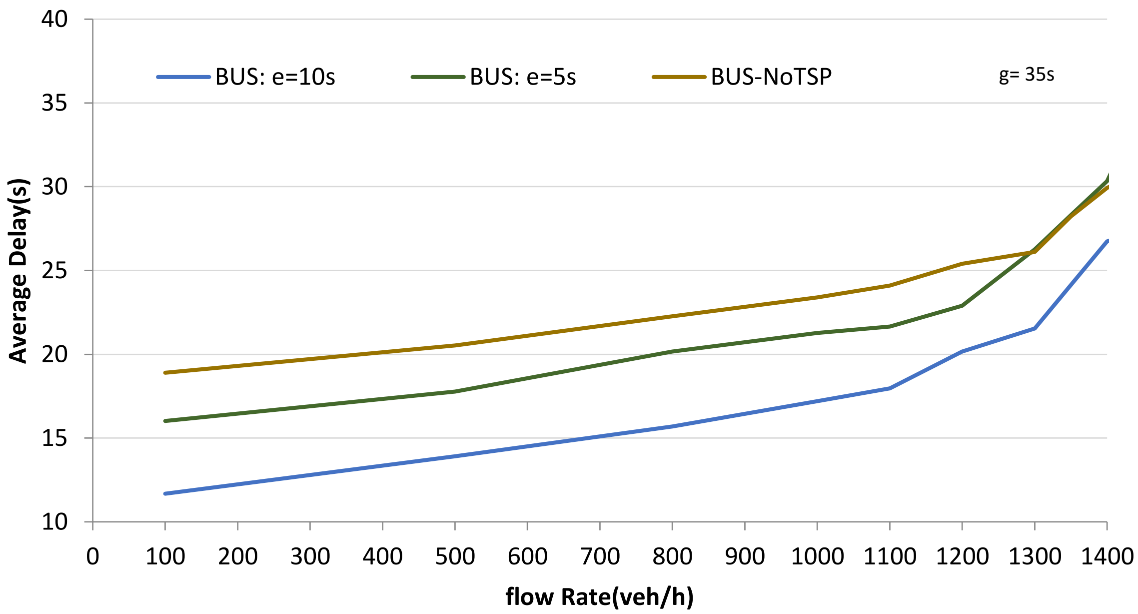


Figure 6-4 The effect of TSP on bus experienced delay

Figure 6-5 shows the effect of TSP deployment on non-prioritized movement in an intersection. As can be seen, the effect of TSP on opposing movement's delay is negligible in undersaturated conditions. However, with the increase of the congestion level, TSP implementation slightly increased the delay in prioritized movement.

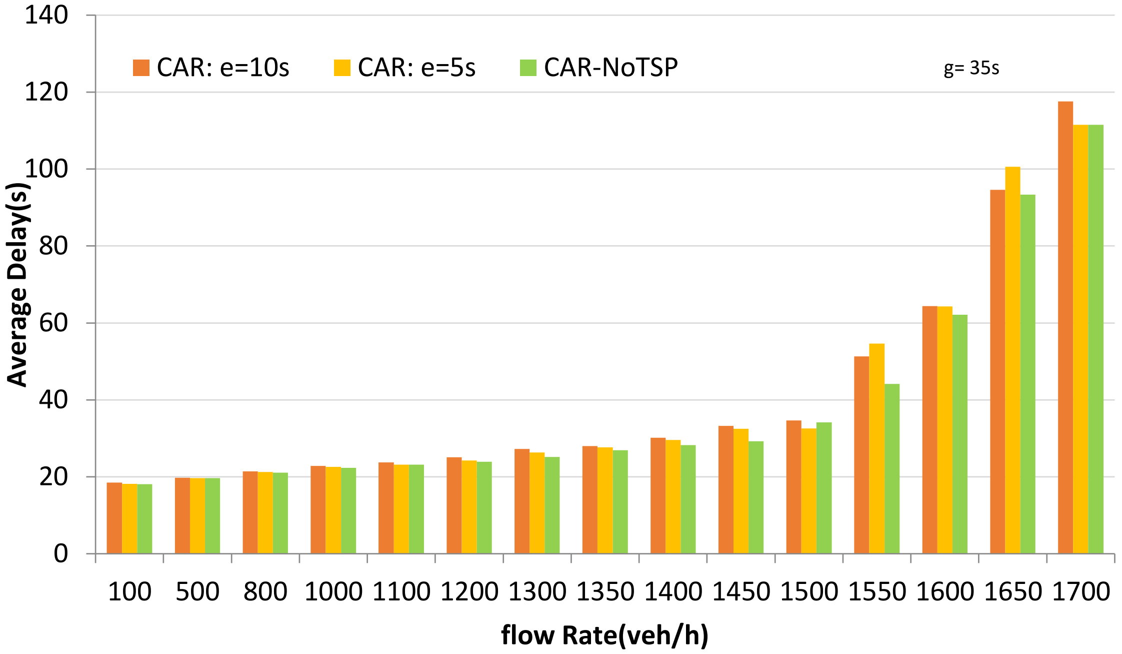


Figure 6-5 The effect of TSP on non-prioritized passenger cars delay

As discussed in section 4, the performance of TSP strategies varies in different TSP logics. One of the developed modules to mitigate the negative impacts of TSP on non-prioritized movements was the cycle recovery module. To observe the effect of cycle recovery module on TSP operations, this module was integrated to the basic TSP logic and simulations were performed for the different levels of congestion. Figure 6-6 shows the effect of the module on car and bus delay of the prioritized approach at different flow rates. As can be seen, implementation of the recovery module has no significant effect on bus delay while comparing with basic TSP average car delay in prioritized movement is slightly increased.

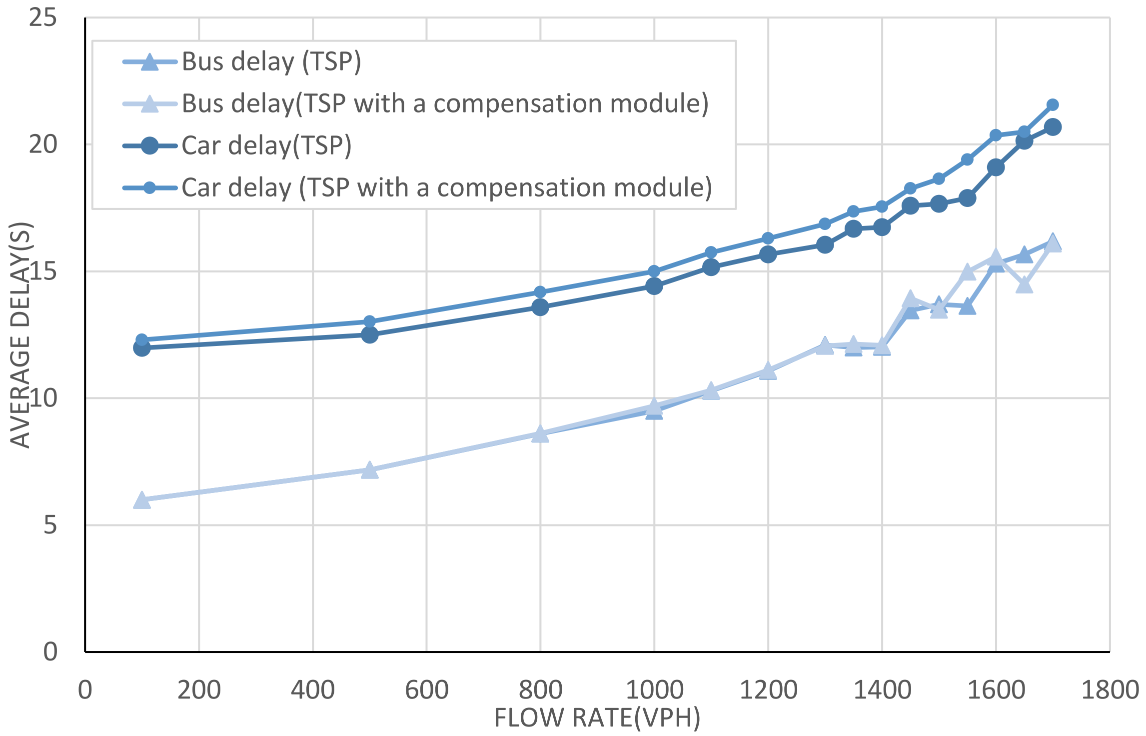


Figure 6-6 Effect of compensation module on car and bus delays of the prioritized approach.

A similar approach was followed to see the effect of cycle recovery tool on the opposing movements. The cycle recovery module compensates the extra green time value in the following cycle. Consequently, no significant change is expected in average delay of the opposing movement in undersaturated conditions where there is no incremental delay. Figure 6-7 compares the delay of one of the opposing approaches for different scenarios in order to show the effect of the compensation module in relieving the negative effect of TSP on the opposing movement. It is noteworthy that for other strategies or traffic regimes different delay function parameters may be obtained, reflecting the effect of implementing TSP on that approach.

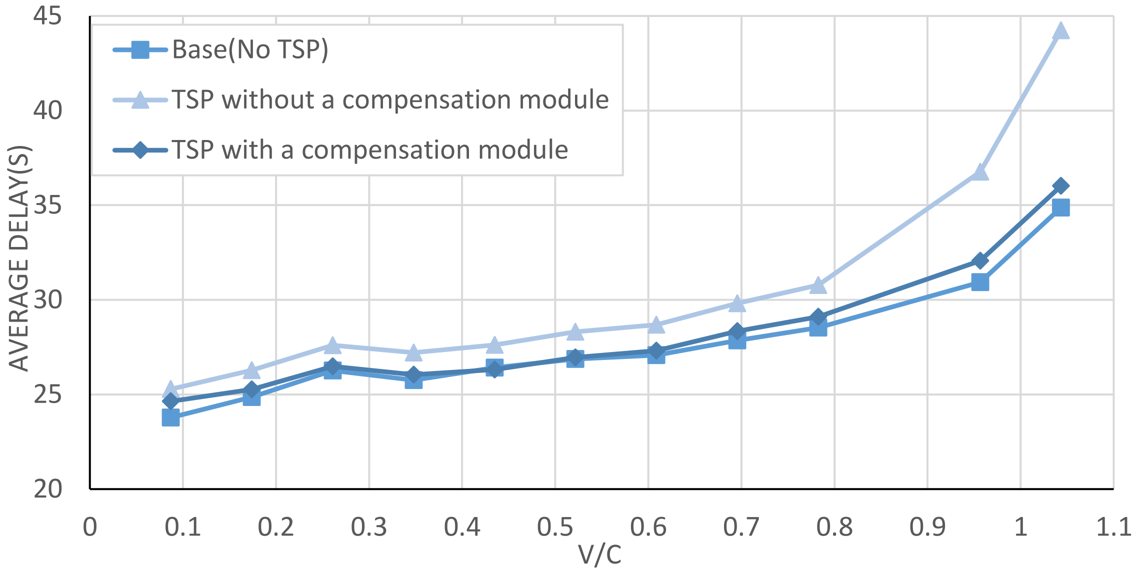


Figure 6-7 TSP effect on the delay of the opposing movement (Gailey Rd-N movement).

Application of the developed TSP module on an isolated intersection confirms its effect on reducing bus travel time with negligible impacts on the opposing movements. Nevertheless, it was observed that when TSP is applied in near or over saturated conditions in opposing movements, it causes exponential delay on the opposing movements. It was also seen that in oversaturated conditions of the prioritized movements, TSP can still save bus travel time as long as the arrival time estimation models can predict their arrival times to the intersection. The next section demonstrates how TSP can affect buses and cars along a corridor.

6.2.2 *Case Study II: Redland Bay Corridor*

The proposed method was applied to a corridor in South-East Queensland, Australia, to test the capabilities of the model for larger networks. The corridor comprises 12 intersections: 8 unsignalized and 4 signalized (with pre-timed signal timings). The total length of the corridor is approximately 12 kilometres. The base condition of the corridor (i.e., no TSP) was modelled in VISSIM. The base model was calibrated for morning peak hour data (Ferreira, 2009). Figure 6-8 shows the area of study and the signalized intersections.

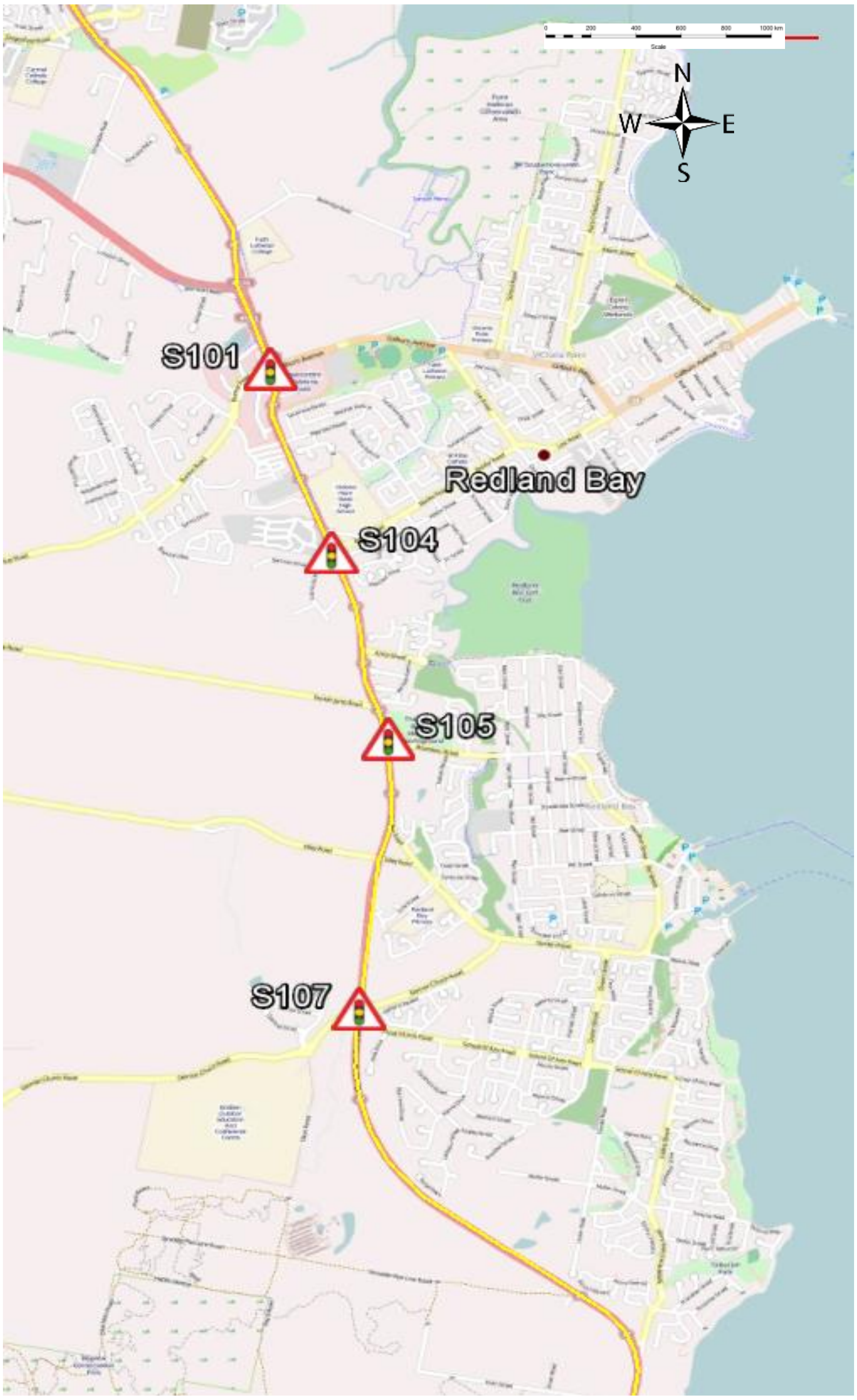


Figure 6-8 Redland Bay corridor and its signalized intersections.

To evaluate the accuracy of the proposed methodology the following procedure was carried out. Firstly, VISSIM microsimulation models for each intersection were developed. Secondly, a TSP strategy 1 was used for all signalized intersections. Thirdly, microsimulation runs were performed for different levels of traffic flow and green time values, and repeated five times with different seed numbers for each scenario. In order to remove the effect of outliers, the highest and lowest obtained delays were discarded and the remaining values were averaged. This mean value was recorded for each scenario.

Traffic flow rates, as well as signal timings for the morning peak, were used to obtain the delay at each signalized intersection. The maximum amount of GE (i.e., e in Equation 1) for all the signals was assumed to be 10 seconds. Table 1 summarizes various characteristics, estimated parameters and delays obtained from simulation in isolated model for signalized intersections of the corridor.

TABLE 6-1 Redland Bay intersection characteristics

Name	flow (vph)	Sat.Flow Rate (vph)	Green Time (s)	Capacity (vph)	Car Delay	Bus(TSP) Delay	Bus(Base) Delay
S101	776	2800	35	1089	23.2	19.8	27.2
S104	704	2800	40	1244	18.6	11.6	20.6
S105	677	2400	40	1067	19.3	18.0	26.3
S107	463	1800	40	800	18.7	18.6	25.7

Sixteen scenarios were investigated (reflecting all possible combinations of TSP applied to the four signalized intersections). For each scenario, microsimulation experiments for the corridor were performed. The duration of each simulation run was 90 minutes: 30 minutes build-up time followed by 60 minutes of recording data. For each scenario, 10 experiments with independent random seed numbers were performed (total of 160 runs). The highest and lowest values of each run were considered outliers and the average of the remaining eight values was used for comparison. Average bus delays at the intersections were recorded and their summation was used to evaluate the effect of TSP implementation across the network. The results were compared with the delays calculated by the proposed method.

Figure 6-9 shows a comparison between the results obtained from microsimulation and the delays calculated by the proposed method. The maximum difference between the calculated delay for passenger cars and buses was 4.5% and 8.5%, respectively. The results were generally within the 95% confidence interval of the microsimulation results for the calculated bus delays. All of the results are within 98% confidence interval of the microsimulation results. In terms of effectiveness of the applied TSP strategy, maximum bus delay reduction was 5%, 9.5%, 13.2% and 13.6% for one, two, three, or four TSP implementations, respectively. Predicted car delay was slightly lower (ranging between 0.6% and 4.8%) than the microsimulation results. In this example, delay at the prioritized approach was estimated. A similar approach may be applied for the opposing movements.

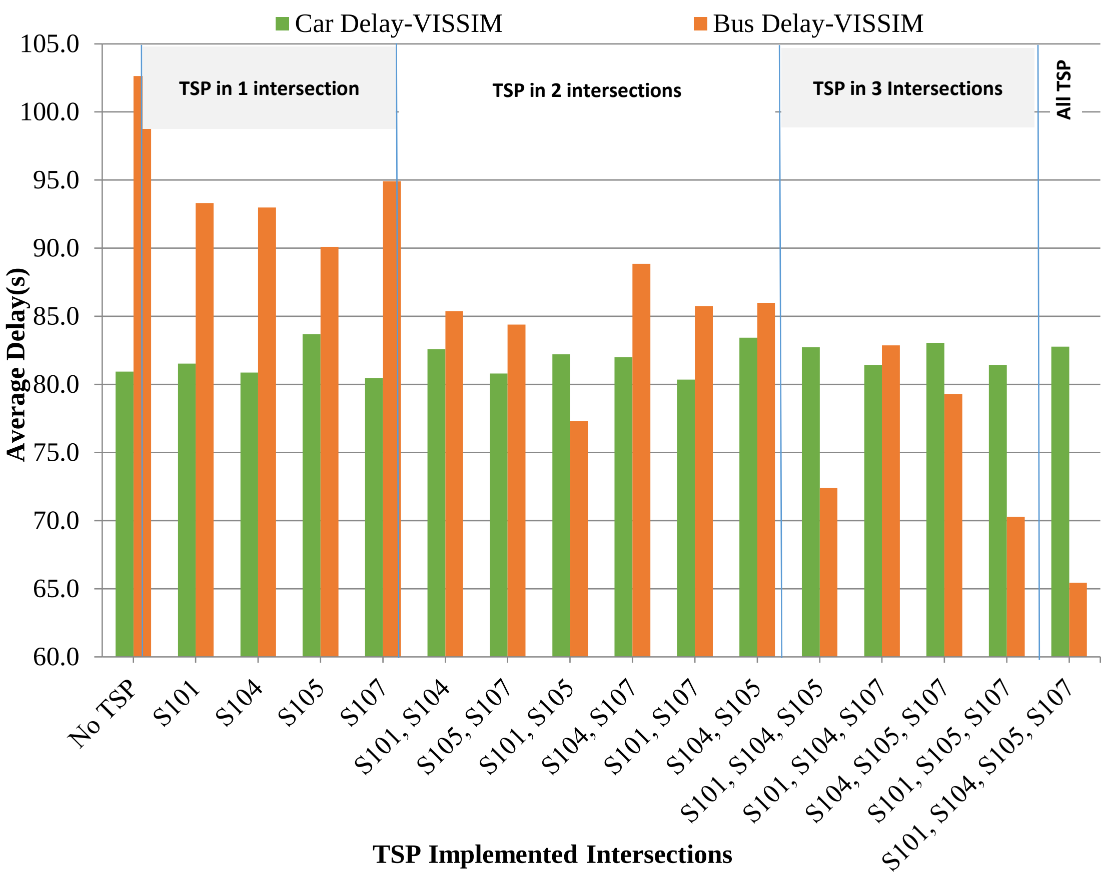


Figure 6-9 Comparison of VISSIM and proposed model estimates for defined scenarios within the Redland Bay corridor.

Performing a corridor level analysis of TSP scenarios showed how different TSP strategies can perform in terms of bus travel time reduction when considered beyond a single intersection level. It was shown how TSP can be implemented for a corridor with a number of intersections. In this regard, it was seen that TSP can have noticeable impact on bus travel time along a corridor with negligible impacts on total car travel times. In addition, looking at the performance of TSP in each single intersection and comparing that with multiple TSP applications supports the idea of evaluation of TSP performance by aggregation of the results obtained for each individual intersection.

6.2.3 *Case Study III: Network Wide Effects of TSP*

TSP strategies were applied to a small grid network to gain ultimate insight about the TSP performance in the network. In a grid network, in addition to the bus and passenger cars travel times that could be evaluated in isolated intersection or a corridor, the effect of multiple TSP requests on the observed delays, shift in routes choice by car travellers due to priority strategies, and the travel time reliability measures were also captured. In this section, before going through the numerical example, the implemented dynamic assignment module is briefly introduced.

Simulation-Based Dynamic Assignment

The dynamic assignment method that is used here is based on an iterated microsimulation model. For each origin-destination trip, the data will be provided for the drivers using their experience from the preceding microsimulation runs. This process can be summarised as below:

In each iteration, first for each origin-destination demand, a set of paths will be obtained. Using simulation results (or free flow travel time if no data is available), an evaluation will be performed to calculate the generalised cost of travelling on each path to sort the paths according to their attractiveness. After finding “k best paths”, the problem of splitting the demand to the paths should be solved. This can be defined as a discrete choice problem. A logit function is used as the most common method to address this selection process. The set of k best paths and travel times experienced in each simulation run will be maintained and used in the subsequent runs. Microsimulation based runs will be repeated until stopping criteria is met. Figure 6-10 diagram illustrates the principle of the Dynamic Assignment.

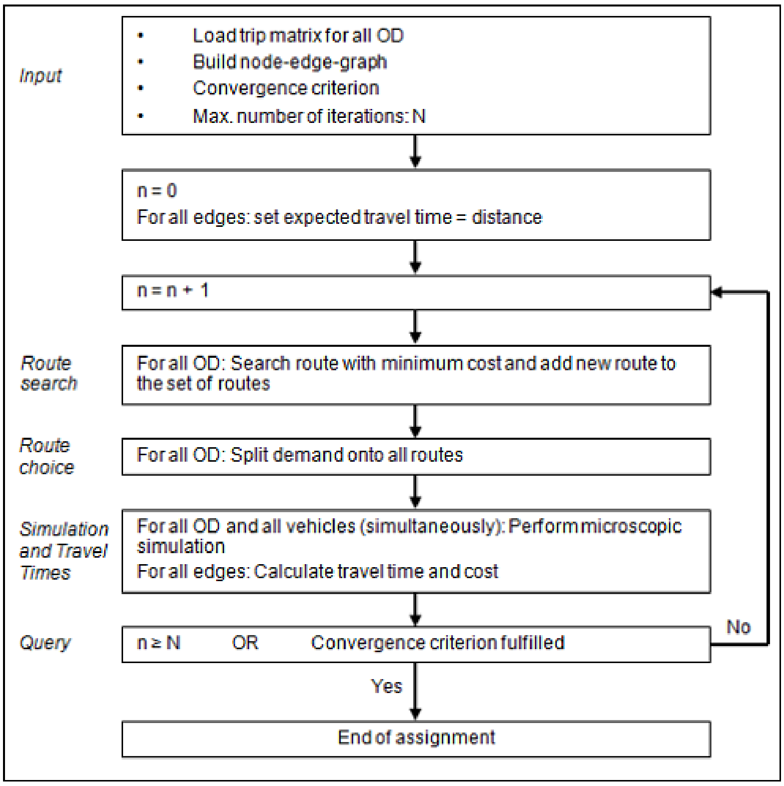


Figure 6-10 Principle of the Dynamic Assignment in VISSIM (PTV, 2013)

The following is a brief summary of each module of the Dynamic Assignment method utilized in this study:

Initialization

To run a dynamic assignment model in VISSIM, a set of data should be provided. Making the network layout, setting the simulation parameters and TSP strategies, setting signal timing parameters and importing the demand array are the main performed processes of this work. To obtain the signal timing, SIDRA software were customized to get flow rates of each movement of every single intersection, and return a VAP file with the obtained signal parameters (cycle length and phase durations). Figure 6-11 shows the procedure in which signal timings are updated.

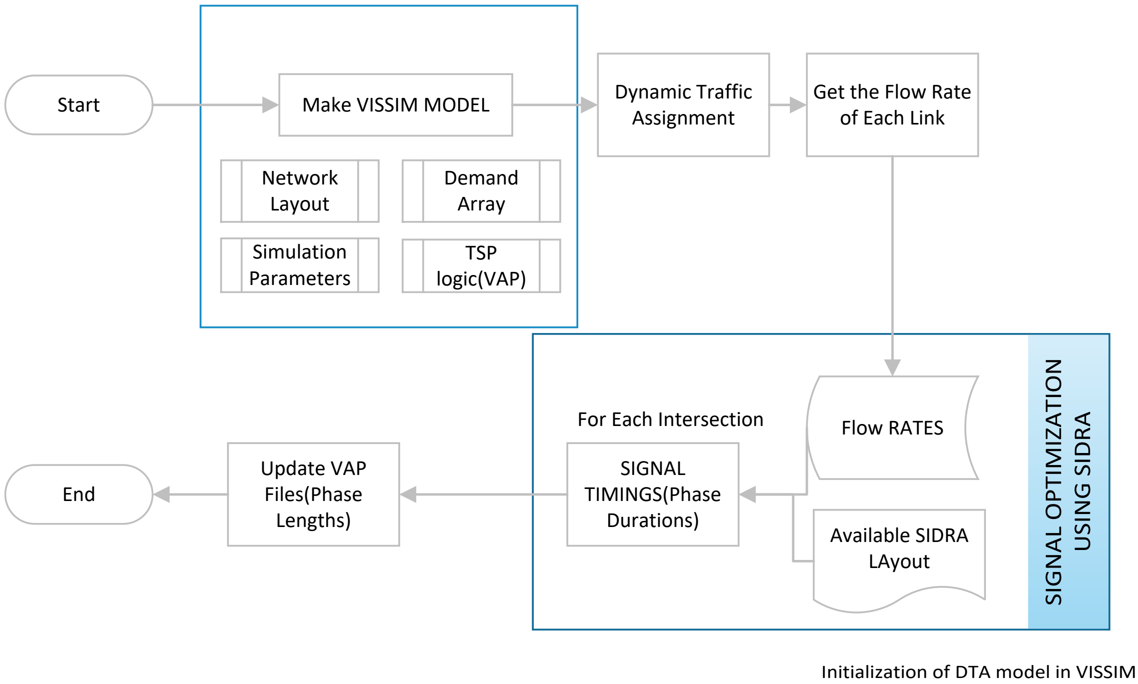


Figure 6-11 Initialization of Dynamic Traffic Assignment(DTA) in VISSIM

Calculation of the simulated generalized cost

The generalized cost of each path is the summation of the generalized costs of each route element (i.e. link segments and nodes). Link generalized cost can be considered as a smoothed value of the travel times obtained from all the prior microsimulations. This smoothing can be performed using either an exponential method (earlier simulations have less importance than the recent results) or a method of successive averages (using the average of a set of prior simulations like the last n simulations). The details of each method can be followed in software user manual (PTV, 2013). After calculation of the generalised cost for each segment, the generalised cost for whole route R can be obtained by summing the general cost of the path elements:

$$C_R = \sum_{a \in R} C_a \qquad \text{6-2}$$

Path search

At the beginning of an iteration of the microsimulation process, a path search procedure would be performed. This procedure uses the length of the paths at the first iteration and then evaluates the paths using general cost of them. In the first iteration, an all or nothing assignment will be used and all the traffic would be assigned to the shortest path. The second generation sends all the traffic to the lower (k^{th} best found path). From the third iteration in which all possible routes have been found the model starts to converge to the equilibrium condition. The paths would be updated after each simulation and more paths will be added to the collected paths for each OD demand.

Path choice

Dynamic Assignment en-route and dynamic equilibrium assignments are two common path choice models that can be found simulation-based DTA models (Florian et al., 2008). In the former, the routing mechanism is done using the reaction of the drivers to information received during travelling. In other words, a driver updates his information during the trip using the available data (e.g. message signs, GPS data, etc.). On the contrary is the equilibrium assignment in which a pre-trip path choice mechanism is suggested. In other words, the driver selects its path through the available options and will not change it during the trip. This is the method which is implemented here. The decision behaviour is modelled using "Kirchhoff function" which is a Logit Function for discrete choice problems:

$$\boldsymbol{p(R_j)} = \frac{\boldsymbol{U_j^k}}{\sum_i \boldsymbol{U_i^k}} = \frac{\boldsymbol{e^{k.\log(U_j)}}}{\sum_i \boldsymbol{e^{k.\log(U_i)}}} = \frac{\boldsymbol{e^{-k.\log(C_j)}}}{\sum_i \boldsymbol{e^{-k.\log(C_i)}}} \qquad 6\text{-}3$$

Where:

$\boldsymbol{C_j}$	Generalized cost of path j
$\boldsymbol{U_j}$	The benefit of path *j*
$\boldsymbol{p(R_j)}$	The probability of path *j* to be selected
$\boldsymbol{k}$	The sensitivity parameter of the model

Using the obtained probability of selecting each path, the demand for each origin-destination data can be distributed to different candidate paths.

Stopping criteria

Two criteria are defined as the stopping criteria of the simulation runs: maximum number of runs and the convergence criteria. When the results of a simulation is no longer changing significantly. This results can be defined as the travel time results of the paths, travel time results of edges (between decision points), or the changes in volumes on the edges. Once one of the stopping criteria was met, the simulation will be terminated.

Application

To examine the performance and capabilities of the proposed framework, it was applied to a grid network, consisting of 12 nodes, 24 links, and 9 intersections (Figure 6-12). Three bus routes were also defined such that TSP conflict may occur at two of the intersections. The links were defined as four-lane (two lanes per direction) segments of 400 meters. All the bus stops were defined to be at the far-side of the intersection.

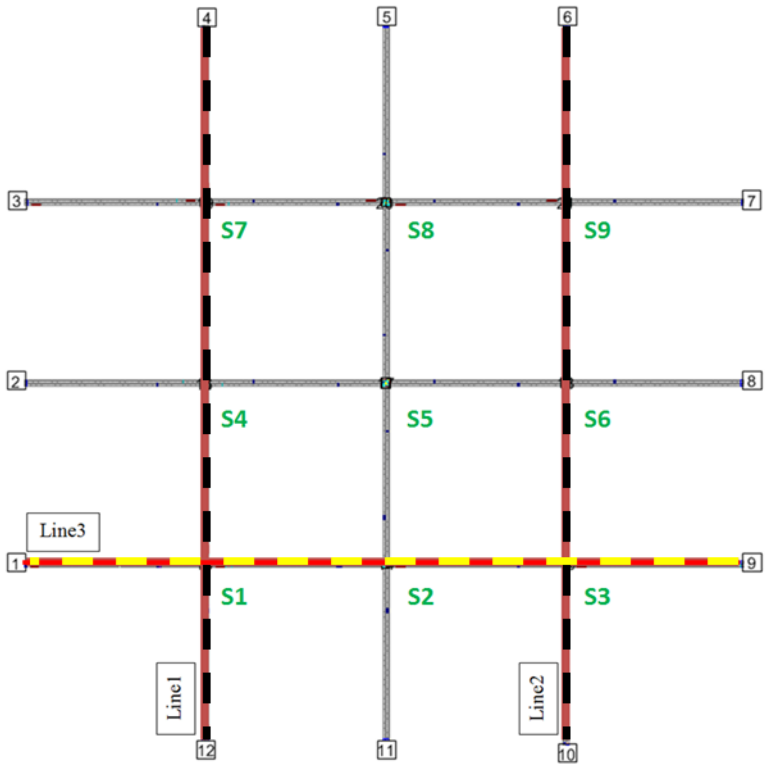


Figure 6-12 Network layout of the example study

In this network, seven intersections can be equipped with TSP strategies where two of those have two crossing bus routes thus may have multiple TSP requests. Bus and car travel time value's and variability indexes were four main measures of performances that were compared together in two scenarios (base-having no bus priority strategy and TSP-prioritizing buses in all the intersections). Note that the conditional TSP logic with compensation module was adjusted for each single intersection.

Figure 6-13 shows the effect of TSP deployment on bus travel time values. It was observed that in uncongested networks, the maximum amount of saving (4.7% of total travel time) is achieved. With the increase of demand, the amount of saving was steadily reduced by around 50% in undersaturated conditions. Furthermore, in demand levels that the demand is higher than network capacity, TSP implementation caused a total increase in travel time value. This can be justified by the incremental delays due to TSP implementation and its negative impacts on the crossing bus services.

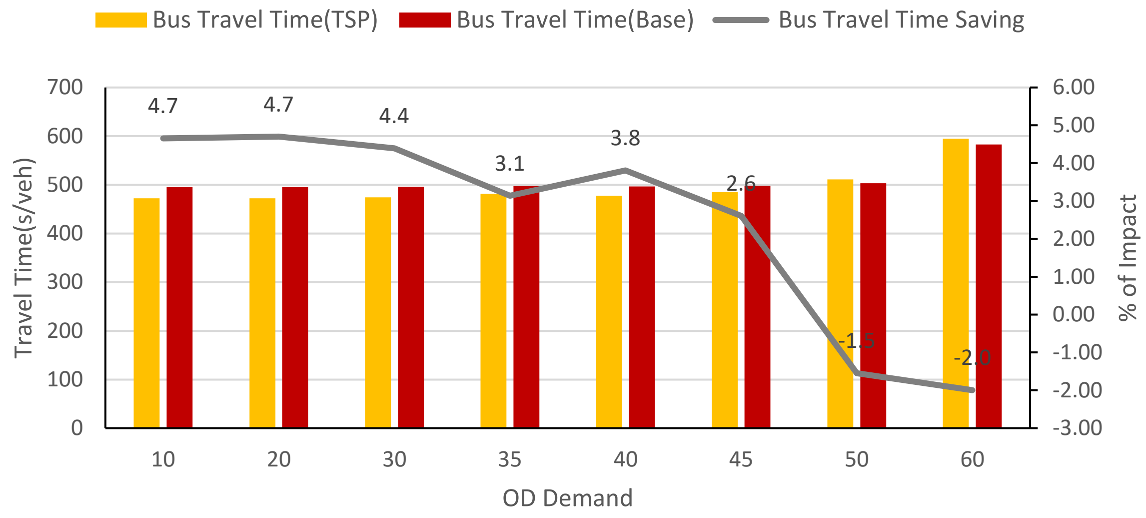


Figure 6-13 Network-wide effect of TSP on bus travel time

Regarding the effect of TSP on the competing mode (i.e. passenger cars), it was observed that in undersaturated conditions, TSP deployment increased the average car travel time by less than 1% (Figure 6-14). Nevertheless, once the demand reached the capacity, a noticeable increase in car travel time was experienced. Note that in the simulation models a dynamic traffic assignment module is implemented where it is assumed that passengers are aware of the TSP impacts on travel times and can update their routes accordingly. Consequently, the travel time changes when TSP is deployed are intuitively minimized.

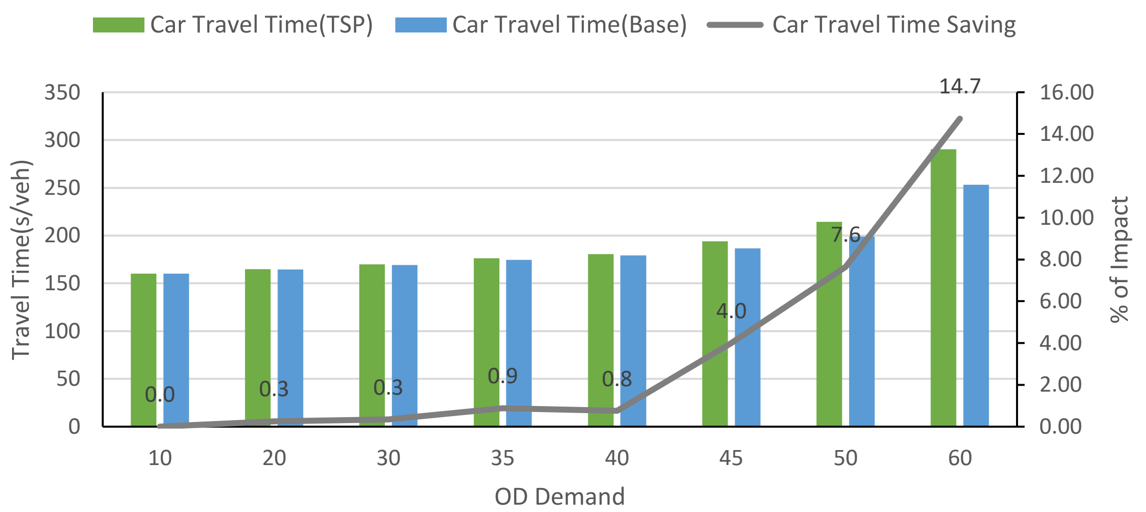


Figure 6-14 Network-wide effect of TSP on passenger cars travel time

. Similarly, car travel times variability was also increased with the increase of demand level. It was observed that TSP increased the level of variability by up to 5% in undersaturated conditions. However, once the demand reached the capacity, an exponential increase was observed, where the variability was almost doubled in saturated conditions shows the effect of TSP on bus travel time's variability. It was observed that in undersaturated conditions, in addition to travel time values, the variability of the service can also be improved by up to 23% by TSP deployment while it can have an adverse impact in saturated conditions. Similarly, car travel time variability was also increased with an increase of demand level. It was observed that TSP increased the level of car travel time variability by up to 5% in undersaturated conditions. However, once the demand reached capacity, an exponential increase was observed, where the variability was almost doubled in saturated conditions.

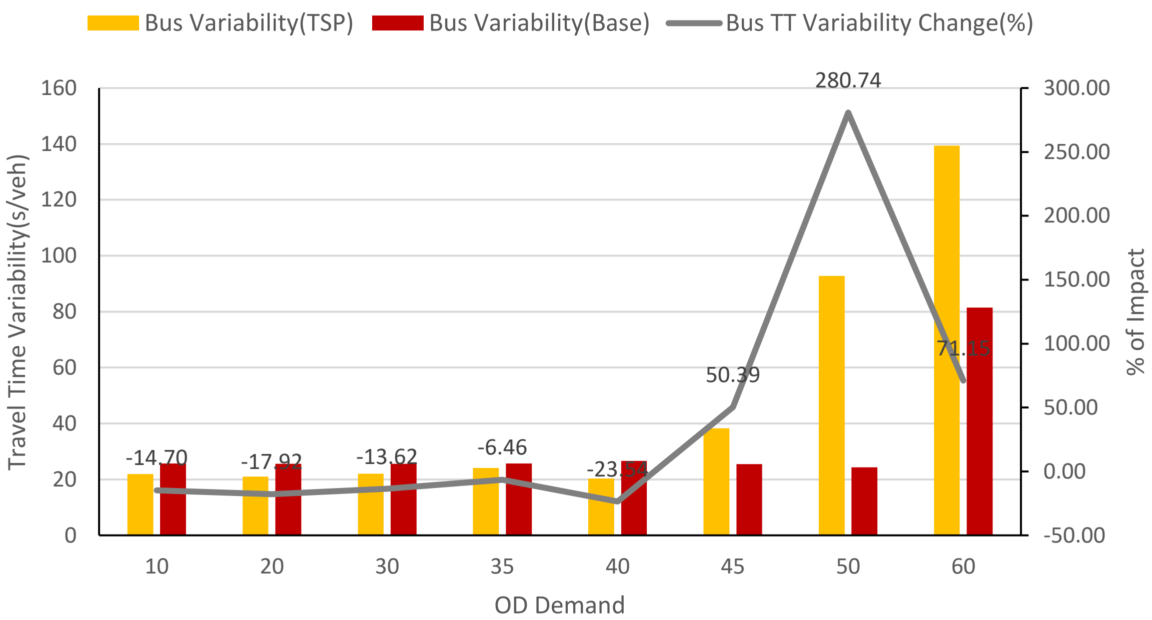


Figure 6-15 Network-wide effect of TSP on bus travel time variability

Similarly, car travel times variability was also increased with the increase of demand level. It was observed that TSP increased the level of variability by up to 5% in undersaturated conditions. However, once the demand reached the capacity, an exponential increase was observed, where the variability was almost doubled in saturated conditions.

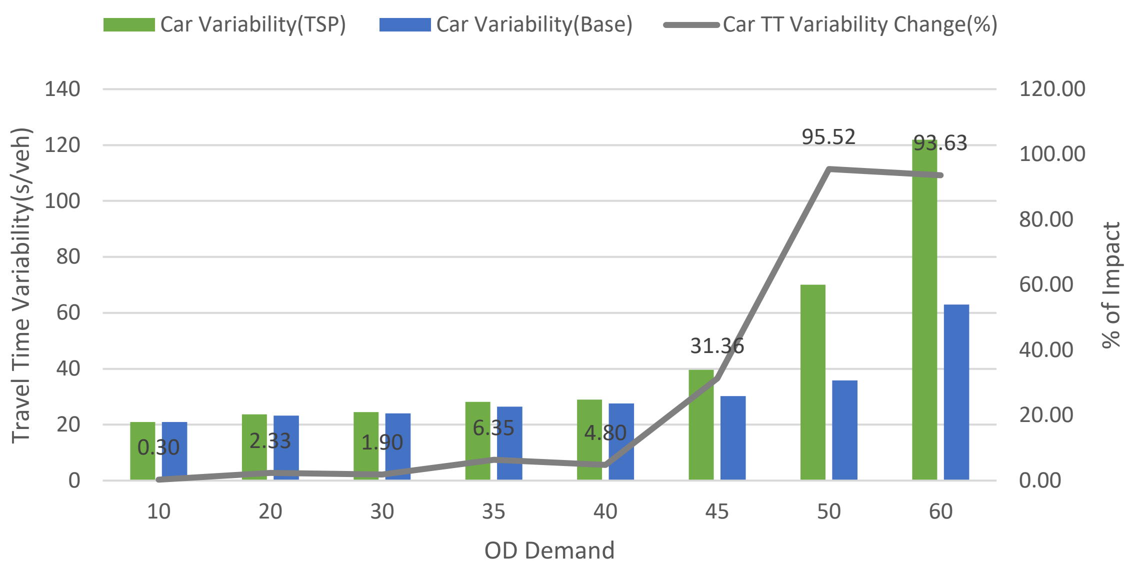


Figure 6-16 Network-wide effect of TSP on car travel time variability

6.2.4 *Remarks on Simulation Based Evaluation of TSP Deployment*

The current section was dedicated to the application of TSP strategy at three different levels (isolated intersection, corridor, and grid network) and the performance of prioritization scenarios were evaluated and discussed in each example. To this end, firstly the performance of TSP logic was tested in an isolated intersection. Then it was shown how TSP can reduce the travel times along a network. Finally, the network wide effect of TSP deployment on bus and car travel time values and reliability indexes was evaluated. It was demonstrated that travel time and reliability measures can be determined by a microsimulation model at any level. Furthermore, it was observed that in undersaturated conditions, TSP can generally cause an improvement in bus performance with marginal negative impacts on the competent mode. However, when the demand is higher than the network capacity, TSP performance is noticeably decreased as the improvements in bus travel time value and variability was negligible, and incremental delays on passenger cars were experienced. Only two scenarios (base and TSP deployment for all intersections) were evaluated for a wide range of congestion levels.

In addition to travel time value and variability, other generalized cost items can also be targeted to be minimized by heuristic approaches. Using a Vehicle to Infrastructure (V2I) communication method, next chapter introduces a new method to minimize the amount of bus fuel consumption at intersections.

6.3. Using Vehicle to Infrastructure Communications to Reduce Bus Fuel Consumption at Intersections

Section 3.7 of this study was dedicate to present a vehicle to infrastructure based method, aiming at reducing transit operational costs by saving bus fuel consumption at intersections. This module is relying on two main components, namely dwell time extension and speed adjustment to smooth the bus trajectory along the intersection. This can happen by adjusting the bus trip so as to have them arrived to the stop line when the signal status is green. It was also shown that due to the nature of the traffic and existing uncertainties in discharging queues, a predefined offset value was defined that can help more buses be successfully served despite they may experience an additional delay. A TSP strategy was integrated to the developed V2I based model to remedy this excess delay component. A numerical example is presented here to show how the V2I based tool reduces the amount of fuel consumption in intersections. The integrated TSP and the fuel consumption minimization module is then evaluated and the results are outlined.

To evaluate the performance of the suggested algorithm, it was implemented on an isolated intersection. To fulfil this task, a code was developed in the .Net environment using C# programming language. V2I communication was modelled and integrated in a microsimulation model using VISSIM Component Object Model (COM). Signal Settings parameters were also introduced using the Vehicle Actuated Programming (VAP) add-on. It is noteworthy that the signal settings (cycle length, splits, and phase sequences and timings) were optimized using SIDRA Intersection module that was integrated by the author (Bagherian et al., 2014b, Bagherian et al., 2014a). To reflect the random nature of the simulations, 10 independent simulations were run for each scenario with different seed numbers and the reported measures are the average value of the results. The duration of each simulation run was 90 minutes (30 minutes build-up time followed by 60 minutes of data recording).

Figure 6-17 shows the study area, including the bus routes to which the method is applied, and the intersection layout in SIDRA. Two bus routes with a relatively high level of frequency (5 to 20 minutes headways) pass this intersection. While the Gailey Road approaches (northbound and southbound travel) do not experience significant changes in daily flow pattern, flow at peak hour toward the University is high. The proposed method was applied to two bus routes passing the Gailey Road approaches.

For each bus route, a different measurement area was defined. Indeed, the proposed method changes bus trajectories at either the bus stop (where extra stopping time can be expected) or the en-route (where changes in acceleration and speed may occur). For the inbound route (Line 1) with nearside bus stop the selected area of study is consequently a 150m segment of the link, starting at the bus stop till 100m after the bus stop where the bus could reach its cruising speed. Considering Line 2, the area of study was defined from the closest upstream bus stop (620m from the bus stop) to the next bus stop which is located after the intersection. The key point in implementing this method is that any reduction in fuel consumption can be achieved without changing the existing signal timing and only by adjusting bus dwell time and speed before reaching the intersection. Consequently, it can be used for any number of approaches as long as the signal settings for that approach (i.e. the moments when the traffic signal is green) is known.

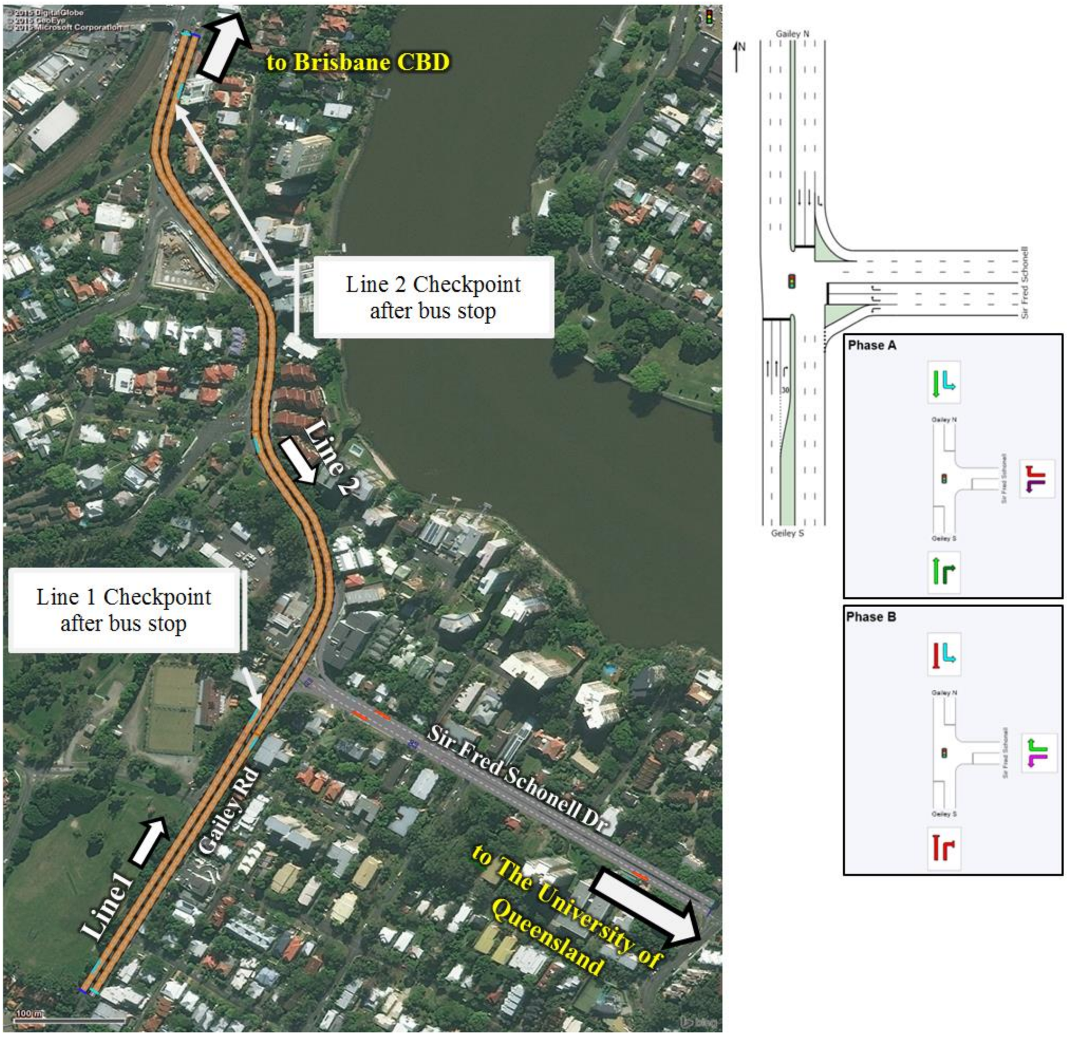
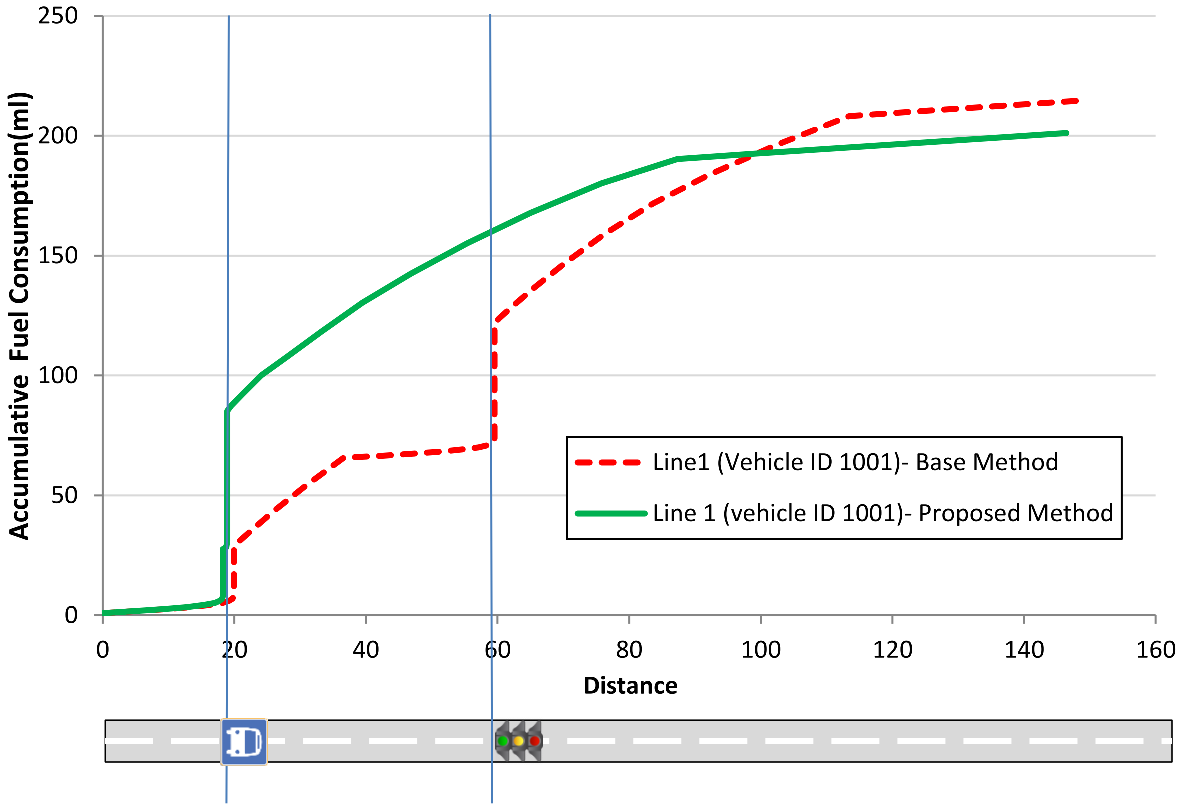
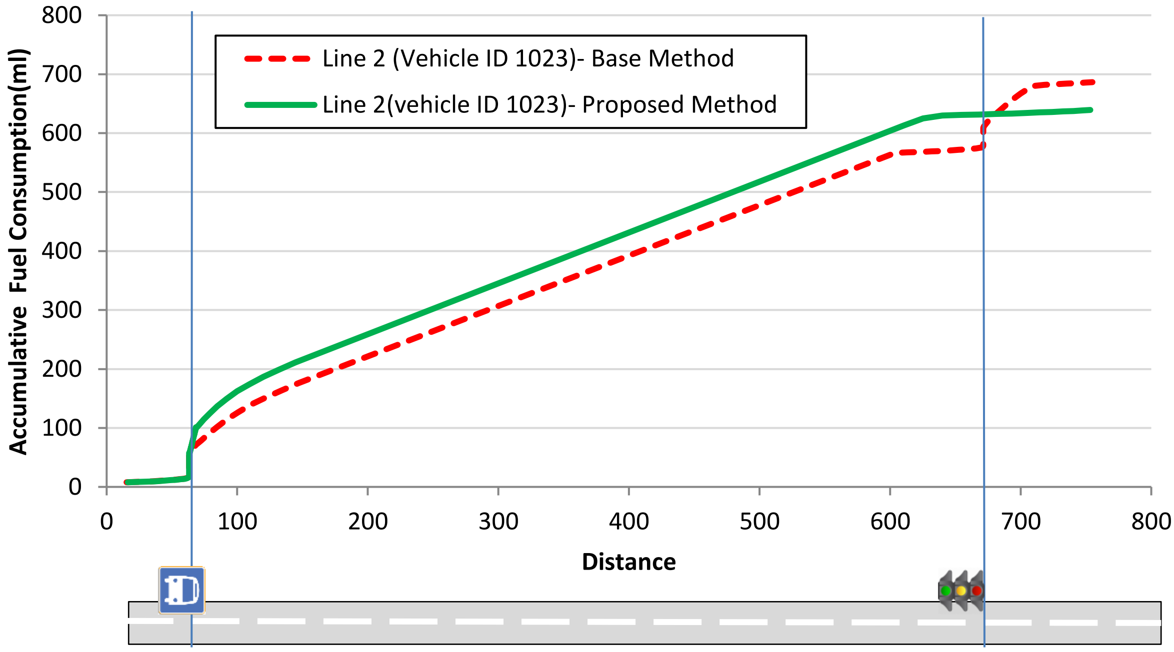


Figure 6-17 Sir Fred Schonell Dr- Gailey Rd intersection, passing bus routes and model layout

Figure 6-18 shows the cumulative fuel consumption for the two typical buses in Lines 1 and 2. It can be seen how fuel can be consumed and saved using the proposed method on each bus route. On both lines, the common characteristic is a smoothed transition through the intersection. Indeed, despite extension in dwell time that increased the delay and thus fuel consumption due to idling, buses circumvented the extra acceleration and deceleration phase behind a red signal, which resulted in a positive net benefit of the bus's fuel consumption. It is noteworthy that for the cruising segment in bus Line 2, which was not influenced by dwell, time extension or a noticeable change in VSP class, it was assumed that buses had a constant fuel consumption rate. This is to remove the potential differences in simulation results and mitigate random errors that may be ascribed to this segment.



(a)



(b)

Figure 6-18 Accumulative fuel consumption along the studied area; (a) Line 1 and (b) Line 2

Table 6-2 shows the results obtained from the simulation models at a moderately congested level where the link flow rate is 400vph. A reduction in fuel consumption is achieved for both bus lines. The average amount of saving for this level of traffic is 6% and 15.7% for Line 1 and Line 2, respectively. The second measure shows the percentage of buses that experienced red traffic signals when they arrived at the intersection. Assuming a fully efficient method, we sought to achieve no bus arrivals on a red signal. Although it could be achieved for line 2, the method would work successfully for 95% of buses on line 1. It can also be seen that while passenger car delays have remained almost unchanged, average bus delay is increased by 7 and 12 seconds. This is mainly due to the applied offset that ensures experiencing a green signal (though a few seconds after the start of green time) at the expense of an additional dwell time period in the bus stop (5 seconds for Line 1 and 15 seconds for Line 2 were assumed as offset values). Since the performance of the proposed method is dependent on the introduced offset value (as we will see in the next section), a trade-off between the saving in fuel consumption and additional passenger delays can be introduced in future studies.

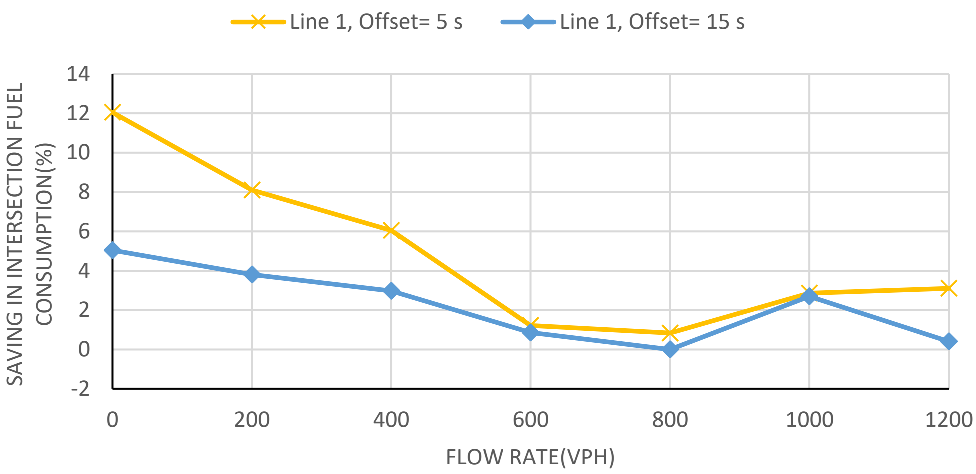
Table 6-2 The effect of the proposed method on different measures

	Line 1		**Line 2**	
Measure	Base	V2I	Base	V2I
Fuel consumption (ml)	934	878	1122	946
Ratio of Buses Experiencing Red Phase	0.73	0.05	0.68	0.00
Average Car Delay (s)	25.85	25.75	24.18	24.06
Average Bus Delay (s)	63.20	70.36	58.05	70.80

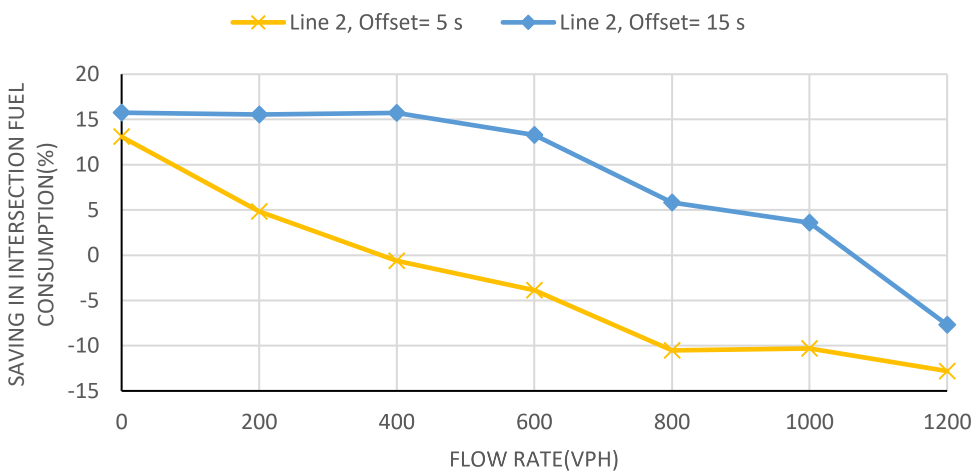
6.3.1 *Sensitivity Analysis*

Sensitivity analyses were performed to reflect the effect of an introduced offset value as well as bus passenger loads along a range of traffic congestion levels. On both lines, it was observed that with an increase in the level of congestion, the performance of the proposed method to reduce bus stop delay was decreased. This behaviour can be justified by considering the uncertainty in arrival time and inefficiency of the bus travel prediction method, especially when the upstream bus stop is far from the intersection. A zero percent market penetration rate of connected vehicles technology was assumed for private cars, thus the bus was not able to have a reliable measure of the flow to have an accurate travel time prediction. Furthermore, the objective of this test was to see the method sensitivity to volume over capacity ratio value thus the green time signal ratios remained unchanged for different congestion levels.

The effect of the offset value in the performance of the proposed method was evaluated. The offset value is defined to enable the queue to clear the intersection, thus allowing the bus to avoid any queue behind the stop line. This value is ideally as small as possible to potentially reduce extra delay a bus may experience due to triggering the dwell time extension module. A comparison between two offset values (5s, 15s) was performed for a whole range of traffic states to see the changes in bus fuel consumption. Figure 6-19 shows the amount of saving in fuel consumption in different scenarios for both studied routes. For line 1 (Figure 6-19a) in free flow conditions, an offset value of 5s is sufficient as additional offsets increased the delay and reduced the efficacy of the method. The fuel consumption values are merged at higher levels of delays, since queue is reached the nearside bus stop. This trend is different in line 2 (Figure 6-19b). On this line, although in free flow conditions, the amount of offset is relatively insignificant; fuel consumption increased more sharply in a 15s offset time. Consequently, a point could be reached when the method does not work with a 5s offset, mainly due to the inaccuracy in estimating exact arrival times at the intersection. Since the offset value is potentially increasing the bus delay to gain time for a cleared intersection, a trade-off between the level of saving in fuel consumption and additional passenger delays should be investigated in future studies.



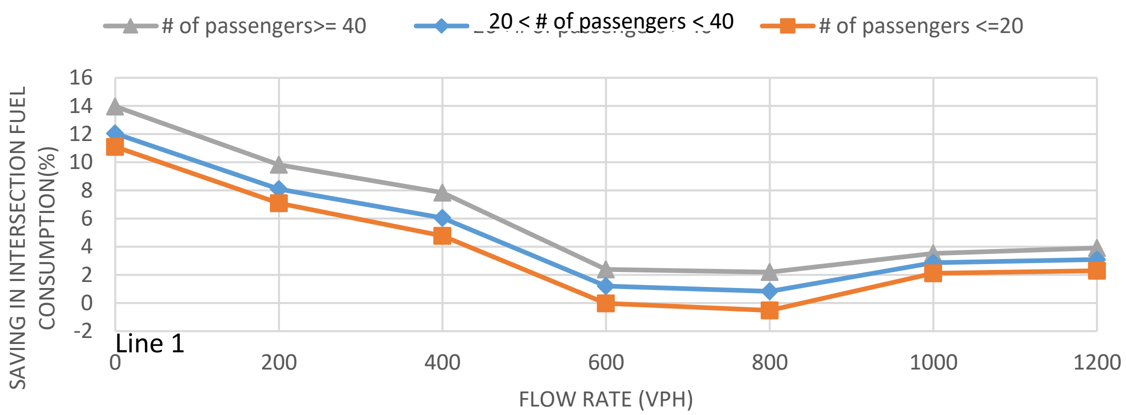
(a)



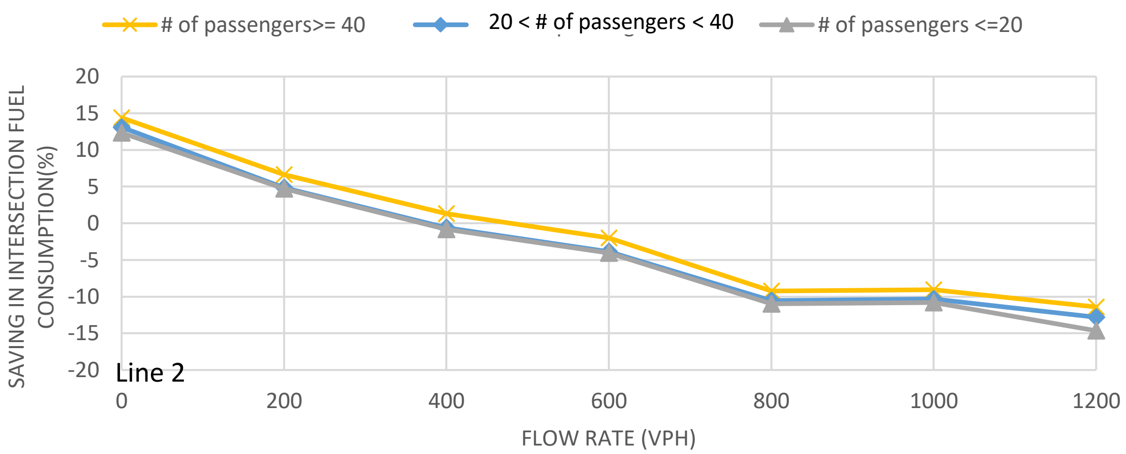
(b)

Figure 6-19 The effect of offset value and flow rates on fuel consumption savings

The second sensitivity analysis was performed to determine the effect of passenger load on fuel consumption and the achievable saving via the proposed scenario. Frey (2007) stated that passenger load has a significant effect on fuel consumption, particularly at the middle and high-speed ranges while it has a negligible effect on speeds below 10 km/h. He developed models to estimate fuel consumption of each VSP mode for three levels of passenger load (less than 20 passengers, between 20 and 40 passengers, and more than 40 passengers). This model was implemented to see the effect of passenger load on the achievable savings through the proposed method. Figure 6-20 shows the effect of bus passenger loads on fuel consumption savings in a range of traffic flow rates. It was observed that along the study area, fuel consumption was increased by up to 38% when higher passenger loads (more than 40) were considered. This difference remained almost unchanged for different levels of congestion. However, the amount of savings in fuel consumption followed a different trend for bus Line 1 and Line 2. It can be seen that in uncongested conditions, the proposed method showed slightly better performance (2%) in higher passenger loads for line 1.



(a)



(b)

Figure 6-20 The effect of passenger load on fuel consumption: (a) Line 1 and (b) Line 2

6.3.2 *Discussion*

The proposed method to reduce the amount of bus fuel consumption at intersections by adjusting the bus cruising speed and dwelling time at stops was applied to an intersection. The main means to achieve a saving in fuel consumption is to shift of the experienced stop time component of the bus at the signal to the dwell time at bus stop, thus reducing the total number of stops and removing accelerations and decelerations at the signal. It was shown that a reduction of up to 15% in fuel consumption at intersections is achievable in uncongested conditions. Considering the share of intersection delays in total fuel consumption, it may result in reasonable savings in operation costs. Since this study implemented the VSP method, its accuracy and outcomes are dependent on the estimated model parameters and further research using alternative fuel consumption models is recommended. Due to the inherent errors in arrival time predictions, extended dwell time caused an excess delay at intersection. Consequently, without changing signal timings, fuel cost consumption reduction may result in increasing travel time component. To address this issue, a TSP strategy was proposed to compensate this excess delay. Application of the integrated TSP-V2I method to reduce fuel consumption with minimum extra delay is presented in next section.

6.3.3 *Integrated Transit Signal Priority and Vehicle-to-Infrastructure Communication*

It was shown that the proposed V2I based method successfully reduced the amount of bus fuel consumption in intersections, especially in nearside bus stops where there is not enough length for the bus to reach its cruising speed. Nevertheless, due to the inherent errors in arrival time predictions, extended dwell time caused an excess delay at the intersection. Consequently, without changing signal timings, fuel cost consumption reduction may result in increasing the travel time component. To address this issue, a TSP strategy is proposed in Chapter 4 to compensate this excess delay. Application of this module is presented in this section.

TSP Logic Assumptions

The TSP strategy is applied using a set of pre-defined fixed signal settings. These signal programs can be called within the simulation period and be activated from the very next cycle. When a bus is approaching the intersection, the appropriate scenario that can benefit the bus would override and set as the active signal timing. Once the bus passed the intersection, default signal settings would be called and activated again. Note that the main aim of implementing TSP is to compensate excess delay that is incurred to a bus due to the dwell time extension. Consequently, TSP is granted unconditionally to all the buses that approach the intersection. The communication of the transit vehicles and signals is formed by continuous tracking of the available buses in the microsimulation model.

The following assumptions were made in developing the TSP logic of V2I-TSP integration of this example:

1. A pre-calculated signal timing is utilized when no bus is approaching the intersection.
2. An appropriate signal program is opted when a bus is detected on an approach. Once the bus crosses the stop line, the default signal program would be reloaded.
3. TSP can be granted unconditionally to all the buses, regardless their passenger load and timing status (e.g. being behind the schedule)
4. The impacts of pedestrians and cyclists are neglected.
5. First-come first-served logic is utilized to handle simultaneous TSP requests.

To evaluate the performance of the developed TSP-V2I integrated module, the model was applied to the simulation model of Sir Fred Schonell- Gailey Road Intersection (Figure 6-17). The key point in implementing this method is that any reduction in fuel consumption can be achieved even without adjusting signal timings. TSP performance is evaluated in terms of the saving it can make to compensate excess bus delay. V2I module can be used for any number of approaches as long as the signal settings for that approach (i.e. the moments when the traffic signal is green) is known.

To address the excess delay incurred by V2I-based method, a TSP strategy was implemented. Figure 6-21 shows the average bus delay in different levels of congestion in a set of scenarios. It was observed that applying dwell extension module can increase the bus delay in all traffic regimes. However, a TSP strategy implementation can significantly reduce the delay at intersections. Although integration of V2I-TSP caused additional delay rather than TSP only scenario, average bus delay is still less than the base and V2I only scenarios. In other words, while a noticeable save in fuel consumption can be achieved, TSP integration can neutralize the excess delay that was imposed to the buses. The TSP application may cause additional delays in non-prioritized movements thus its integration to V2I based method should be justified.

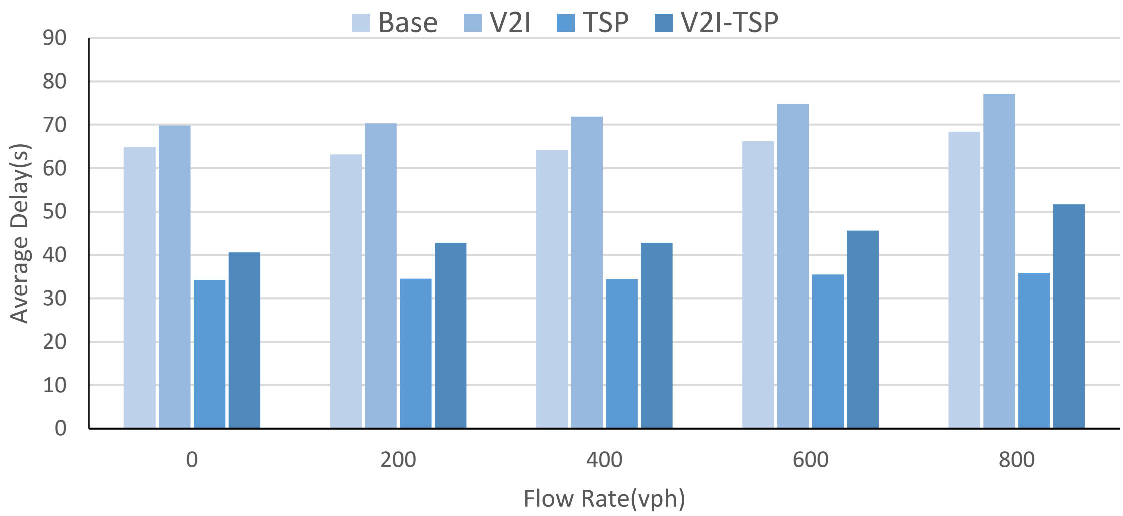


Figure 6-21 The effect of the studied methods on bus average delay

In order to see how savings can be achieved using the proposed method, a second-by-second comparison of the fuel consumption values was performed. Fuel consumption can be measured using a Vehicle Specific Power (VSP) based method. In addition to the vehicle power, VSP is a function of vehicle speed and acceleration that are changing continuously and the proposed method is aiming at changing them so as to reduce total fuel consumption. Figure 6 shows how the vehicles VSP mode in each scenario is distributed in the study area. It can be seen that around 30% reduction in VSP mode 1 which is reflecting stationary and decelerating status is achieved. This reduction is due to the bus delay reduction in intersection that is gained using TSP strategy. In addition, a shift from modes 4-6 (i.e. VSP values 4 to 10 m^2/s^2) to mode 7(10 to 13 m^2/s^2) is occurred, reflecting an improved performance in bus fuel consumption.

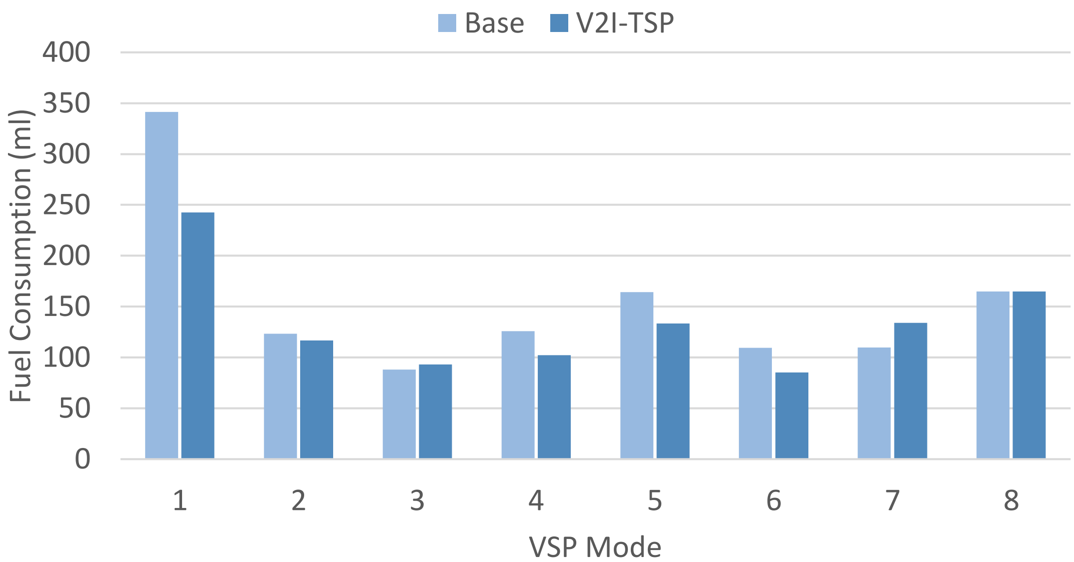


Figure 6-22 The Second-by-Second comparison of VSP modes during the trip

Sensitivity Analysis on Passenger Load and Traffic Congestion

A sensitivity analysis was performed to determine the effect of passenger load and traffic congestion on fuel consumption and the achievable saving via the proposed method. Frey (2007) stated that passenger load has a significant effect on fuel consumption, particularly at the middle and high-speed ranges while it has a negligible effect on speeds below 10 km/h. He developed models to estimate fuel consumption of each VSP mode for three levels of passenger load (less than 20 passengers, between 20 and 40 passengers, and more than 40 passengers). This model was implemented to determine the effect of passenger load on the achievable savings through the proposed method. Figure 7 shows the effect of bus passenger loads on fuel consumption savings in a range of traffic flow rates. It was observed that along the study area, the amount of saving in fuel consumption was increased by around 13% when higher passenger loads (more than 40) were considered. This difference remained almost unchanged (12.2%-13.5%) for different levels of congestion. In addition, it was observed that with the increase of traffic congestion along the link, total amount of saving is decreasing. The proposed V2I-TSP method increased the amount of consumption in saturated conditions.

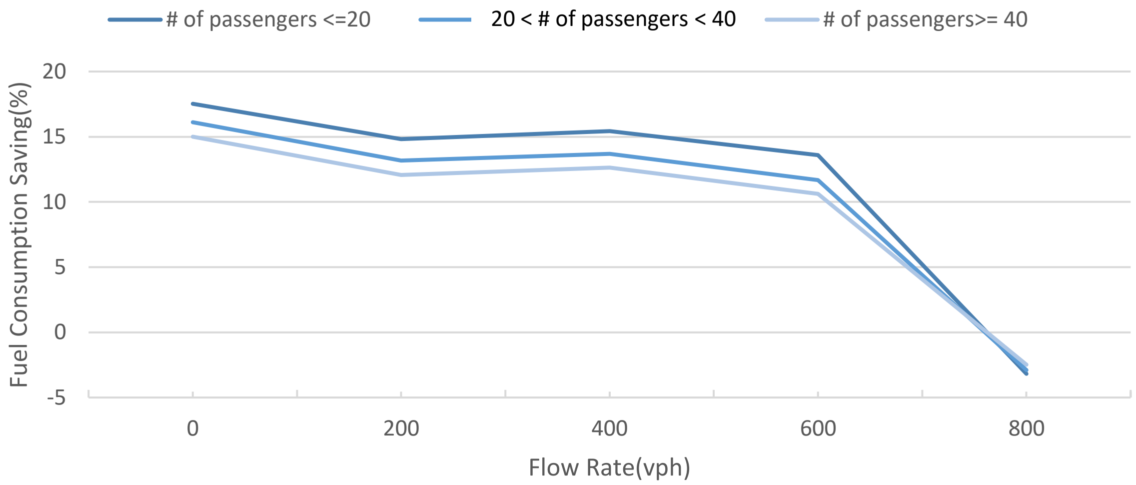


Figure 6-23 The effect of passenger load on fuel consumption

6.3.4 *Remarks on V2I Based Method*

A V2I-based approach is effective in reducing the amount of bus fuel consumption at intersections at the expense of an excess delay for the buses. A TSP strategy was integrated to the proposed V2I-based method that can simultaneously reduce the amount of fuel consumption and delays at intersections. In this module, saving in fuel consumption can be achieved by shifting the stationary situation behind the signal to the dwell time at a previous stop thus reducing the number of bus stoppings. It was observed that elimination of additional stop and thus its corresponding acceleration and deceleration could noticeably save the amount of fuel consumption at intersections. In addition, a reduction in bus delay at an intersection was gained by applying a TSP strategy whenever necessary.

TSP reduces the probability of facing a red signal and thus mitigates total bus delay at the intersection. To evaluate the proposed method, a standalone application was developed using VISSIM API in the .Net environment and the results confirmed that while the V2I based method reduced the amount of bus fuel consumptions at intersections, the TSP component can reduce bus delay, including the excess delay incurred by the dwell extension module.

6.4. Chapter Summary

This section was dedicated to the development and application of the implemented priority strategies and modules. Firstly, the TSP logics were applied to a set of scenarios in three different levels (isolated intersection, a corridor, and a grid network) and the performance of prioritization scenarios were evaluated and discussed in each example. It was shown that depending on the signal setting parameters, network structure, deployed logic, and congestion level, a wide range of the performance can be achieved by TSP strategies. Network wide analyses of priority strategies revealed that in a network-wide prospect, special attention can be put for a systematic approach for preferential treatment deployment so that maximum efficacy can be achieved with tolerable negative impacts on competent modes. This task required developing an optimization tool to search for the optimum location of priority strategies throughout the network, elaborated in Chapter 8 of this study. In addition to the priority strategies, the developed V2I based module was also applied to an intersection and it was shown how the module can operate and gain saving in fuel consumption value.

One of the main challenges of performing simulation based analyses is the computational costs of running the model. It was observed that the basic simulation based evaluation of preferential strategies can be smoothly performed for analyses such as the detailed effects on an isolated intersection or a corridor. Nevertheless, with the increase of the network size, an exponential augmentation in computational cost was observed. As a result, it was practically infeasible (in terms of computational cost) to utilize simulation based methods to perform a network wide search for optimum preferential combinations. To address this issue, a set of analytical approaches are developed and introduced in Chapter 7. These analytical methods along with the simulation-based evaluation method were implemented in Chapter 8 to evaluate different scenarios through an optimization module.

7. Analytical Evaluation of Preferential Strategies

Despite the popularity and capability of simulation based models to evaluate priority strategies, their application is limited to isolated intersections and corridors. This is mainly due to the computational cost of simulation based approaches, making them challenging to be used for network-level studies. Analytical approaches can be considered as an alternative of simulation based models to evaluate priority strategies at network level studies.

Firstly, application delay functions to evaluate priority schemes are proposed and validated through two case study examples. It is shown that delay functions' results are consistent with the ones obtained from simulation models and can be considered as an alternatives to costly simulation based models. In addition, an adjustment factor method is implemented as another analytical method to reflect priority strategies for the network. This method is then applied to a network example to be tested against other methods. It is shown that despite the simplifying assumptions, the analytical evaluation process is much faster than simulation methods and results roughly matches the ones obtained from microsimulation methods. Figure 7-1 depicts the relation of this section to this study.

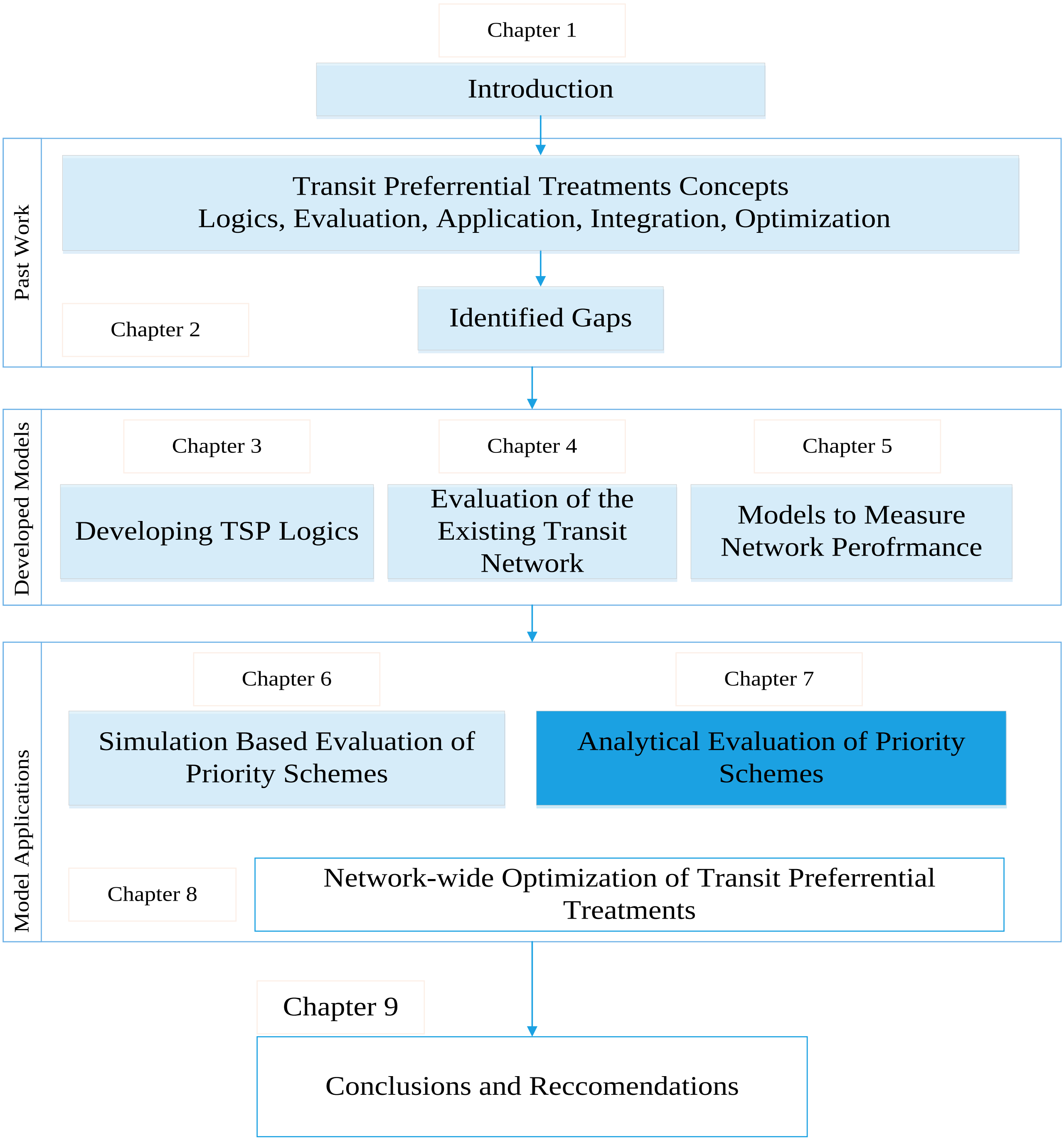


Figure 7-1 Thesis outline and highlighted current chapter

In macro level studies, delays at links and intersections can be estimated using delay functions. The latter utilizes link and junction attributes to estimate average speed and/or delay at a link (Rouphail and Huntsinger, 2011). They can be used to estimate the delays at a link based on the link capacity and flow, and are usually implemented through a traffic assignment module. The functions of the Bureau of Public Roads (BPR) and Akcelik (1991) are the most well-known functions. Nevertheless, neither directly estimate the effect of signal timings or TSP attributes. Combined link and node delay functions (Aashtiani and Iravani, 1999), which consider the effect of signal timing at junctions, are still unable to model the effect of TSP. In brief, neither of the delay functions in the literature considers the effect of TSP on intersection delay. Further details on the volume delay functions can be found in Rouphail and Huntsinger (2011) and Skabardonis and Dowling (1997).

With non-prioritized junctions it is common to assume a single delay function for both buses and passenger cars in mixed traffic flow. To reflect the impact of different vehicle types, a passenger car equivalent can be implemented where the effect of a bus is typically assumed to be 2-3 passenger car units (pcu). Once all the models are converted to pcu this value is used to calculate the delay at each intersection (Willumsen and Ortúzar, 2011). This method is common in both theoretical and practical contexts. Mesbah et al. (2011), for example, considered the same delay function parameters for both buses and cars and obtained bus travel times using such functions. Nevertheless, the assumption of equal delay times for different modes may not be justified once priority is given to buses. Consequently, there is a need to have volume delay functions that reflect the effect of this prioritization. These functions not only allow estimation of travel times at an intersection, but also enable modelling of TSP at a network level. This methodology is what is suggested in this paper.

A volume-delay function is developed to be used in a traffic assignment model thus circumventing time-consuming microsimulations. The efficiency of a TSP strategy depends on a set of variables and conditions. Among them are the roles of flow rate, congestion and volume to capacity (v/c) ratio. Garrow and Machemehl (1997) performed a microsimulation analysis using CORSIM software and reported a severe negative impact of TSP on cross-street traffic for oversaturated or even near saturation (v/c > 0.9) conditions. Balke et al. (2000) examined general traffic performance at bus approaches and reported a noticeable benefit of TSP strategies in moderate traffic levels (v/c < 0.9). Also, Ngan et al. (2004) performed an analysis on the effect of different parameters and confirmed the applicability of a TSP strategy for slight-to-moderate cross street v/c ratios. Consequently, the application of this approach is on the evaluation of TSP effect on undersaturated traffic and it is assumed that there is no incremental delay due to cycle failure or sustained oversaturation.

As reviewed earlier, delay imposed by TSP varies case-by-case. Some of the parameters affecting TSP efficacy include bus headway, traffic flow rate, bus stop location and geometric characteristics of the intersection. The proposed model estimates delay as a function of signal timing parameters (green time, cycle length), TSP parameters (maximum GE value) and traffic characteristics (traffic flow and saturation flow rates). The following equation is the proposed model to estimate the delay (D) at intersections:

$$D = \frac{(C-g)^2}{2 \times C \times (1 - {}^{v}/_{s})} + k_1\, e\, (1 - \left(\frac{v}{c}\right)^{k_2}) + k_3 \qquad \text{7-1}$$

Where *C* is cycle length(s), *g* is the amount of green time (*s*), *v* is flow rate (*veh/h*), c is the link capacity (*veh/h*), *s* is saturation flow rate (*veh/h*), *e* is maximum GE and/or RT allowed(*s*) and k_1, k_2, k_3 are the parameters of the function, considering the impact of other parameters like bus service layout (e.g. bus frequency, bus stop location, etc.). different parameters need to be used for buses and cars to reflect the effect of prioritizing a mode over the other. The first term of this function is derived from the control delay function presented in the Highway Capacity Manual 2010(Council, 1985). As can be seen from this term, the flow rate (*v)* should be less than the saturation flow rate (*s*) to avoid the result approaching infinity. The second term reflects the effect of TSP on the intersection. With the increase of the v/c ratio, the effect of TSP on reducing the delay would decrease. Depending on the developed TSP strategy, this term of the equation might have no effect on car delays. Indeed, movements in the same phase of the prioritized buses can even benefit and have their delays reduced when TSP is applied.Parameter k_3 is the constant of the model which adjusts the calculated delay for cars and buses. The proposed method is comparable to that presented by Aashtiani and Iravani (1999), who sought to consider the effect of signal timing in a delay function. Calibration and validation of Equation 1 is presented using two numerical example, presented in the next section

7.1. Numerical Examples

Two case studies were tested to validate the VDF model and to compare it with microsimulation results. Firstly, the model was applied on a single intersection and a micro-level comparison between simulation method and the proposed model is presented. In the second case study, the proposed method was used to calculate the delay on a corridor located in South-East Queensland, Australia. A set of scenarios were defined to assess applicability of the model on larger problems.

7.1.1 *Case Study I: An Isolated Intersection*

In the first case study the developed TSP strategy was applied to an intersection which is pre-timed with three fixed phases. Intersection characteristics (including geometric layout and phasing) and the prioritized bus route are presented in Figure 7-2. The cycle length here was fixed at 90 seconds. Following the presented procedure, a set of scenarios were defined to model a delay function for each approach.

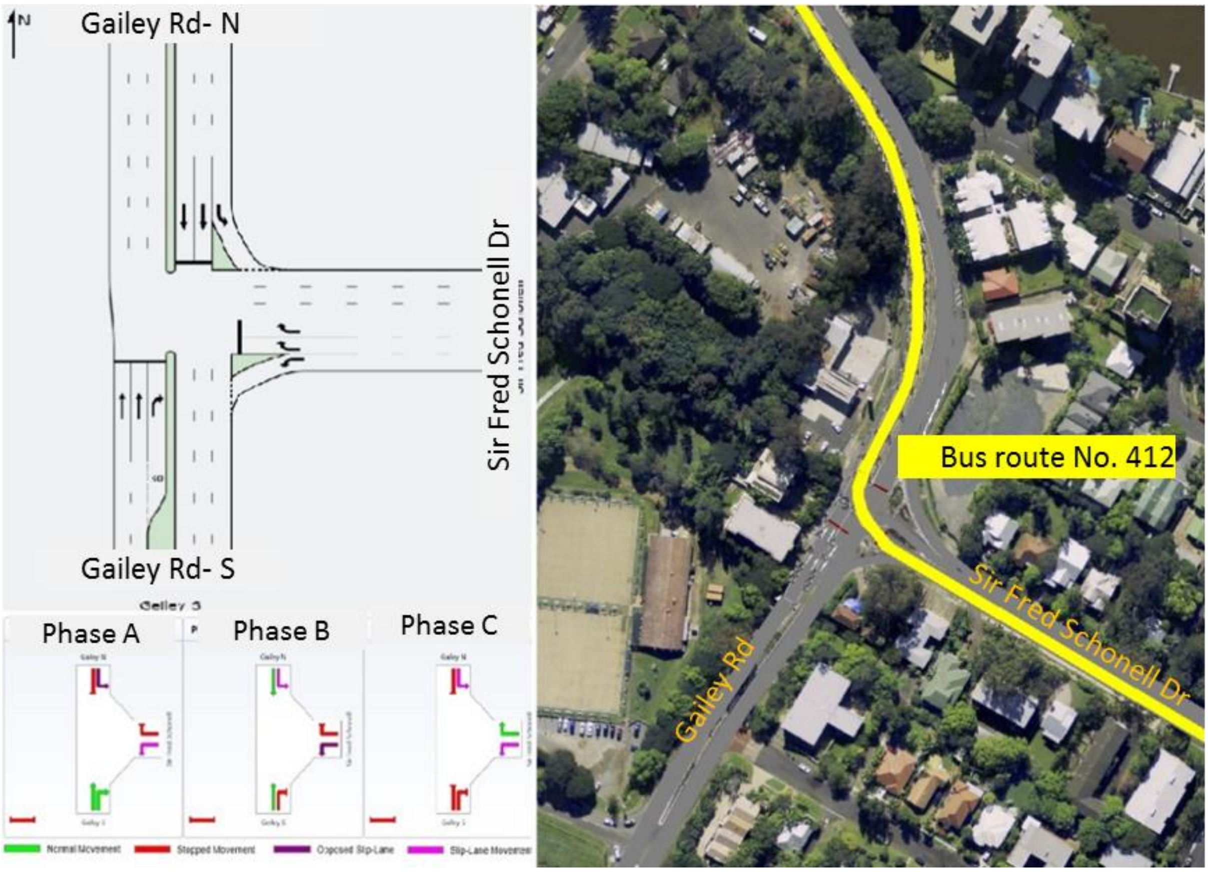
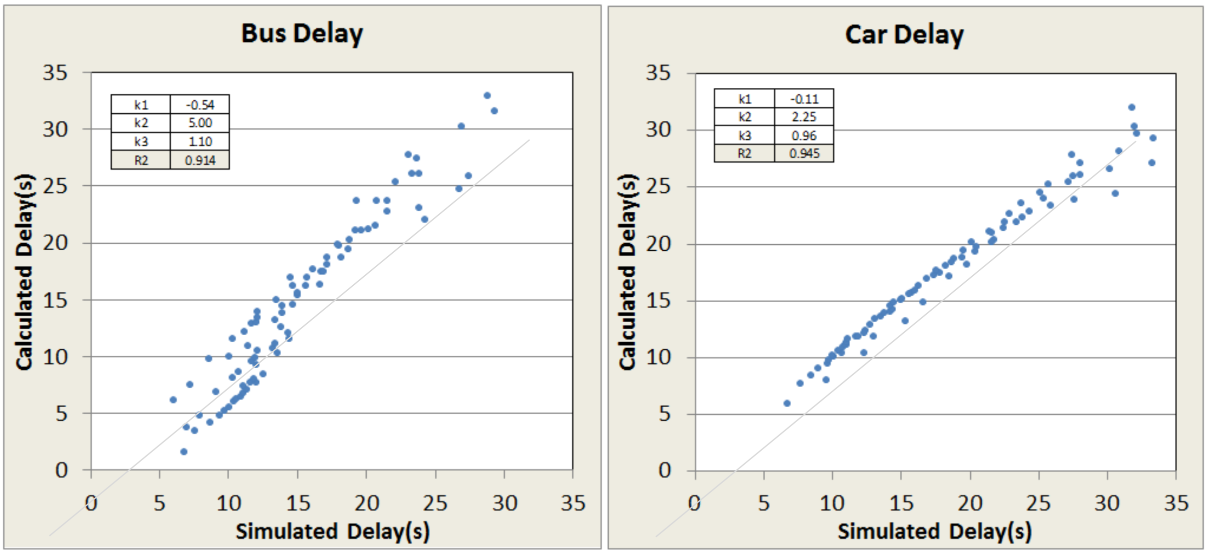


Figure 7-2 Sir Fred Schonell Dr- Gailey Rd intersection: layout, phasing, VISSIM model and prioritized bus route.

In this case 27 scenarios were defined assuming three green extension values of 0, 5 or 10 seconds, and nine green time values (changing between 15 and 55 seconds). For each scenario 15 levels of flow rate (ranging between 100 and 1500vph) were considered. Five different microsimulation runs (i.e., different random seed numbers) were performed for each scenario.

The parameters of the proposed model (k_1, k_2, k_3 in Equation 7.1) were obtained using a nonlinear regression. Figure 7-3 shows the model estimated delays for both passenger cars and buses compared with the results obtained using microsimulation. Calculated and simulated delays follow a 45-degree line, indicating a close match between the results. This is a comparison between microsimulation results and the ones estimated by the proposed model, assuming the microsimulation model reflects actual drivers' behaviour.



(a) (b)

mode/parameter	k1	k2	k3	R2
(a) Bus	-0.5	5	1.1	0.914
(b) Car	-0.1	2.3	0.9	0.945

Figure 7-3 Microsimulation versus calculated delays for (a) bus delay and (b) car delay.

7.1.2 *Case Study II: Redland Bay Corridor*

The proposed approach was applied to a corridor in the South-East Queensland, Australia to test the capabilities of the model for larger networks. The corridor is comprised of twelve intersections including eight unsignalized and four signalized (with pre-timed signal timings). The total length of the corridor is approximately twelve kilometres. The base condition of the corridor (i.e., no TSP) was modelled in VISSIM microsimulation package. The base model is calibrated for morning peak hour data (Ferreira, 2009). Figure 7-4 shows the area of study and signalized sections.

Figure 7-4 Redland Bay corridor and its signalized intersections.

To evaluate the accuracy of the proposed methodology the following were carried out: firstly, the VISSIM microsimulation model for each single intersection was developed. Then, a TSP strategy based on the conditional TSP algorithm presented in chapter 3 was used for all signalized intersections. Thirdly, for different levels of traffic flow and green time values, microsimulation runs were performed and repeated five times with different seed numbers for each scenario. In order to remove the effect of outliers, the highest and lowest obtained delays were discarded and the remaining values were averaged. This mean value is recorded for each scenario. Finally, for each link and its downstream intersection, a non-linear regression model was fitted to obtain the parameters of the delay function (for both cars and buses). Once these parameters were determined, delay was calculated at each intersection.

Traffic flow rates as well as signal timings for the morning peak were used to obtain delay at each signalized intersection. The maximum amount of green extension (i.e., the term e in Equation 1) for all the signals was assumed to be 10 seconds. Table 7-1 summarizes various characteristics, estimated parameters and delay for each intersection of the corridor.

Table 7-1 Redland Bay intersection characteristic and calculated parameters

Intersection Name	flow (vph)	Sat.Flow Rate (vph)	Green Time (s)	Capacity (vph)	VDF Parameters				Calculated Delay(s)	
					Vehicle Type	k1	k2	k3	TSP	Base
S101	776	2800	35	1089	car	-0.8	4	0	23.2	23.2
					bus	-1	4	2	19.8	27.2
S104	704	2800	40	1244	Car	-0.8	4	0	18.6	18.6
					Bus	-1	4	2	11.6	20.6
S105	677	2400	40	1067	car	-0.8	4	0	19.3	19.3
					bus	-1	4	7	18.0	26.3
S107	463	1800	40	800	Car	-0.8	4	0	18.7	18.7
					bus	-0.8	4	7	18.6	25.7

Figure 7-5 shows a comparison between the results obtained from microsimulation and the delays calculated by the proposed method. The maximum difference between the calculated delay for passenger cars and buses is 4.5% and 8.5% respectively. For the calculated bus delays the results are generally within the 95% confidence interval of the microsimulation results. All the results are within 98% confidence interval of the microsimulation results. In terms of effectiveness of the applied TSP strategy maximum bus delay reduction was 5%, 9.5%, 13.2% and 13.6% for one, two, three, or four intersections with TSP respectively. Predicted car delay is slightly lower (ranging between 0.6% and 4.8%) than the microsimulation results. In this example, delay at the prioritized approach was estimated. A similar approach may be applied for the opposing movements.

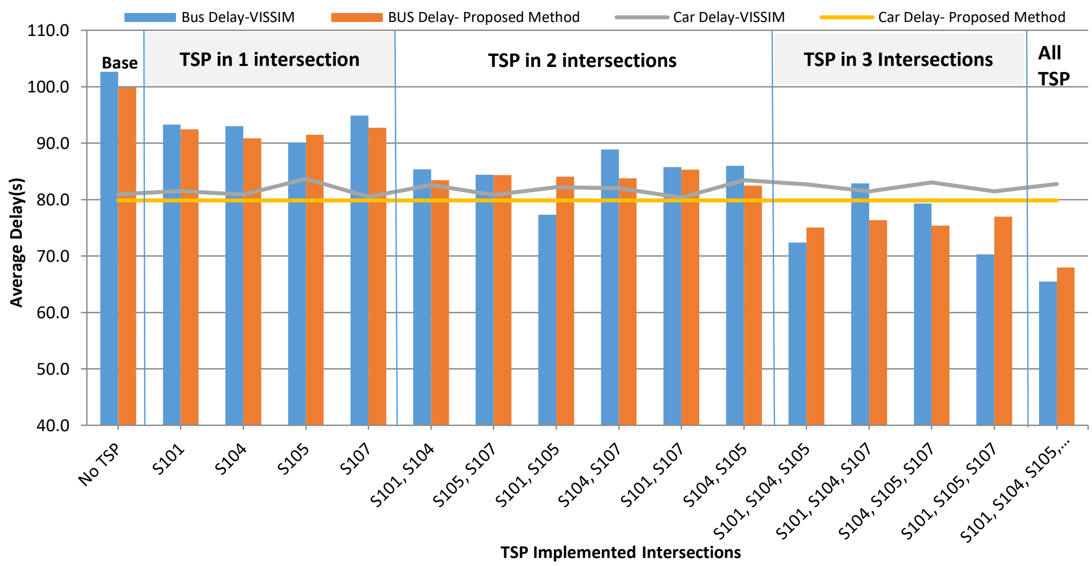


Figure 7-5 Comparison of VISSIM and proposed model estimates for Redland Bay corridor's defined scenarios.

In this section a new method to estimate delay at intersections with an active TSP strategy was presented. The proposed method developed a delay function which took signal timing and traffic flow characteristics as inputs and estimated delays at the intersection. In this regard, a non-linear regression method was used to obtain optimal parameters of the function. The results obtained from the model were compared with the delays obtained from VISSIM microsimulation package and it was shown that the estimated results closely matched. Such an analytical approach, therefore, can be implemented to evaluate the effect of TSP at the planning level in a timely manner more efficiently than time-consuming microsimulation models. Nevertheless, the model application may be challenging, mainly due to the cost of updating delay functions. Indeed, one of the fundamental elements of transport modelling tools is to implement an appropriate delay function and calibrate its parameters for the study area. Consequently, there might be circumstances where there is reluctance to change delay functions type and parameters. To address this issue, use of adjustment factors was proposed, introduced and validated in the next section.

7.2. Using Adjustment Factors

Skabardonis and Christofa (2011) presented an analytical approach to estimate the impact of TSP on an intersection as an alternative for microsimulation models. In their method, the effect of TSP can be considered by applying a set of adjustment factors, depending on the intersection structure and transit service parameters. This method is compared to the microsimulation results and it was shown that considering the significant improvement in computational costs, the difference is almost negligible. Their methodology to reflect the impacts of TSP implementation on private cars was formulated as below:

$$D^{bus} = E(d|\, Bus)\, P(Bus) \;+\; E(d|\, No\ bus)\,(1 - \, P(Bus)) \qquad \text{7-2}$$

Where $P(Bus)$ is the probability of bus arriving to the intersection during a cycle, $E(d|\, Bus)$ is the estimated delay on the link a bus is approaching the intersection and TSP is applied, and $E(d|\, No\ bus)$ is the estimated delay when the signalized intersection is operating with no enabled TSP (i.e. calculated normal intersection delay). The probability of a bus with the headway h arriving during the cycle length C can be calculated as below:

$$P(Bus) = C/h \qquad \text{7-3}$$

To estimate the delay at each movement when TSP is not activated ($E(d|\, No\ bus)$), either using delay functions or HCM formulations can be applied. Indeed, these methods estimate the delay as a function of flow ratio (volume to saturation rate), green time, and cycle length.

Calculation of $E(d|\, Bus)$ as the expected delay for the buses that are granted TSP needs more parameters and complexities. In this regard, Skabardonis and Christofa (2011) suggested estimating the delay by applying the TSP changes for any given green time and g/C ratio. They used adjustment factors for every single signal setting and traffic state using the HCM formulations. Although such simplification may limit the TSP strategies to green extension and early green strategies, it can provide a rough estimation of TSP impacts on a planning level. Consequently, their approach was used to calculate the expected delay of each link when TSP is applied. Assuming a uniform distribution on bus arrival pattern, the average amount of green time for the transit service can be estimated as below:

$$T_g^p(TSP) = T_g^p(Base) + \frac{e_{max}^T}{2} + \frac{e_{max}^G}{2} \qquad \text{7-4}$$

where $T_g^p(TSP)$ is the expected amount of green time of a prioritized movement when TSP is applied, $T_g^p(Base)$ is the assigned green time to a prioritized movement in typical condition, e_{max}^T is the maximum amount of red truncation that can be given, and e_{max}^G is the maximum amount of green that can be given to the prioritized movement. Since the amount of green extension or early green can be equally distributed between the other phases, the amount of green time in other phases can be calculated as below:

$$T_{r,i}^{np}(TSP) = T_{r,i}^{np}(Base) - \frac{1}{N_j}(\frac{e_{max}^T}{2} + \frac{e_{max}^G}{2}) \qquad \text{7-5}$$

where $T_r^{np}(TSP)$ is the amount of red time in non-prioritized phase i when TSP is applied; and N_j is the number of defined phases within the signal cycle time. Having the amount of the approaches' green time for the base and TSP scenarios, estimation of the delay can be performed, as discussed. To calculate the amount of bus delay at intersection, $P(Bus) = 1$ thus the bus delay can be estimated using $E(d|\ Bus)$ term only.

Figure 7-6 shows the impact of TSP on average delay values (two phases with g/C=0.45, h=10min, C=90 sec, e_{max}^T =10 second extension). It can be seen that the vehicles in prioritized movement can benefit from TSP while the crossing movement experience an extra delay. In addition, in congested regimes, the negative impacts of TSP implementation on the opposing movements are significant, making TSP implementation practically challenging to be triggered.

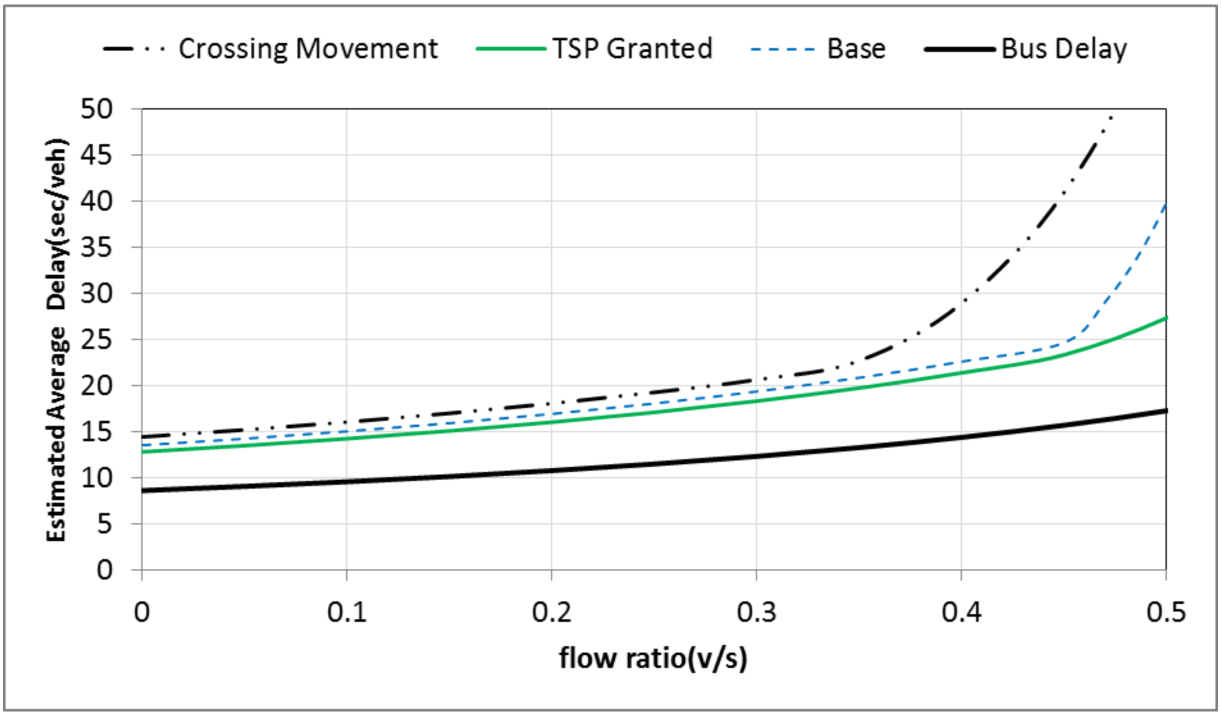


Figure 7-6 Estimation of the effect of TSP on average delays

To reflect the effect of TSP on an intersection, a set of adjustment factors were defined. In this regard, two factors p_c^{TSP}, p_c^{NTSP} adjust the passenger car delays due on prioritized and non-prioritized approaches, respectively. Following a similar strategy, an adjustment factor $\boldsymbol{p_B^{TSP}}$ for bus delays when TSP is implemented can be defined. This factor reflects the achieved benefit in reducing bus delay at an intersection. These three adjustment factors (p_c^{TSP} , p_c^{NTSP}, and p_B^{TSP}) can be estimated either through analytical methods, microsimulation models, or observations. Once they were estimated, the network can be updated for each link as an initialization phase of transport modelling procedure. A numerical example is presented next to show how TSP can be considered in a network-wide prospective.

7.2.1 *Numerical Examples*

To validate the model, it was applied to a small grid network with nine intersections. Figure 7-7 shows the model layout in VISUM environment along with the defined zones, link IDs and node IDs. Three bus routes are also defined, forming seven candidate intersections for TSP implementation. Two of these intersections have two crossing bus lines thus a multiple (conflicting) TSP logic may be suggested on them. For the initial validation of the model, it was assumed that TSP implementation can decrease 20 percent of the bus travel time while the capacity would have a 10 percent decrease and impact for the prioritized and non-prioritized phases, respectively (i.e.$p_c^{TSP} = 1.1, p_c^{NTSP} = 0.9, and\ p_B^{TSP} = 0.8$). Adjustment factor for multiple TSP requests (p^{MTSP}) were considered to be

0.95. A flat demand of 100 vph (for private car system) and 100 bus passengers (only six nodes that have access to PT) were defined for origin-destination pairs.

In the first experiment, two scenarios, base and TSP for all the intersections were considered for this network. It was assumed that TSP is active on all the links where a bus is commuting. Consequently, five single and two multiple TSP systems is suggested for the network.

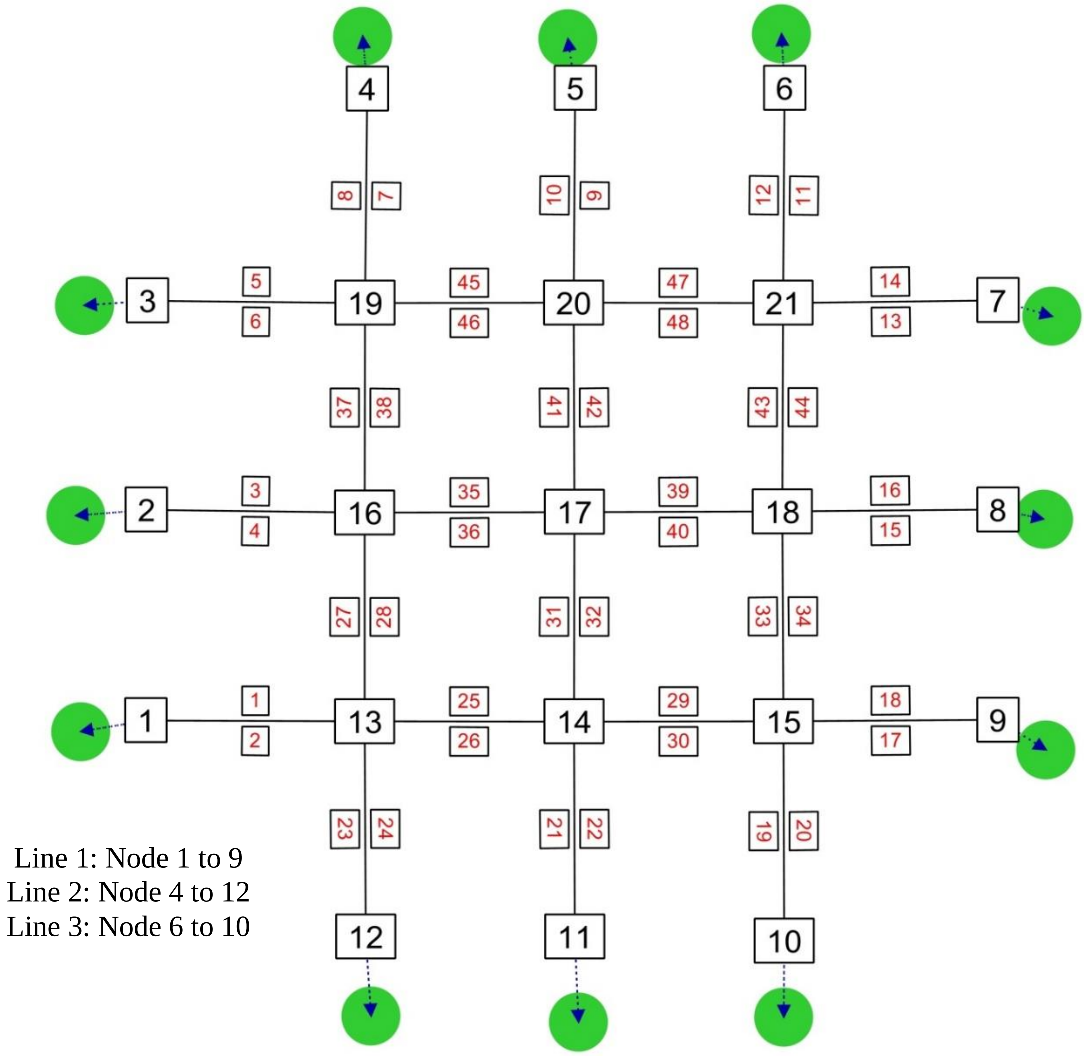
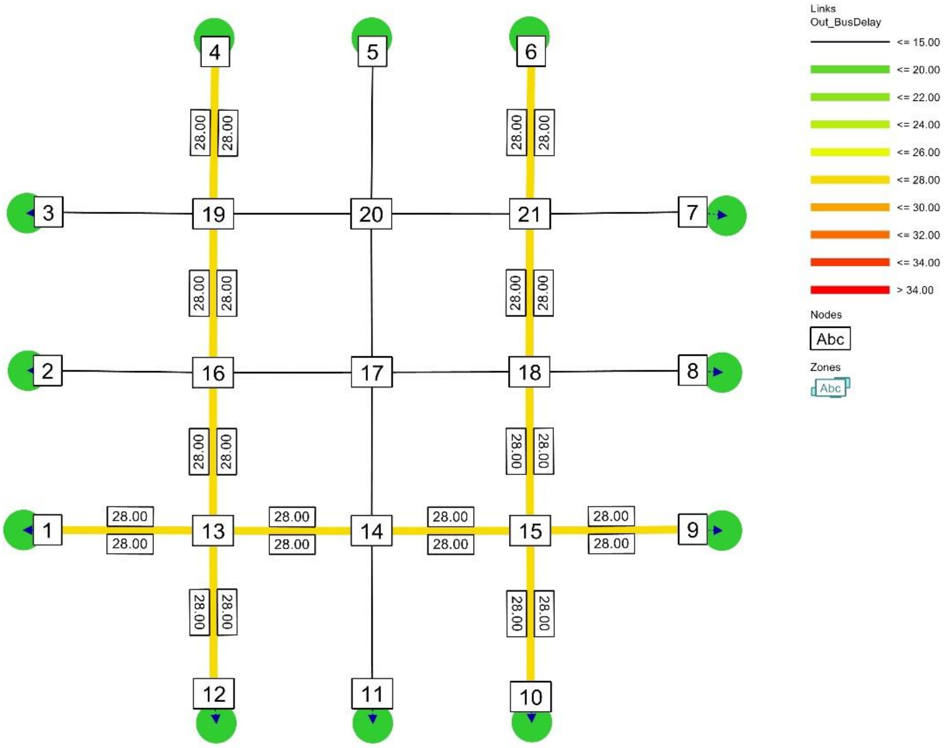
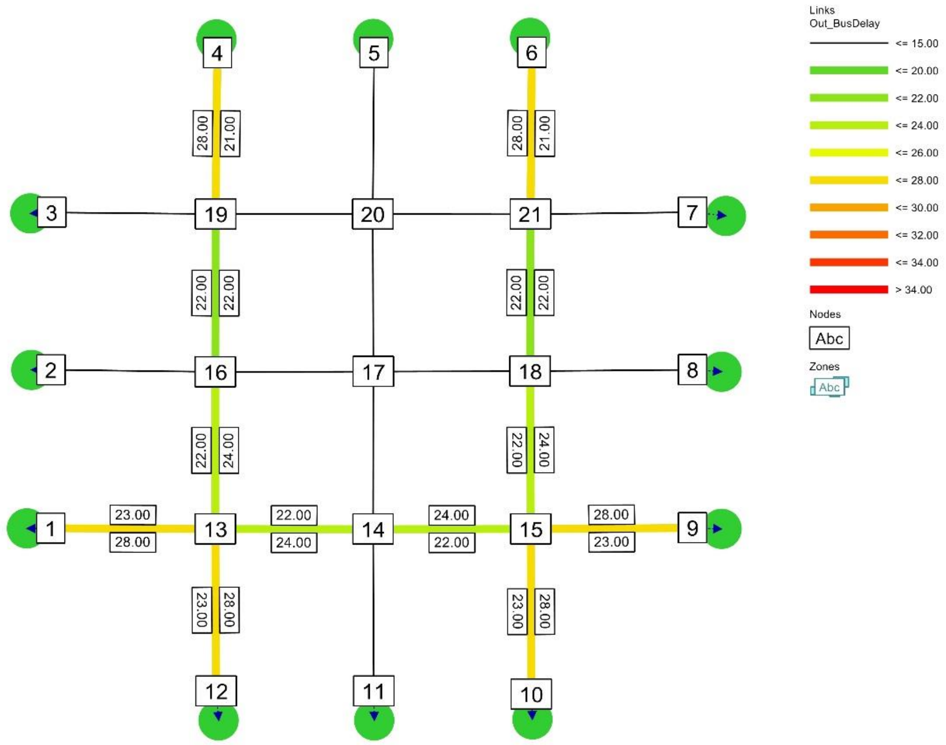


Figure 7-7 Small grid network layout

Figure 7-9 and Figure 7-10 show the results of running the model for both base and TSP scenarios. Considering the bus delays, it can be seen that the expected improvements are achieved along the TSP equipped corridors. This amount of saving in nodes 13 and 15 where multiple TSP requests are possible is slightly less than the other intersections. Comparison of the traffic flow in the network, it can be seen that TSP implementation can noticeably affect the route choice of the traveller in a network. Indeed, it is expected to experience less delay in prioritized movements while the crossing movements are suffering from granting priority. However, it was observed that when the system is trying to minimize the overall travel time, prioritised approaches experienced more flow and potentially higher level of delay compared to the base scenario. Following the figures, a higher flow ratio is estimated along the prioritized movements whereas the flow and delay is decreased in alternative routes.

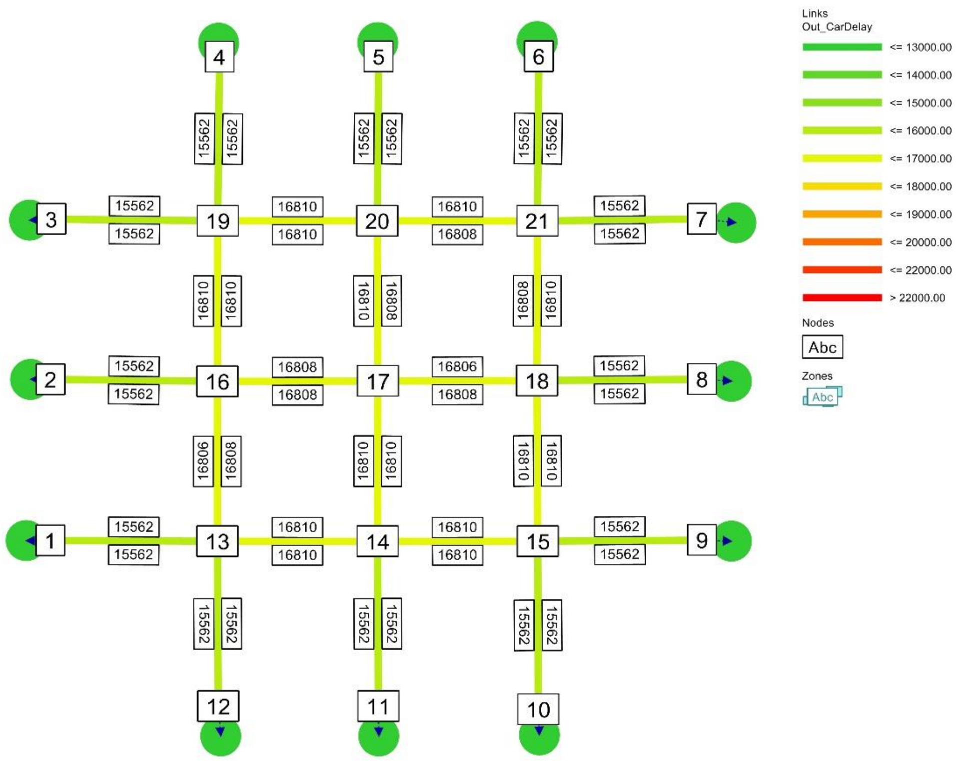


Bus Delay (Base)

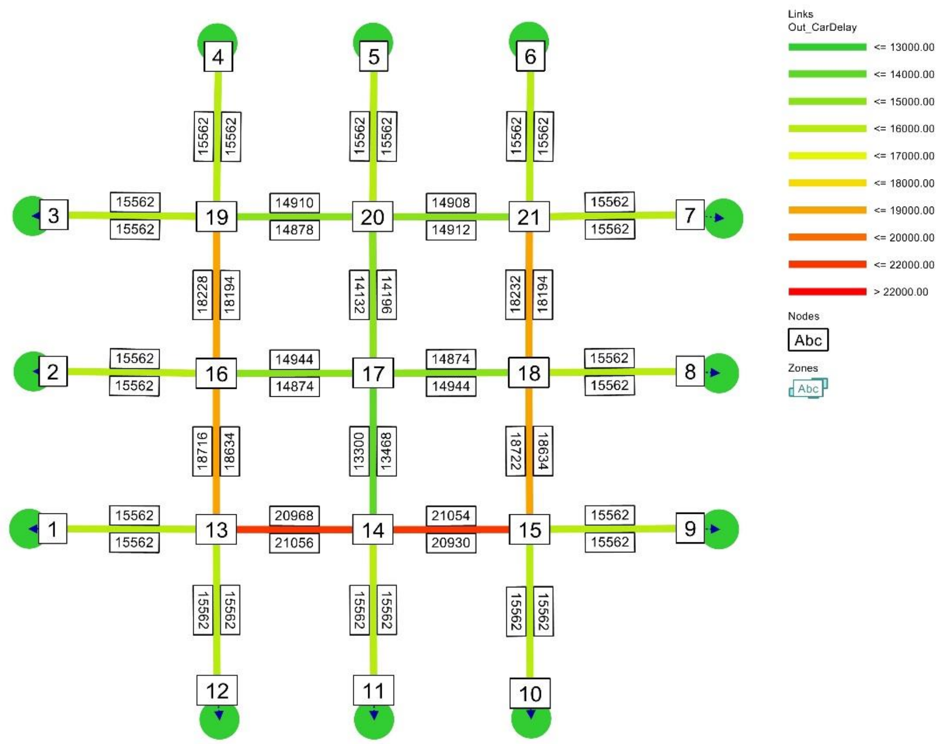


Bus Delay (TSP)

Figure 7-8 The effect of TSP on bus delay



Passenger cars delay(person-seconds)- Base



Passenger cars delay(person-seconds)- TSP

Figure 7-9 The effect of TSP on bus and passenger cars delay and route choice

Table 7-2 shows how TSP implementation can change the overall performance of the network for an uncongested condition For the network and implemented TSP settings, around 17% saving in bus travel time was achieved while less than 0.85 percent increase in average passenger delays was observed. These changes are mean a total of 2.61% saving in total travel time of the network.

Table 7-2 Network wide effect of TSP application for different measures of performance

Measure of Performance	Base	TSP	% of improvement
Bus Total Travel Time(Person-Minutes)	12040	10040	16.61
Average Bus TT(minutes)	1.67	1.39	
Car Travel Time(Person-Minutes)	48755	49171	-0.85
Average Car TT(minutes)	1.85	1.86	
Total Travel Time(Person-Minutes)	60795	59211	2.61

Figure 7-10 shows the effect of TSP on bus and car delays at different levels of congestion. An adjustment factor was applied to the default private and public transport demand arrays and the results of running the model for base and TSP scenarios were depicted. It was seen that with an increase in demand, the negative impacts of TSP implementation on the private cars were linearly increased. Nevertheless, average person-delay for transit service is experiencing a dip before reaching the saturated condition and then linearly increases.

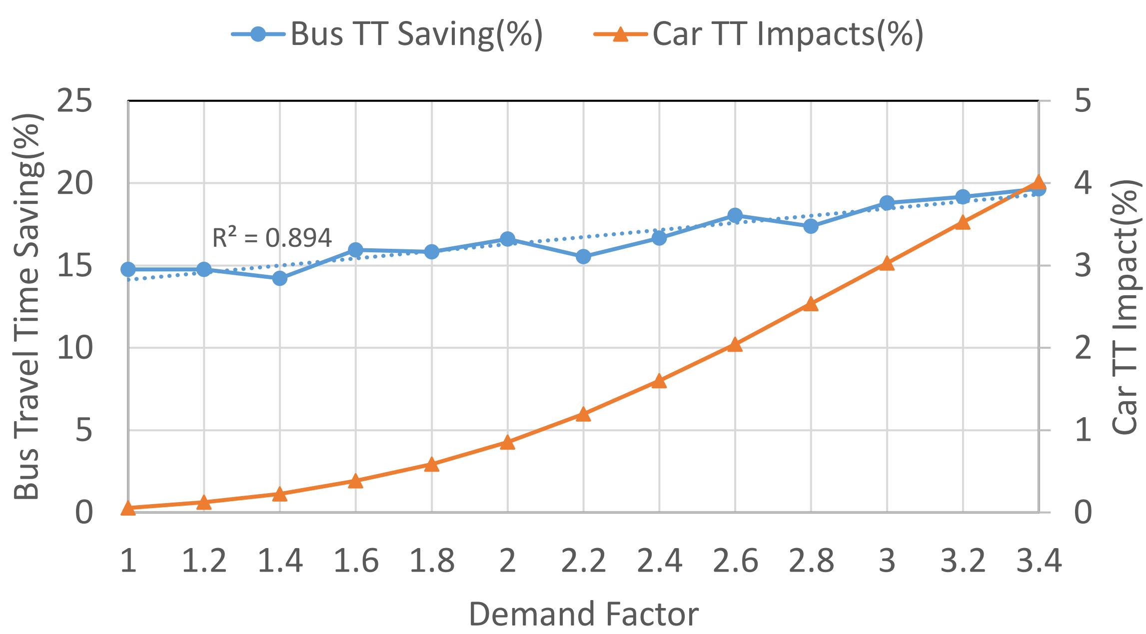


Figure 7-10 The effect of traffic congestion on TSP effects

7.2.2 *Sensitivity analysis*

A sensitivity analysis on the assumed adjustment factors was performed to reflect their impact on TSP implementation. Following the discussion presented in this section, adjustment factors are representative of the TSP logic and thus their value will be reflected in TSP performance outputs. A sensitivity analysis on the adjustment factors can reveal how sensitive the model outputs are to these factors.

For different p_c^{TSP} *and* p_c^{NTSP} values, a sensitivity analysis was conducted on p_B^{TSP} to see how it can change the overall travel time saving when the candidate intersections are all equipped to an active TSP. Since the travel time values are directly driven from link travel time, it is expected to have a linear change with changes if p_B^{TSP} value. This trend can be clearly seen for all three regimes within a buffer of around 5 percent. Indeed, it can be seen that if the effect of TSP on the prioritized movements is considered, a higher value of saving is achieved, mainly because of the reflected reduced reduction in a prioritized movement.

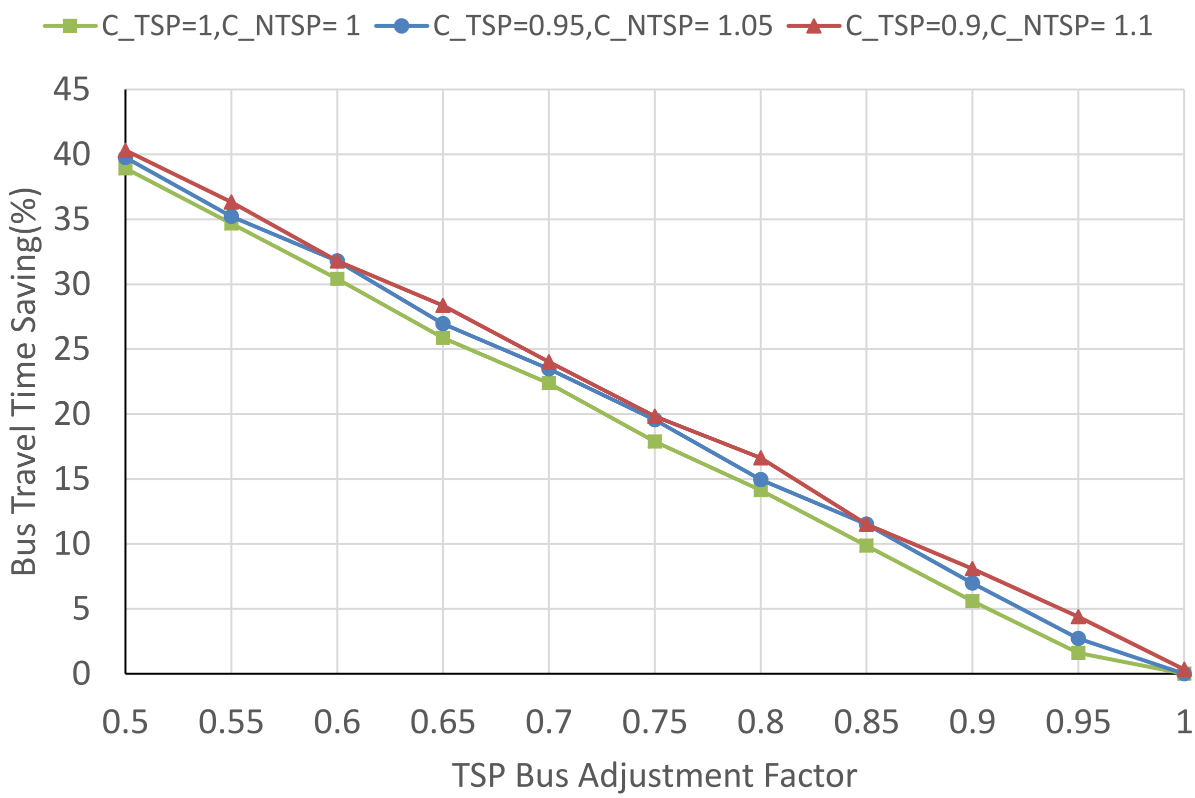


Figure 7-11 The effect of bus adjustment facotr parameter p_B^{TSP} on bus travel time savings

A test on the values of p_c^{TSP} *and* p_c^{NTSP} was also performed two different levels of congestions (200 and 300 vph for each OD pair). In this regard, assuming a symmetrical propagation of capacity changes, the sensitivity analysis was performed by changing a factor w such that ($w = p_c^{TSP} - 1 = 1 - p_c^{NTSP}$). Figure 7-12 shows the trend of TSP impacts on private cars for different values of *w*. As can be observed, for an uncongested condition, the impact of TSP employment on experienced delay is slightly increased with an increase in w. Indeed, it is estimated that using a TSP scenario that can incur around 20% reduction on an approach can reduce the average travel time of private cars by around 5%. Having said that, in congested conditions these changes are much more than the initial regime where for w=0.2 around 18% increase in total travel time can be expected. It can be concluded that in design and deployment of TSP scenarios, it is critical to consider the level of congestion in non-prioritized movements so as to avoid significant amounts of delay on the network.

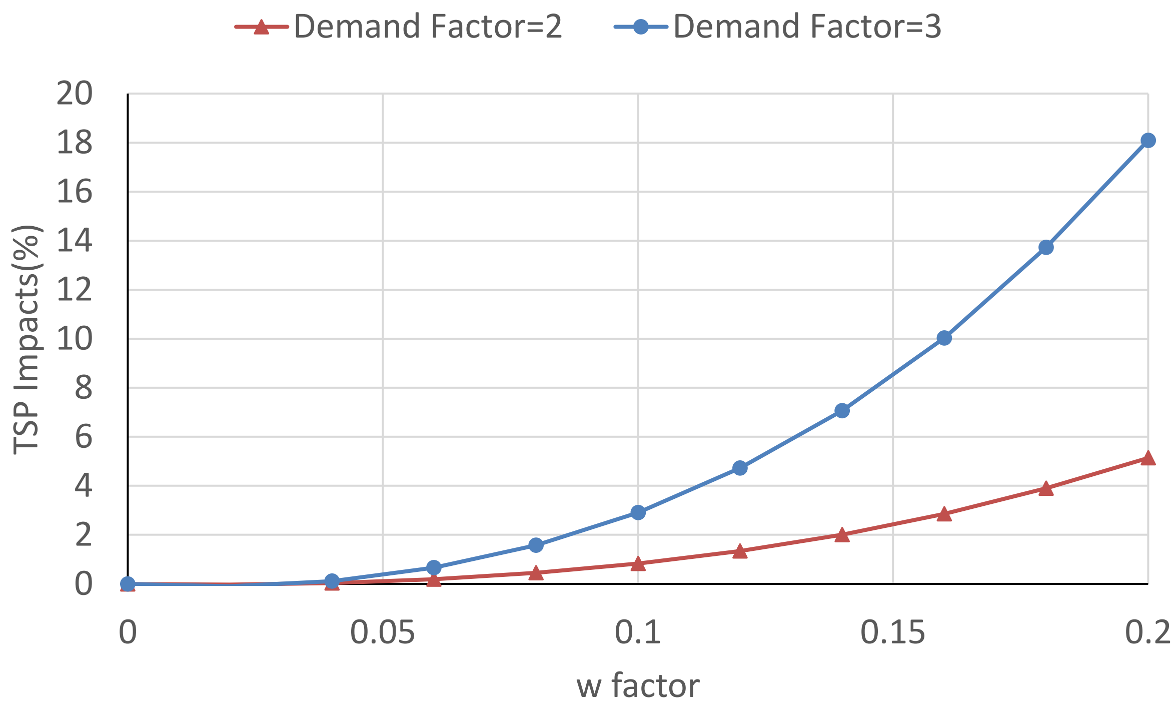


Figure 7-12 The effect of bus adjustment factor parameter p_c^{TSP}, p_c^{NTSP} on bus travel time savings

As it was shown, the effect of TSP implementation on the network depends on the factors such as the level of congestions, TSP logic, and transit service frequencies. Although micro level studies are required to evaluate any single intersection, TSP effect on the network urges a macro level framework for evaluation. Moreover, aiming at optimizing TSP performance on transit and traffic regimes, it is crucial to identify the set of location where TSP can be applied thus the objective function can be minimized. Such task can be fulfilled by integrating an optimization tool to search for the optimal scenario in the whole network. A method to optimize the location of TSP strategies in the network is presented in the next chapter.

7.2.3 *Network wide Evaluation of TSP Scenarios*

In its simplest form, TSP locating problem can be defined as a decision which intersections in the network should be equipped with TSP to maximize the service performance. For each intersection, depending on the circumstances, conditional TSP strategies (discussed in section 2.2), TSP strategies with the objective of reducing fuel consumptions, and traffic states (travel times and vehicle counts) can be implemented.

A key step in analysing TSP impacts on the network is to address to what extent adjusting signals can affect the travellers. TSP implementation can have a significant change on the passengers of both private and public systems where it is supposed to be in favour of the buses and can cause extra delays to cars. If the delay incurred on some non-prioritised links is considerable by the drivers, they may change their route in order to have shorter trips. Prioritizing transit over cars can also cause a modal shift, attracting more passengers to transit services.

The main objective of this section is to evaluate the performance of a set of given TSP scenarios in the network. Using a strategic approach, total passengers travel time value was considered as a measure of performance for each TSP scenario. In addition, a transport modelling procedure is suggested as a practical tool to estimate traffic and transit performance for a given scenario. These two modules can be convoluted and presented as a unique optimization problem to find optimum TSP setting for a large scale network for a given analysis period. In this section, a methodology to introduce TSP setting to the model, evaluating different scenarios, and integrating the model into an optimization tool is presented.

It was suggested in section 7.2. to use adjustment factors to reflect the effect of TSP in a planning study. For each link, three adjustment factors (for the capacity of car on a prioritized approach, capacity of cars on a non-prioritized approach, and buses on a prioritized approach) are suggested. Note that throughout this section, it is assumed that we have already estimated the adjustment factors for TSP strategies in each single intersection. For each scenario, these parameters should be defined for all the links in the studied network. Introducing such adjustment factors has several benefits:

1. A wide range of TSP strategies can be evaluated and compared together in a large scale network.
2. Factors can be extracted from observations, simulation methods, or recommendations.
3. For each link, a separate set of factors is defined thus TSP effects on each movement can be defined independently.
4. TSP conflictions can be modelled by introducing appropriate parameters.
5. Parameters are introduced as the planning module is initialized thus there is no extra computational cost in assignment modules.

Integration of TSP settings to transport modelling is the key part of the suggested framework. The basic form of network-wide TSP analysis is to locate optimum set of intersections to equip them with TSP hardware.

To evaluate such a TSP scenario through a transport modelling framework, firstly the type of TSP effect (i.e. benefit, disbenefit, neutral) on each approach of the intersection should be identified. Depending on the type of effect, appropriate adjustment factor (p_c^{TSP} and p_c^{NTSP}) would then be used to update link capacity. In addition, for the link that is candidate for TSP implementation, bus travel time can be adjusted using p_B^{TSP} . The model is then ready for further modelling procedures as transit and traffic assignments can reflect TSP impacts. The procedure to evaluate a given scenario is outlined in Figure 7-13.

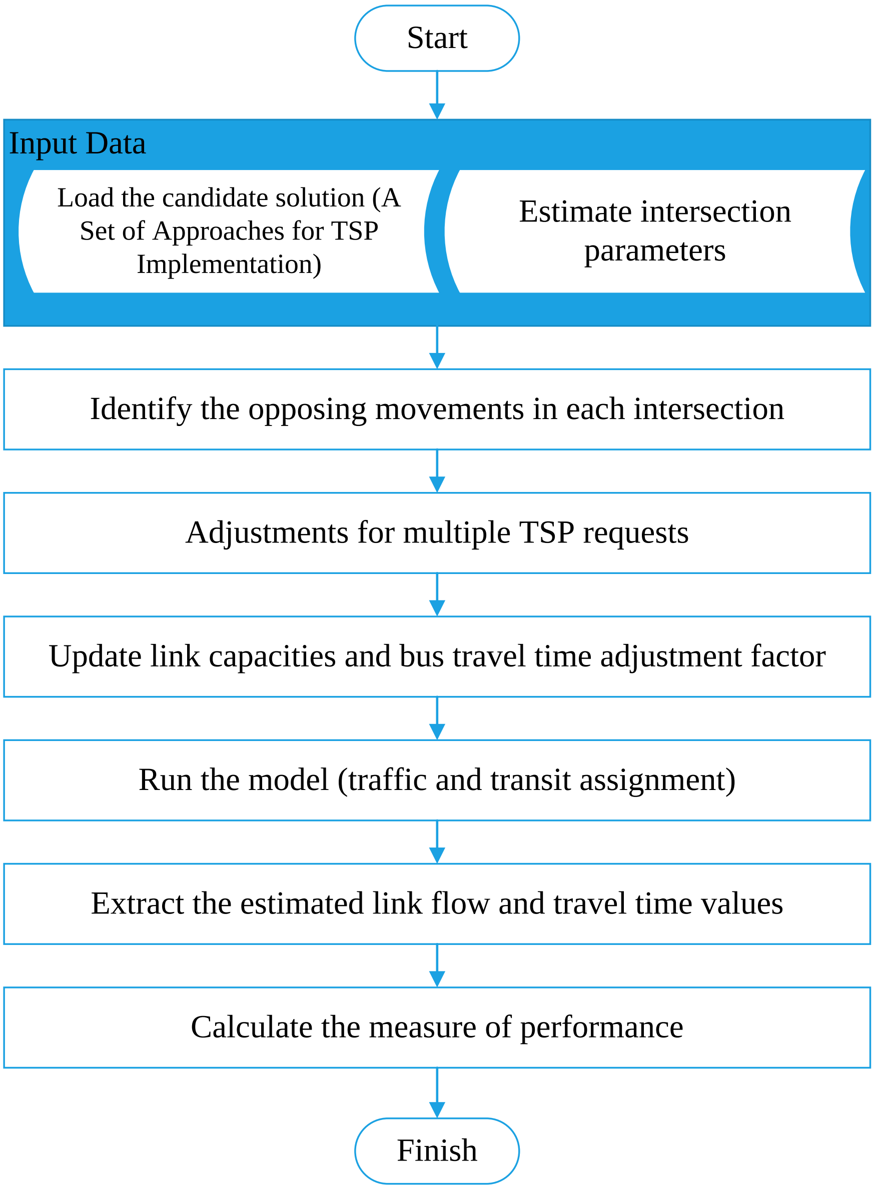


Figure 7-13 Procedure to consider TSP effects in a transport model

As can be seen in Figure 7-13, a defined scenario (i.e. a list of links that are equipped with TSP in the network) as well as estimated parameters for TSP implementation are two input datasets of this module. To measure the performance of TSP scenarios, firstly the opposing movements of the intersections with TSP implementation are identified. Bus travel time adjustment factor and capacity change factor are two required values to proceed to the next level. Note that if there exist any intersection equipped with TSP, the parameters of capacity and bus delay changes should be updated. Table 7-3 summarizes the adjustment factors of bus travel time and capacity values in each condition.

Table 7-3 Adjustment factors for capacity and bus travel times

	Movement	Capacity	Bus TT
No TSP	Both	1	1
Basic TSP	Prioritized	p_c^{TSP}	p_B^{TSP}
	Crossing	p_c^{NTSP}	1
Multiple TSP	Prioritized	$p_c^{TSP} \times p^{MTSP}$	$1/p^{MTSP}$
	Crossing	$p_c^{NTSP} \times p_c^{NTSP}$	$1/p^{MTSP}$

For each link, an appropriate pair of factors is used to update link capacity and estimated travel time of buses. Traffic and transit assignment models can then be run to estimate the flow and travel times on each link for each mode. In this research, VISUM is used to perform assignment tasks. Once the flow and travel times were extracted, the objective function can be calculated.

7.3. Integration of TSP and Transit Priority Lanes (TPL)

TPL is another popular preferential strategy that provides an exclusive space to the transit services thus they can commute along a link without experiencing the congestion delays of a mixed traffic stream. This strategy can be used at the expense of a significant decrease in a targeted link capacity and thus may cause extra delays to the competent modes. On the contrary to time-based preferential strategies, the effect of such strategies on transit travel time is noticeable. Nevertheless, they can have more severe impacts on the competent modes than TSP. Indeed, TPL application effects can be stated as:

a. Reduction in the capacity of the link for the competent mode
b. Minimizes the delay of the transit vehicles along a link.

For a given network, TSP can be implemented for each intersection approach. Similarly, TPL can theoretically be suggested to be considered along the bus paths. While the former is targeting the delay at the intersections, TPL can mitigate the congestion delays along the links, causing a potentially great combination to reduce transit delay and improve travel time variability. Such benefits are, however, prone to cause additional delays for the other modes. While the capacity of a link after an TPL implementation will be significantly decreased, TSP can cause additional delay on the opposing movements. Consequently, it is crucial to consider the benefits and impacts of both strategies on all the movements and modes in an intersection. In this section, a method to evaluate the effect of TSP and dedicated transit lanes integration is presented.

For each link in a netwok, the following scenarios are defined:

- Scenario 1: Do nothing
- Scenario 2: Define dedicated lanes along a link
- Scenario 3: Define TSP to prioritize buses when approaching an intersection
- Scenario 4: Apply both TSP and a dedicated lane

The effect of applying any of the scenarios on the bus travel time can be formulated as bellow:

$$T_i^b = T_i^0 + (1 - \boldsymbol{a_i^L})\ d_i^c + (1 - \boldsymbol{a_i^{TSP}})\ d_i^s + \boldsymbol{a_i^{TSP}}\ p_{B,i}^{TSP}\ d_i^s \qquad 7\text{-}6$$

Where

T_i^b Travel time of the buses on link *i*
T_i^0 Free flow travel time along link *i*
d_i^c congestion delay along link *i*
d_i^s Intersection delay of approaching link *i*
p_B^{TSP} TSP adjustment factor of bus delay for approach *i*
a_i^L Decision variable of Lane allocation for link *i* (1 if dedicated lane is suggested and 0 otherwise)
a_i^{TSP} Decision variable of TSP implementation for approach *i* (1 if TSP is suggested and 0 otherwise)

As can be seen in the formulation, the aforementioned four scenarios can be represented as two binary values for each candidate approach.

The impacts of implementing preferential strategies can be considered by reflecting the changes in traffic stream. For the case of TPL, the main change is a significant decrease in the link capacity due to allocating one or more lanes to the buses. The new capacity can be calculated as below:

$$c_i' = c_i\ \times k^l \times \frac{n_i^c - n_i^{RSA}}{n_i^c} \qquad 7\text{-}7$$

Where

c_i' New capacity of link *i*
c_i Default capacity of link *i*
k^l Adjustment factor for demand distributions
n_i^c Existing number of lanes in link *i*
n_i^{RSA} Suggested number of lanes to be allocated to the transit service

7.3.1 *The Effect of TPL and TSP on Bus Delay*

An analytical method was developed in the current thesis to reflect the effect of TSP and TPL scenarios on the experienced delay. If a bus can approach the intersection through a dedicated lane, it experiences no delay due to the congestion. However, depending on the logic implemented for TSP it may experience intersection delay if it arrives when the signal is red. The amount of delay a bus experiences can be formulated as below:

$$\begin{cases} p(d = 0) = \dfrac{g}{C} \\ p(d > 0) = \dfrac{C - g}{C} \end{cases} \quad 7\text{-}8$$

$$E(d) = p(d > 0) \times U(d) = \frac{C - g}{C} \times \frac{1}{2}(C - g) = \frac{(C - g)^2}{2C} \quad 7\text{-}9$$

Where $p(d > 0)$ is the probability of bus delay being greater than zero during the analysis period; C is the cycle length; g is the green time value of the approach; and $E(d)$ is the expected amount of delay at intersection. Application of TSP can change the amount of green time in this equation. Assuming e to be the amount of green time at this intersection, bus delay at an intersection with no queue can be estimated as below:

$$E(d) = \frac{(C - g - e)^2}{2C} \quad 7\text{-}10$$

Figure 7-14 shows the results of applying the model to an intersection to estimate the effect of TPL and TSP strategies on an approach. As it can be seen, the suggested method could reflect the effect of TPL by estimating a delay independent from the level of congestion. If TSP and TPL are applied together, minimum amount of delay can be achieved.

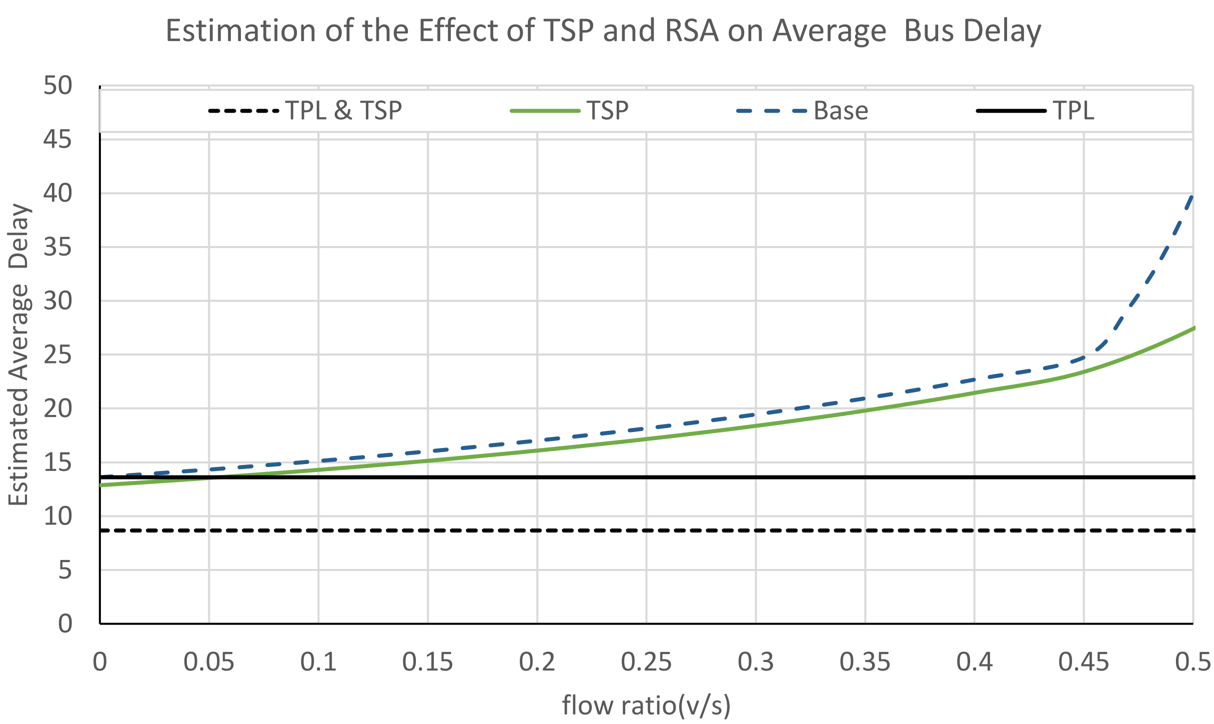


Figure 7-14 Estimated delays for different congested levels and preferrential strategies

The negative impacts of introducing dedicated lanes on a link is the major drawback of their application. TPL significantly reduces the capacity of the link, causing incremental delay in the link to be augmented. Figure 7-15 shows the effect of reducing the number of lanes on the experienced delay by private cars (delays estimated using a BPR delay function). As can be seen, for a 2 lanes approach with 2000 vehicles per hour flow (assuming the capacity of a link to be 700vph), if one lane is dedicated to the buses, travel time value will be increased by around 10 times. Such a significant sensitivity urges a wise approach to be implemented to design bus exclusive lanes so as to prioritize buses with minimum impacts on cars.

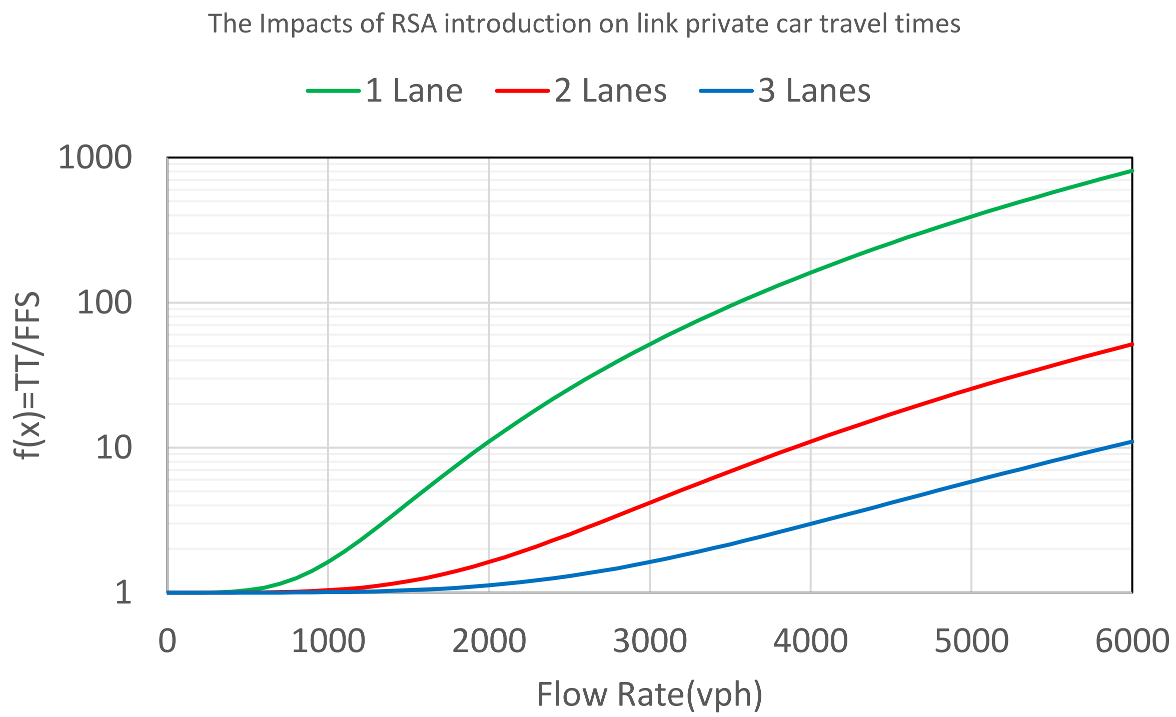


Figure 7-15 The effect of the number of lanes on experienced delay by cars

To be able to evaluate the effect of TSP and TPL at the network level, it is necessary to consider the effect of the strategies on car drivers' route choice. To fulfil this task, a methodology was developed similar to that presented for sole TSP evaluation. Nevertheless, one concern would be the distinction of the delay at intersections and the delay along the link. The adjustment factors for TSP effects would be applied to the delay estimated by assignment results, that is for both node and link delay components. To address the issue, TSP adjustment factors are considered to adjust delay at intersections only when there is a mixed traffic. Consequently, delays for each scenario can be simplified as below:

Table 7-4 Delay estimation method for different scenarios

Decision Code	Scenario	Delay Estimation method
0	Do Nothing	$T_i^b = T_i$
1	TSP Only	$T_i^b = T_i^0 + p_{B,i}^{TSP} \times (T_i - T_i^0)$
2	TPL Only	$T_i^b = T_i^0 + \frac{(C-g)^2}{2C}$
3	TSP & TPL	$T_i^b = T_i^0 + \frac{(C-g-e)^2}{2C}$

Where T_i^b is the travel time of the buses on link *i*, T_i is the car travel time of link *i*, derived from the assignment procedure, T_i^0 is the free flow travel time along link *i*, $p_{B,i}^{TSP}$ is the adjustment factor to reflect the effect of TSP on intersection delay, and *e* is the average amount of green time extension that can be granted to the prioritized buses. Application of this approach is presented in the next section.

7.3.2 *Numerical Example*

To evaluate the performance of the developed framework, four scenarios were defined for the small grid network (see Figure 7-7):

1. Do Nothing
2. Apply TSP on all the candidate intersections (9 approaching links in 7 intersections)
3. Apply TPL to all the candidate links (18 links)
4. Apply TPL and TSP to all candidate intersections and links simultaneously

These scenarios were introduced to VISUM and the evaluation process was performed for different levels of congestion. Figure 7-16 shows the effect of different strategies on transit service delays. It can be seen that although in non-congested conditions these delays are following a similar trend and are not imposing noticeable changes to the network, with an increase in demand, the role of TPL in mitigating bus delay is becoming significant. Indeed, TPL allows the bus to jump to the stop line and just wait at the red light. Integration of TSP and TPL can even reduce such amount of delay, making a minimum delay for almost any approach in the network. Note that the discrepancy in the amount of delay at uncongested levels (e.g. OD pair demands of 150 vph) is mainly due to implementation of two different approaches (i.e. HCM and BPR delay function) to calculate the demand for dedicated lane and mixed traffic.

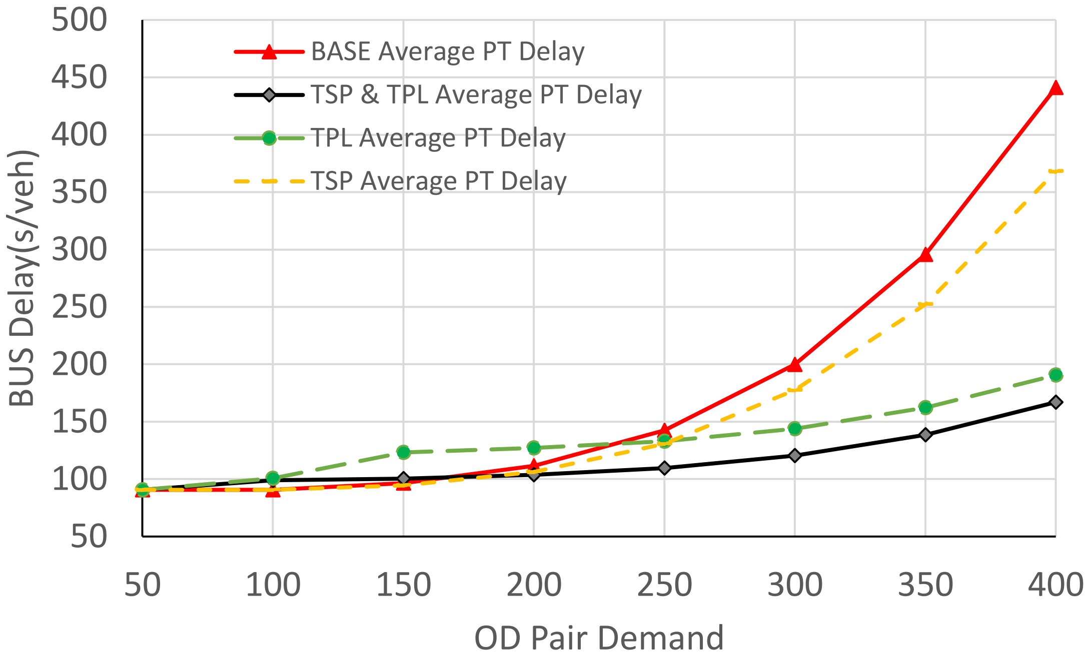


Figure 7-16 The effect of different preferential strategies on bus delays

Figure 7-17 shows the effect of implementing different preferential strategies on average delay of private cars. It can be observed that dedication of space (i.e. TPL) to transit service can have a significant impact on the delay of the competent modes. Although such delays can be minimal in non-congested conditions, they practically make TPL implementation an infeasible strategy in congested conditions.

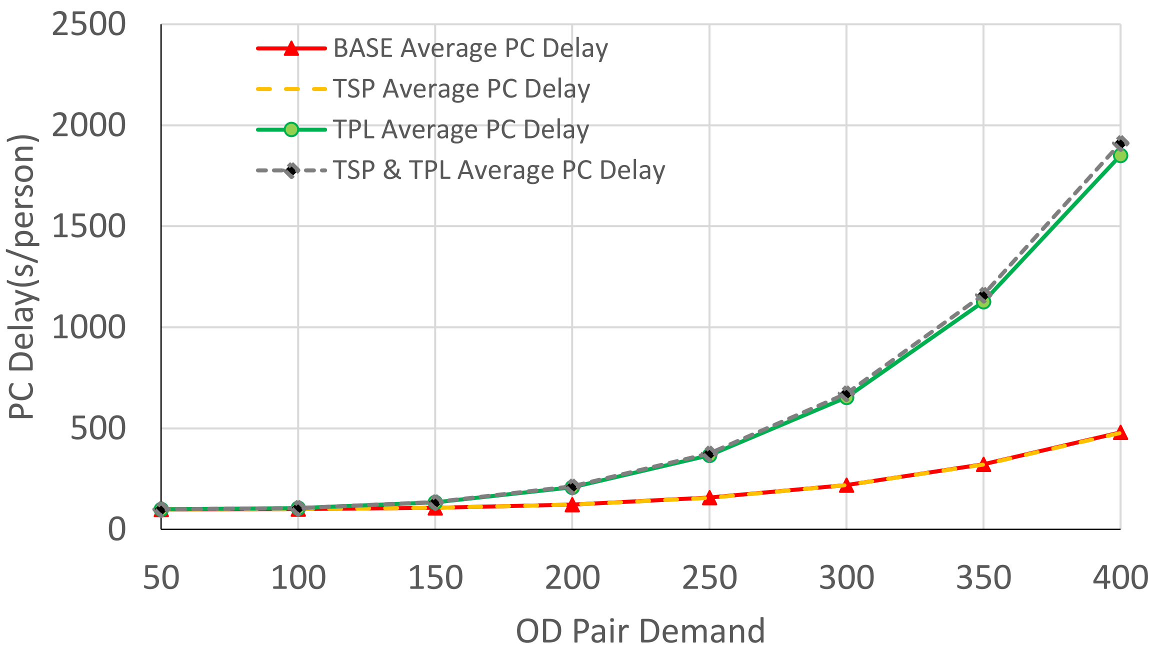


Figure 7-17 The impact of different preferential strategies on passenger cars delays

Finally, average person delays were calculated using the estimated bus and car delays and their occupancies. Figure 7-18 shows the average person delay for the defined scenario over a range of traffic congestion. It can be seen that the optimal scenario may change for different levels of congestion. For the given regime, the scenario in which intersections can be equipped to TSP is a reasonable solution to minimize delay in undersaturated conditions.

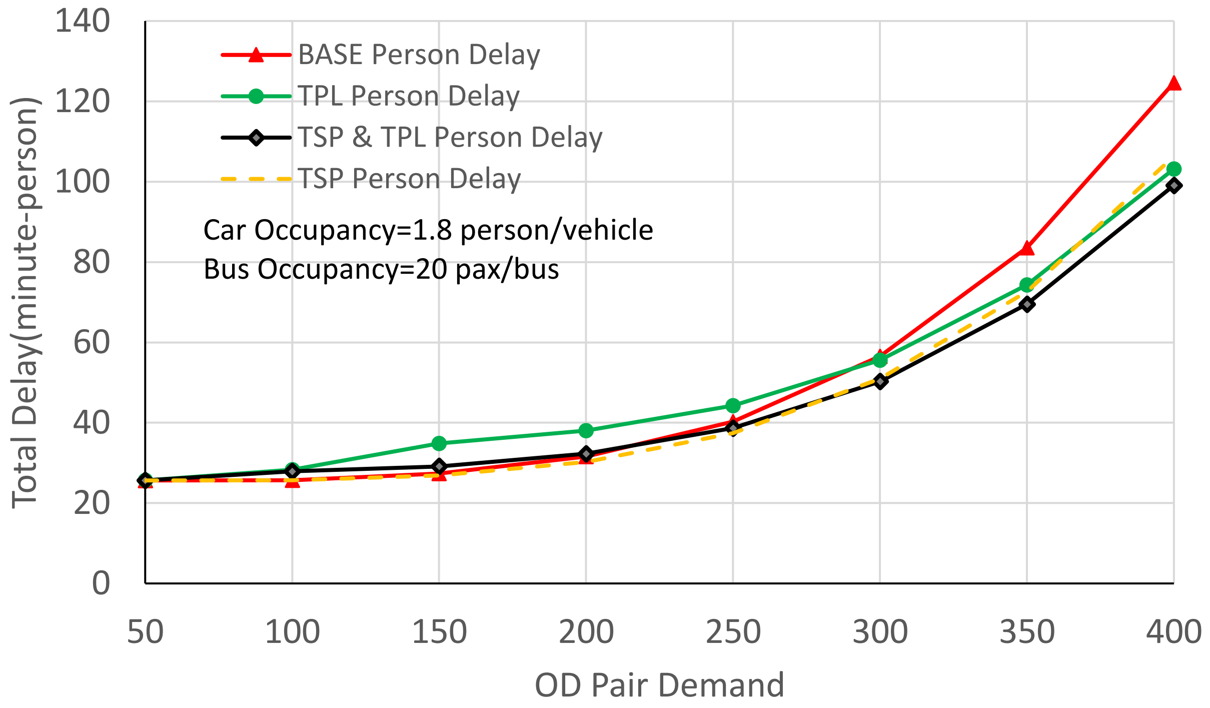


Figure 7-18 The effect of different preferential strategies on total network delay

Figure 7-19 shows the status of the network for mixed TSP-TPL scenario. It can be seen that implementation of dedicated lanes along the bus routes causes significant delay in congested networks.

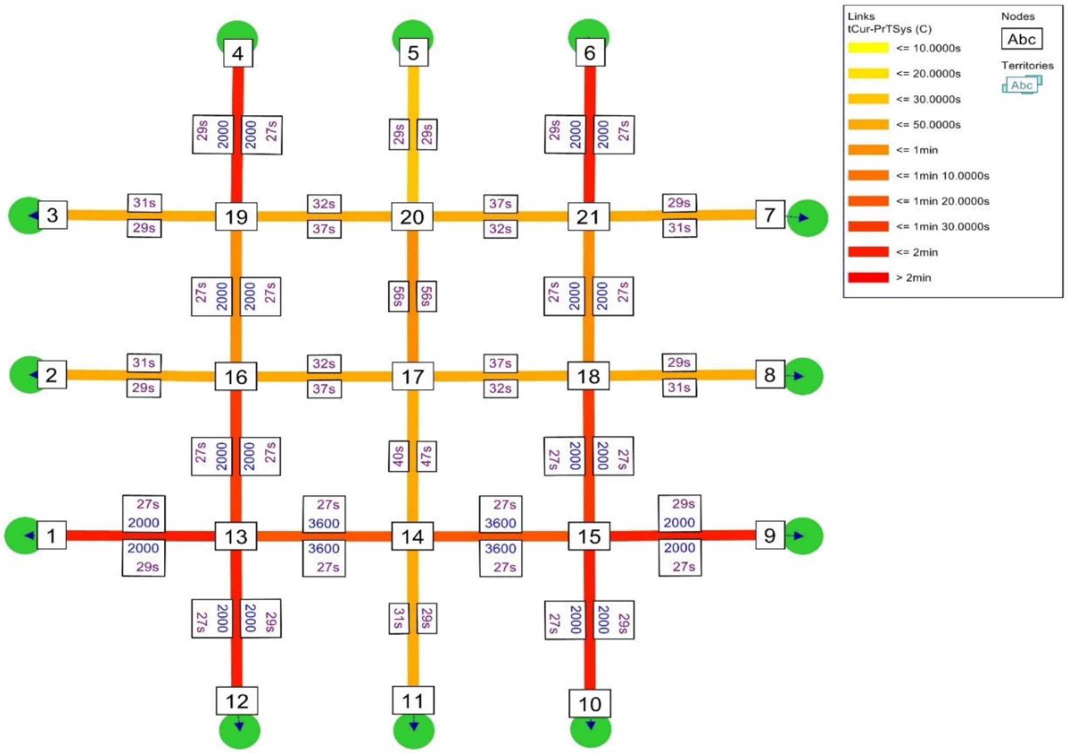


Figure 7-19 The impact of TSP&TPL deployment on passenger cars delays

7.4. Chapter Summary

This chapter was dedicated to introduction and evaluation of two analytical methods to perform network-wide evaluation of priority strategies. Firstly, application of delay functions to reflect the effect of priority strategies was shown in two example studies. Delay functions have a set of parameters to be calibrated and implemented in transport modelling studies. Secondly, application of adjustment factors to evaluate TSP impacts was demonstrated. The results show that the proposed approaches can be used for planning level studies. Due to the flexibility of the method, the adjustment factors approach was identified as superior to updating delay functions. This adjustment factor method was also used to show an evaluation of integrated TSP-TPL approaches in a network. Integration of TSP and TPL showed how the combination of priority strategies can make a noticeable saving in bus travel times. It was observed that depending on the congestion level and network layout, implementation of TSP and TPL (either together or exclusively) may cause additional delay for travellers with marginal improvements for the transit service. To address this issue, a systematic approach can be suggested to locate optimum location of such priority strategies in the network through an optimization process. Therefore, a number of optimization tools are developed in this study and are introduced and elaborated in Chapter 8.

8. Network-wide optimization of Transit Priority Strategies

In former chapters, a wide range of priority strategies were developed and evaluated across isolated intersections, corridors, and grid network examples. TSP performance was observed in different circumstances and settings, and a need for a systematic approach for their deployment was highlighted. It was also shown that in a network-wide perspective, priority strategies can have significant impact on total transit travel time and thus their effect on travellers can be extended to the whole network. Consequently, developing an optimization method to find the optimum locations of priority strategies was suggested as a seminal step in this realm. This chapter is dedicated to develop such optimization tools. Firstly, a simulation based optimization method to find the location of transit priority strategies is presented. The methodology is elaborated and applied to a numerical example. This method is then followed by forming an analytical optimization tool which is relying on the approaches presented in sections 4 and 7 of this study. It is shown how the method can be used to optimize the combination of strategies at intersection (by TSP) and segments (by TPL) simultaneously. These optimization modules are relying on metaheuristic algorithms (Particle Swarm Optimization) methods that is validated by an analogy to enumeration methods.

Figure 8-1 depicts the relation of this section to other parts of this study.

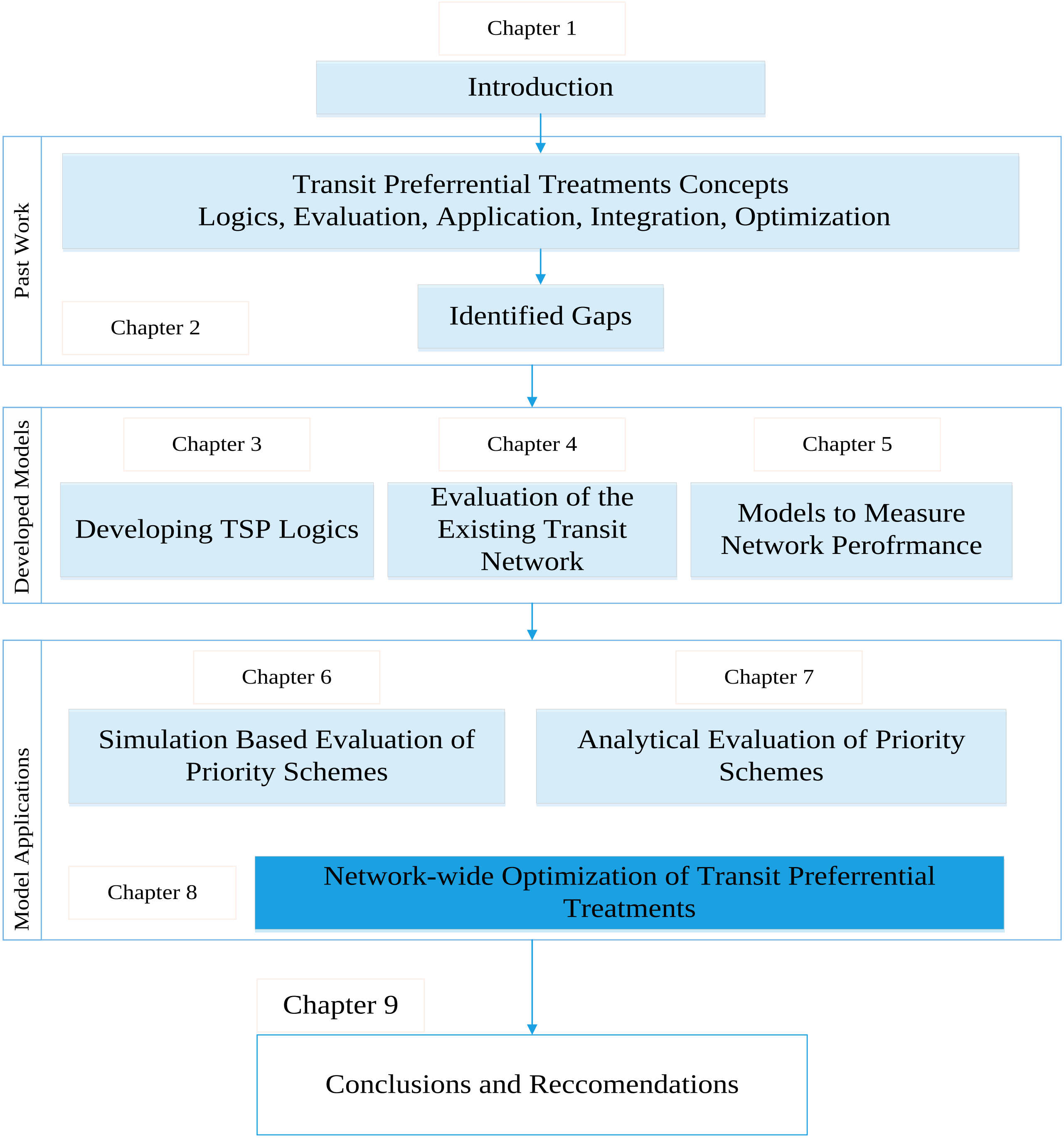


Figure 8-1 Thesis outline and highlighted current chapter

8.1. Simulation Based Optimization of Transit Signal Priority

In this section, a simulation-based optimization method is presented, aiming at finding the optimum location of TSP strategies in a network. Such a framework reflects the effect of TSP strategies on every single individual (i.e. bus or car passenger) and thus measures travel time value and variability changes in different scenarios. After elaborating the methodology and the mathematical formulation of this method, the basic components of the method is discussed and it is shown how simulation based evaluation method and the searching algorithm are developed and integrated together to form an optimization framework. The model is then applied to the grid network example that was used in former chapters to find optimum locations of TSP there.

8.1.1 *Methodology*

The proposed framework consists of three main modules: a measuring of performance(evaluation) formulation, microsimulation model, and a searching algorithm(Figure 8-2). The evaluation method is presented in chapter 4 of this study and simulation based model was discussed in chapter 6 as well. this section shows how these two modules along with the searching methodology are integrated together to optimize the location of transit priority strategies in a network. Numerical example of the next section shows the application this model to a network.

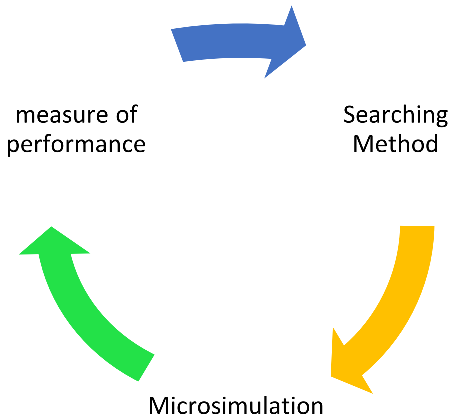


Figure 8-2 Proposed framework for TSP location optimization problem

To reflect the impact of TSP deployment, a generalized cost function was proposed and presented. This function considers both travel time value and reliability as measures of performance. Consequently, using buses and cars travel time values as inputs, for any candidate priority scenario (i.e. location and type of priority strategies in the study area), a measure of performance can be calculated. The inputs of the module are the travel time records of the vehicles for each mode and origin-destination pair, post-processed to obtain vehicle travel time value and deviation throughout the network. These input data were extracted from a microsimulation model. In this study, the microsimulation model was developed using VISSIM microsimulation package (PTV, 2013), a behaviour-based discrete traffic simulator that can be implemented to evaluate transportation policies and scenarios. Chapter 6 of this dissertation was dedicated to the implementation of priority strategies in microsimulation models. In order to identify the optimum location of priority strategies in the network, a systematic searching approach is required to be developed where different scenarios can be initialized, tested using microsimulation, and evaluated. To this end, firstly a systematic optimization module should be developed to perform these tasks in an automated way. In addition, while the trivial enumeration based approach can be implemented for small size problems, with increase of the network size (searching space), more efficient algorithms are necessary to search the optimal solution. The optimization module and its connection to other elements is presented in the next section.

Optimization Module

Figure 8-3 is a schematic holistic view of the proposed search methodology. In this approach, after initializing the search algorithm (optimization parameters), a set of candidate solutions are defined. For each scenario, signal setting parameters are updated, and a set of microsimulation runs are performed. Results obtained from the simulation are then processed and the measure of performance for each candidate solution is calculated using the proposed model. This measure is then reported to the searching algorithm as the objective function, enabling the algorithm to generate new candidate solutions. This process is iterated until a defined stopping criterion is met.

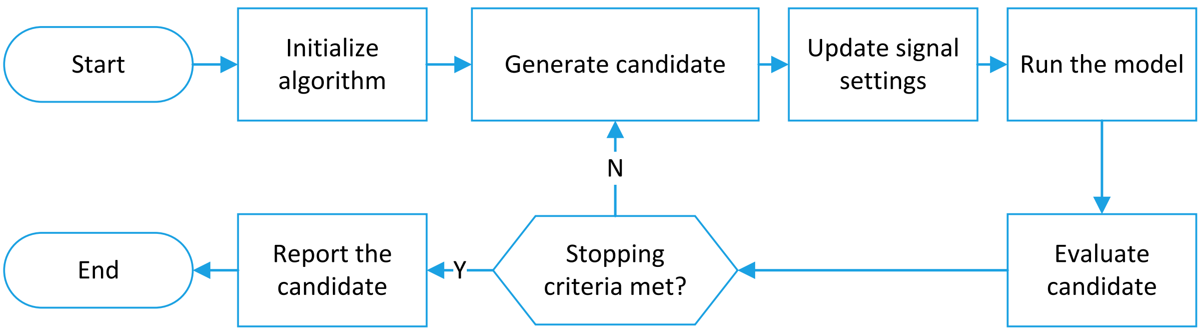


Figure 8-3 Flowchart of the searching methodology

Considering the combinatorial nature of the problem and high computational cost of evaluating TSP scenarios using a microsimulation model, utilizing an efficient search method is required. Using metaheuristic algorithms is known as a viable approach for optimization of complicated problems (Engelbrecht, 2007). Over the past few years, application of metaheuristic algorithms in engineering problems has attracted researchers' attention. Swarm intelligence is a branch of such methods, which is based on the study of individual's behaviour in various decentralized systems(Teodorović, 2008).

To solve an optimization problem using metaheuristic models, three requirements should be met. Firstly, the variables that we seek to optimize should be encoded to be able to be read by the searching algorithm. Depending on the defined problem, the variables can be continuous, discrete (integer values), or binary (0 or 1). The variables to define optimum locations of the TSP strategies can be considered as a binary value. In other words, the decision variables are a string of binary values with the size of total number of priority strategies that can be deployed. The values of this string would be

1 for the intersections in which TSP strategy will be deployed. The second task is to be able to evaluate every single scenario. Indeed, the microsimulation module should be able to take the encoded solution and return the measure of performance as the objective function. Calculated objective function for a given scenario should be unique (i.e. the algorithm should produce a unique answer for a given input) . Finally, we need an optimization tool to be implemented to search for the optimum solution. This module can be considered as a black box that should be linked to the encoded candidate. Through an iterative process, a directed stochastic search is performed to evaluate different scenarios and find the optimum combination among them.

The Particle Swarm Optimization (PSO) algorithm is one of the most popular swarm-based methods which has been successfully utilized in different transportation problems (e.g.Shafahi and Bagherian, 2013, Bagherian et al., 2013, Lv et al., 2012), as presented in Chapter 2 of this thesis. The binary version of this algorithm (Kennedy and Eberhart, 1997) is implemented in this study. In this method (hereafter BPSO), instead of updating the velocity of the particles, the probability of changing their location is updated. Consequently, the velocity equation 2.4 remains unchanged whereas equation 2.5 changes as below:

$$\begin{gathered} if\ \Big(r < S\big(v(t+1)\big)\Big) \rightarrow\ x^i(t+1) = 1 \\ else\ x^i(t+1) = 0 \end{gathered} \qquad \text{8-1}$$

Where r is a generated random number in (0, 1) interval and $S(x)$ is the sigmoid logistic transformation function. The mathematical formulation of the TSP locating problem was then linked to the BPSO algorithm. In this regard, for each intersection phase, a string of binary values was defined, representing all the possible movements that can benefit from a TSP deployment. The problem variable is defined by concatenation of the binary strings:

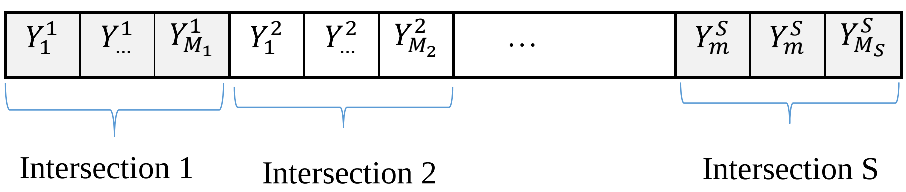


Figure 8-4 Encoding of TSP locating problem for BPSO algorithm

Once the microsimulation module is linked to the optimization tool, the search procedure can be performed. Note that BPSO algorithm can be replaced by other binary searching algorithms as long as the problem is encoded appropriately for that algorithm. A case study example is presented in the next section, elaborating the application of the developed framework.

8.1.2 *Numerical Example*

This section applies the proposed optimization framework to a numerical example. To fulfil this task, a code was developed in the .Net environment using C# programming language. All the runs were performed on a desktop computer with an Intel® Core™ i7 3.4-GHz processor and 16 GB of installed memory (RAM). The stopping criterion was assigned to be met when no improvement was observed in 50 iterations. The maximum speed for microsimulation was assigned when the simulation resolution was set to 3 time steps per simulation second.

To examine the performance and capabilities of the proposed framework, it was applied to a grid network of Figure 8-5, consisting of 12 nodes, 24 links, and 9 intersections. Three bus routes were defined such that TSP conflict may occur at two of the intersections. The links were defined as four-lane (two lanes per direction) segments of 400 meters. All the bus stops were defined to be at the far-side of the intersection. The network was modelled in VISSIM 6.0 microsimulation software.

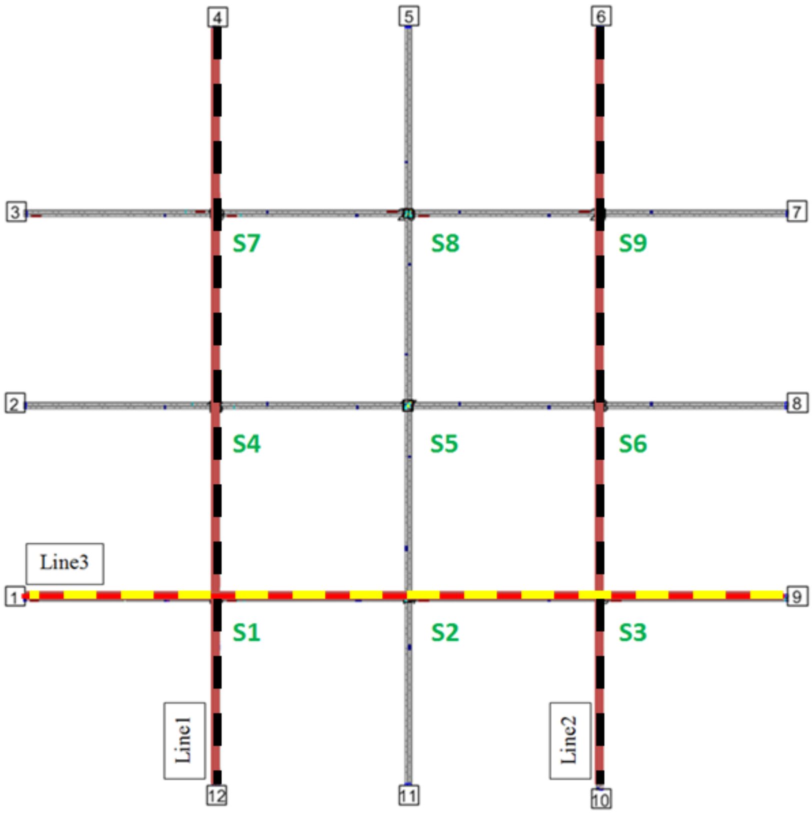


Figure 8-5 Network layout of the example study

Encoding the Model

To encode the problem for the optimization module, two intersections where no bus was approaching (*S5, S8*) were excluded from the searching space, thus a total of seven intersections, two with possible multiple TSP requests were defined as the search space. In addition, bus routes in both directions were both running in the through movements and can have been served in the same phase. Consequently, each route can be served by one TSP at each intersection. Consequently, having seven intersections, two serving two routes, the optimum solution was selected from a search space comprising 2^9 scenarios.

Optimization Results

The proposed objective function of this study considered the impacts of TSP in terms of car and bus travel time value and variability. A set of auxiliary objective functions were defined to investigate the effect of this generalized cost function and compare it with the other approaches. Minimization of average bus travel time (objective 1), total travel time (both cars and buses- objective 2), bus variability (objective 3), bus travel time and variability (objective 4), and bus and car travel time value and reliability measures (objective 5) were considered as the objective functions of the optimization problem. Table 8-1 shows the results of the optimization process and TSP impacts considering different objective functions. For each objective function, the optimum combination was obtained and the effect of deploying TSP was measured as the percentage of changing travel times and variability measures, compared with the base scenario. For the proposed objective function (objective 5), the optimum TSP combination for the given network consisted of six TSP equipment in five intersections, as shown in the table. In addition, as a result of introducing a bus reliability index (objective 3- objective 5), the average bus travel time saving was slightly less to achieve a higher level of improvement (8% more) in the measure of reliability. Considering bus variability as the only measure of performance could make the transit service up to 26% more reliable than the base (no TSP) scenario. Regarding the impact of TSP on the vehicular traffic stream, it was generally expected that once the car traffic related elements were included in the objective function, the results demonstrate less negative TSP impacts on cars. Nevertheless, the results showed that for this network and its level of demand, the impact of TSP on vehicular traffic was negligible (less than 0.03% on average travel time and less than 0.76% in variability) and introducing traffic related elements to the objective function did not change the optimum solution. A sensitivity analysis on the demand (and hence congestion level) in the next section shows, however, that this is not always the case.

Table 8-1 Optimization of TSP location problem with different objective functions

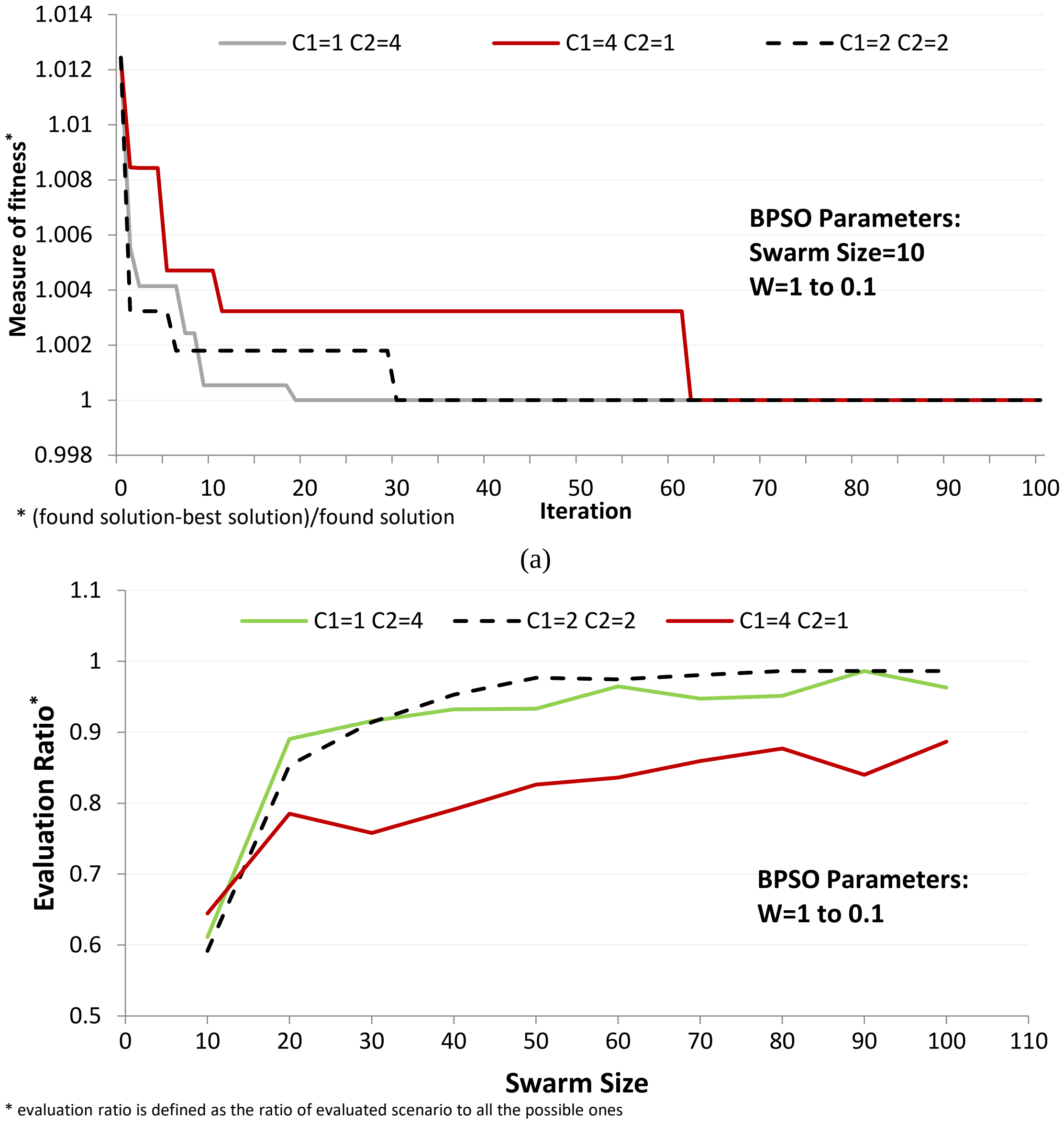
Objective Function	Optimum Combination	Car TT Impact* (%)	Bus TT Impact (%)	Car Reliability Impact (%)	Bus Reliability Impact (%)
objective 1 ($\mathbf{t_b}$)	$1^{1,3},3^{2,3},4,6,7,9$	0.0030	-4.658**	0.296	-14.698
objective 2 ($\mathbf{t_p}, \mathbf{t_b}$)	$1^{1,3},3^{2,3},4,6,7,9$	0.0030	-4.658	0.296	-14.698
objective 3 ($\mathbf{var_b}$)	$1^{1},2,3^{3},5,6,7,9$	0.0296	-4.358	0.772	-26.399
objective 4 ($\mathbf{t_b}, \mathbf{var_b}$)	$1^{2},2,3^{2,3},6,7,9$	0.0295	-4.534	0.753	-23.618
objective 5 ($\mathbf{t_b}, \mathbf{t_p}, \mathbf{var_b}, \mathbf{var_c}$)	$1^{2},2,3^{2,3},6,7,9$	0.0295	-4.534	0.753	-23.618

*impact is defined as $x^{opt}-x^{base}/x^{base}$ where x^{opt}, x^{base} are optimum and base measures, respectively
** max values of each component are reported in bold

Performance of the Optimization Algorithm

To measure the performance of the implemented heuristic algorithm in solving the TSP location problem, an exhaustive enumeration method over whole search space was performed. Consequently, all possible TSP combinations were first simulated and the results were stored in a database. Then the exact solution (the global best TSP combination) was identified by which PSO convergence behaviour could be measured not only for efficiency (how fast the algorithm converged) but also for accuracy (how good the solution was).

Figure 8-6(a) shows the convergence behaviour of the optimization process in reaching the optimal answer for different social and cognitive (i.e. C_1, C_2, respectively) parameters. According to the figure, although different convergence paths were observed for different parameters, the optimal solution was successfully found in all cases. It was observed that in scenarios with a lower swarm size, having a higher C_1 value led to a broader search, thus a higher number of calling the objective function was required. Nevertheless, this was not the case in optimizations with a higher number of particles. In other words, although increasing the swarm size can increase the convergence time, less calls of the objective function may be required (Figure 8-6b). Since each evaluation requires performing a number of simulation runs, well-tuned optimization parameters can decrease the total computational cost of the process. Tuning the parameters for the defined problem will be performed as an extension of this research.



(a)

(b)

Figure 8-6 Convergence behaviour of the optimization algorithm (a) and the effect of swarm size on the performance of the algorithm (b)

Effect of Changes in the Network Congestion

In the numerical example, the traffic demand was assumed to be 10 vph for each O-D pair and a headway value of 5 minutes was assumed for all bus routes. It is shown how defining the objective functions can change the optimum solution, and the importance of considering a generalized objective function is confirmed. In order to inspect the impacts of network parameters, a sensitivity analyse on the level of congestion and bus frequencies is performed, and the changes in results are identified.

Sensitivity Analysis on Congestion Levels

A sensitivity analysis is performed on the level of congestion to see its impact on different terms of the objective function. To perform this analysis, a scale factor for the defined O-D demand array is defined. The optimization process is then performed, seeking the minimum objective function. As can be seen in Table 8-2, the number of prioritized sections in the optimum solution is the same for lower levels of congestion while different measures follow the same trend. However, once a greater demand is imposed on the network, fewer TSP strategies are suggested as the optimum solution. In addition, the impact on private cars is more crucial, thus the optimization module introduced solutions that favoured passenger cars. In other words, the bus prioritization task of TSP was sacrificed to mitigate passenger cars travel time and variability. The weighting parameters can be used to control the level of bus prioritization.

Table 8-2 The effect of congestion on the performance of TSP deployment

O-D Demand(vph)	Optimal combination	Car TT Impact(%)	Bus TT Impact(%)	Car Reliability Impact(%)	Bus Reliability Impact(%)
10	$[1^{1},2,3^{2},4,6,7,9]$	0.03	-4.53	0.75	-23.62
20	$[1^{2},2,3^{2,3},6,7,9]$	0.12	-4.63	1.22	-25.79
30	$[1^{2},2,3^{2,3},6,7,9]$	0.13	-4.44	0.35	-22.80
40	$[1^{1},2,3^{2},4,6,7,9]$	0.20	-3.83	1.40	-27.97
50	$[1^{1},3^{2,3},4,6]$	-0.90	-3.59	-1.58	-18.69
60	$[2,3^{3},4,6]$	-1.24	-2.93	-1.52	-10.45

Sensitivity Analysis on Bus Frequencies

To identify the impact of bus headway on TSP performance, a simulation model was developed for different levels of bus frequencies. The model was developed for four different headway values (2, 3, 5, and 10 minutes) and critical impacts of TSP on every element were captured (Table 8-3). It was observed that at a lower level of transit frequencies, a higher level of reliability was achievable. While the maximum improvement in the measure of reliability was around 12% in 2 minute headways, 30% improvement was achievable if the headway was 10 minutes, possibly due to less probability of having multiple TSP requests. This trend could not be seen in the measure of bus travel time saving where a slight decrease in this index was observed. Regarding the negative impacts of TSP on the traffic state, more frequent services imposed slightly higher impact on passenger cars (less than 0.4% and 1.4% for travel time value and reliability indexes, respectively).

Table 8-3 Potential impact of bus headway on network-wide TSP performance

Headway (min)	**Bus TT Saving (%)**		**Bus Var (%)**		**Car TT Impact (%)**		**Car Var Impact (%)**	
	Best	Worst	Best	Worst	Best	Worst	Best	Worst
2	-3.6	1.6	-12.3	6.6	-0.6	0.3	-3.3	0
3	-3.9	1.2	-22.1	2.1	-0.2	0.3	-3.4	0
5	-2	0.2	-26.4	5.1	-0.3	0.2	-4.4	0
10	-2.4	0.7	-30.3	8.5	-0.2	0.1	-4.7	0.4

8.1.3 *Remarks on Simulation Based Optimization of TSP*

This study presented an optimization framework to assist decision-makers to select the best potential locations for deploying TSP strategies. In the developed mathematical formulation for the evaluation of TSP strategies, the objective function was minimization of the travel time and its variability for both buses and cars. This framework was found to be applicable to grid networks and can consider the possible interdependency of signal settings at neighbouring intersections, allowing practitioners to implement different TSP logics or settings at a network level. A heuristic algorithm (BPSO) was implemented and linked to the model to perform the search process. The model was then utilized to solve a case study example. The impacts of TSP on vehicular traffic were shown to be crucial only at higher levels of congestion. In addition, it was shown how the impact of TSP on different parameters varies at different bus frequencies. The framework shows the abilities of the proposed framework in helping decision-makers plan for TSP deployment from a small network-wide perspective.

Despite the detailed results and validity of the searching algorithm, computational cost of the model was raised as the main concern of network-wide simulation-based optimization of priority strategies. Indeed, microsimulation models are yet costly to be implemented as the evaluation model of a network level optimization process where only rough insight through the network is sufficient. In addition, integration of TSP and dedicated lanes hugely increases the computational cost of doing an optimization. To address these issues, an analytical method is introduced as the evaluation method, with the aim of having a more efficient optimization model thus be able to evaluate a wider range of priority strategies. The next section elaborates the developed analytical optimization method to address simulation based shortcomings.

8.2. Analytical Optimization of Transit Priority Strategies

The second part of this chapter is dedicated to propose an analytical optimization approach which is relying on the 'adjustment factors' method, presented in Chapter 7. In this regard, in a fixed computational time, significantly more number of scenarios could be evaluated with the expense of having aggregated calculations to derive travel time values only. As a corollary of this improvement, integration of TSP and Transit Priority Lanes (TPL) at the network level can be optimized for a given network, using the developed analytical approach to evaluate the effect of TSP and TPL integration in a network. This method can be used to evaluate a set of candidate scenarios as an optimization problem where the objective is to find the optimum location of priority strategies in the network. This section is dedicated to present a systematic optimization tool for this goal. Firstly, the method is developed to optimize TSP strategy locations and then integration of TSP and TPL location are targeted to be optimized.

8.2.1 *Optimization of TSP Strategy Locations in a Network*

A common problem in network wide analysis of TSP realm is to find optimum location of TSP equipment to reach the best solution of a defined objective function. To this end, the mathematical formulation of the problem was defined as below:

$$\boldsymbol{Min}\, Z(X) = \sum_{i=1}^{I} (\alpha\, O^c\ t_{X,i}^c f_{X,i}^c\ + \beta\, t_{X,i}^b p_{X,i}^b) \qquad 8\text{-}2$$

Where Z(X) is the objective function for each scenario X, $i \in I$ are the set of links in the network, O^c is the car occupancy value, $t_{X,i}^c$ is average car travel time of link *i* when priority scheme *X* is applied, $f_{X,i}^c$ is the flow rate of link *i* during the analysis period, $t_{X,i}^b$ is bus travel time of link *i* when priority scheme *X* is applied, and $p_{X,i}^b$ is total number of bus passengers traversing link *i*.

The decision variable (*X*) is a binary vector, stating whether an approach is equipped to TSP or not. The size of the decision variable of this problem equals to the number of links, although it can be practically abstracted to only candidate intersections to implement TSP on a specific phase. The size of the searching space is consequently 2^n where *n* is the number of candidate approaches for TSP implementation. Since in the developed measuring approach each scenario can be solved in a shorter amount of time than the microsimulation based methods, enumeration method is feasible to be used thus all the scenarios would be independently evaluated and the global optimum solution can be found. The weighting parameters (α, β) can reflect the share of public transport or adjust the importance of prioritizing buses over private cars.

For the defined small grid network, the exhaustive enumeration method was used to find optimum locations of TSP implementation on whole the network. In this example, nine candidate approaches form 512 scenarios for TSP implementation. Figure 8-7 shows the results of optimization process in an undersaturated condition and its sensitivity to the ratio of transit ridership ratio. For different levels of bus to car passengers' ratio, Objective function and the number of suggested TSP implementations are identified. Results confirm that with an increase in the ratio of bus passengers, TSP implementation can improve total travel time of the passengers. In addition, such increase urges more prioritization scenarios to be implemented in the network. For the grid network, while no TSP is suggested when transit ridership is zero, for bus passenger ratio of up to 24%, a scenario with four equipped intersections was suggested.

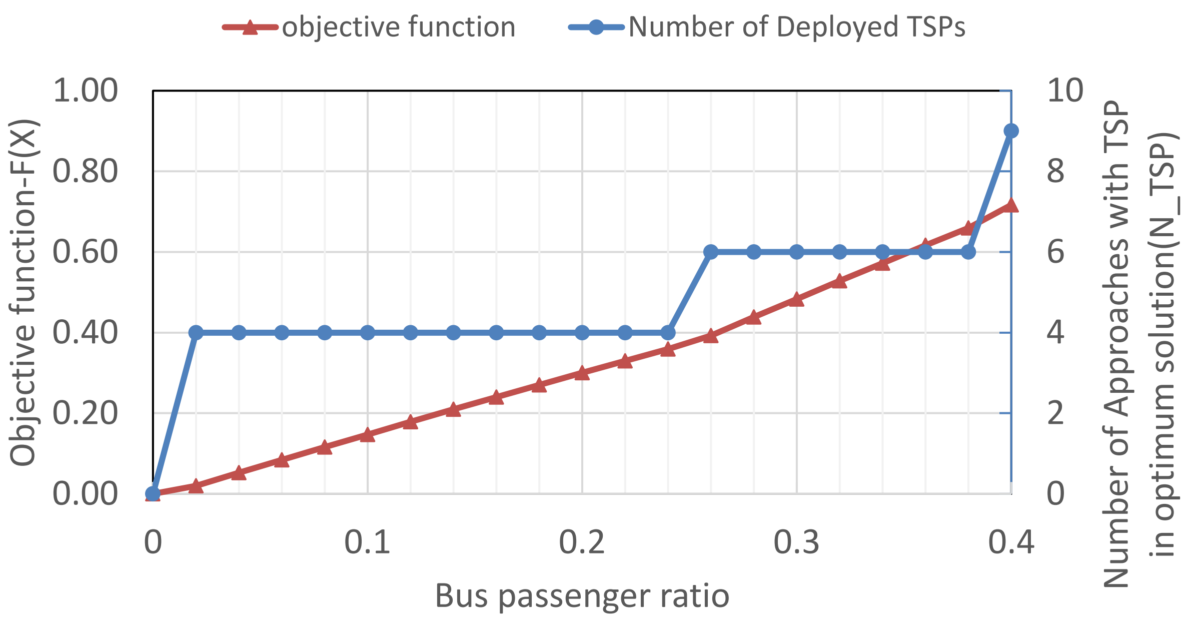


Figure 8-7 Analytical TSP locating optimization results

Figure 8-8 shows the optimal solution effect on the network for a 15% bus passenger ratio. As can be seen, in this example, a multiple TSP strategy is suggested for both intersections that bus routes are intersecting. When the bus passenger ratio exceeds 0.24, intersections 19 and 21 (denoted by yellow circle), would also be selected to introduce TSP on. Finally, in cases where buses have a much higher priority, all the intersections in which a bus was present were selected as optimal solution (i.e. TSP in all nine approaches).

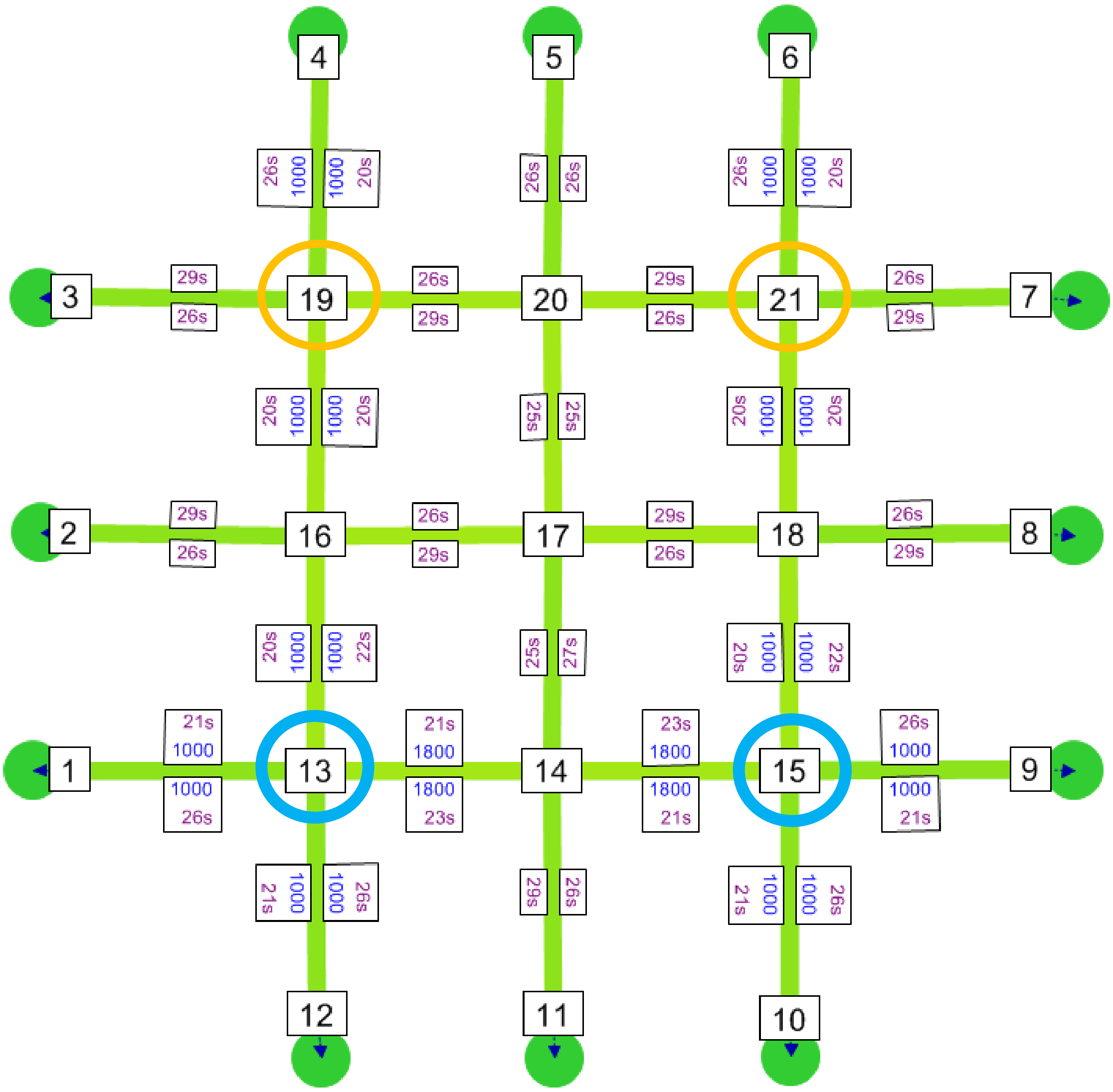


Figure 8-8 Selected intersections for TSP implementation

8.2.2 *Analytical Optimization of Integrated TSP-TPL Scenarios*

TSP strategy can be integrated with other preferential strategies such as bus dedicated lanes to achieve maximum transit performance if required. Indeed, integration of TSP and TPL policies in a network level study can have significant impacts on the delays of buses and cars. In one side, bus delays can be mitigated and on the other side such strategies can cause significant delays on the competent modes. Looking for the best set of links and intersections to employ these strategies on, the evaluation method was integrated to a searching algorithm procedure. The methodology to integrate TSP and dedicated lanes is presented in the next section.

Assumptions

To be able to evaluate a scenario, it is necessary to encode each solution so as to have a unique identifier for them. To fulfil this task, the following assumptions were firstly made:

1. An approach can have three statuses: Do nothing, TSP only, and coupled TSP-TPL.

2. Dedicated lanes are bidirectional and affect the capacity of both directions of a link.
3. When TSP is applied to an approach, all the approaches in the same phase will also be granted for TSP
4. For each intersection, the effect of TSP and TPL strategies are independently derived and introduced using adjustment factors

The first assumption considers TPL as a higher class of preferential strategies thus whenever it is suggested, it is assumed that TSP is already enabled. This is based on the results obtained from Chapter 7, implicitly confirming that TPL only cannot be the optimal solution in any level of congestion. Finally, as discussed in chapter 7, it is assumed that for each intersection the TSP and TPL impacts can be quantified through the three calibration factors. Note that although forming such preferential strategies may let the operators expand the system by increasing fleet or changing the bus routes, it is assumed that no further decision may be made along with such strategies. In other words, The only imposed operator cost is the cost of equipping intersections to the TSP strategies (if any) and construction of bus dedicated lanes.

Decoding TSP-TPL Scenarios

The main objective of developing the presented method of TSP-TPL integrated optimization is to minimize the overall delay of passengers, from both private cars and buses, by TSP and TPL provision. To be able to perform the minimization procedure, the scenarios should be uniquely encoded for the searching algorithm. Similar to the binary encoding that was suggested for TSP optimization, TSP-TPL scenarios are also encoded via binary strings.

Figure 8-9 shows a simple representation of encoding TSP and TPL scenarios in a network. Assuming link numbers to be sequential for each direction, for a study network with *n* links, *n/2* and *n* binary values was used to encode all the scenarios including infeasible (e.g. TSP without approaching bus route) ones. Consequently, a searching space of $2^{1.5n}$ is formed to search for the optimal combination. Given the small grid network, for example, 2^{72} solutions may be formed as the searching pool. For the sake of generality and scalability of the model (e.g. possibility of adding a new bus route), we formed the candidate binary code as an encompassing string. In practice, however, many of the links have no defined route or have duplications (e.g. TSP deployment in approaches in same signal phase) and thus their corresponding TSP or TPL parameter can be defined using a zero constant. Applying such a constriction to the example network, nine TSP decision parameters and twelve TPL ones form a searching pool of 2^{21} solutions. Through the searching process, as stated in the first assumptions of this model, solutions where a link is suggested to have TPL with no TSP will be treated as infeasible answer as well. Through a projection procedure, the binary string would be converted to a set of decisions y_i^{TSP}, y_i^{TPL} that can define the implemented scenario on each link.

Consequently, the link data can be updated consistently for evaluation purposed. While y_i^{TPL} is a binary value, indicating whether a line of the link *i* is allocated to buses only, y_i^{TSP} can be any of introduced scenarios (i.e. base, single TSP, multiple TSP, Crossing a prioritized movement).

$\overbrace{\hspace{6em}}^{\text{TPL Parameters}}$ $\overbrace{\hspace{6em}}^{\text{TSP Parameters}}$

1	2	3	4	…	…	n-1	n	1	2	3	4	…	n-1	n
x1		x2		x3		xn/2		u1	u2	u3	u4	…	un-1	un

1	2	3	…	n-1	n
y_1^{TSP}, y_1^{TPL}	y_2^{TSP}, y_2^{TPL}	y_3^{TSP}, y_3^{TPL}	$y_{...}^{TSP}, y_{...}^{TPL}$	$y_{n-1}^{TSP}, y_{n-1}^{TPL}$	y_n^{TSP}, y_n^{TPL}

Figure 8-9 Encoding candidate TSP and TPL solutions in a network

Even with the smaller searching space, making the search procedure to check every single solution is practically infeasible. This is mainly because the scenario evaluation (initializing the model, updating parameter, performing the assignments, post-processing data and calculation of objective function for each scenario) is computationally costly and takes a couple of seconds to be performed. Consequently, running all of the scenarios can take an enormous amount of time. It is worthwhile to mention that with the integration of TPL to TSP in an optimization problem, the searching space exponentially increases. For instance, for the small grid network with nine candidate approaches, the candidate solutions are augmented from 512(2^9) solutions to 262144(4^9) ones, causing an extraordinary increase in computational cost of enumeration methods to find optimal solution. Indeed, since each scenario can be evaluated in around 10 seconds, introducing TPL changes increases the required computation time from 85 minutes to more than 30 days. To address this issue, two approaches were developed. Firstly, the searching space was fragmented into a set of smaller searching spaces that are likely to contain the global optimum. Secondly, metaheuristic algorithms were implemented to do a search through all of the candidate solutions. These evolutionary algorithms were firstly validated through the answers obtained from the decomposed search spaces (of the first method) and then applied to perform a global search over the entire set solutions. The next two sections are devoted to searching methods used to solve the given TSP-TPL locating problem.

Disaggregated Searching Method

The search space of the given problem is comprised of deciding whether to use TSP in any of nine intersections and develop TPL in any of the 12 candidate bidirectional links. The following scenarios are defined as the subsets (potentially elite) of the whole searching space:

1. All intersections are equipped with TSP, search for the best TPL locations
2. TSP is not implemented, search for the best TPL locations
3. TPL is used on all candidate links, search through optimum TSP location
4. TPL is not permitted, search only for optimum TSP locations
5. TPL is permitted along the lines (three lines), search for optimum TSP and continuous TPL location

Figure 8-10 shows how these five scenarios can cover the searching space. It can be seen that such decomposition let the search to be performed over the boundaries of searching space.

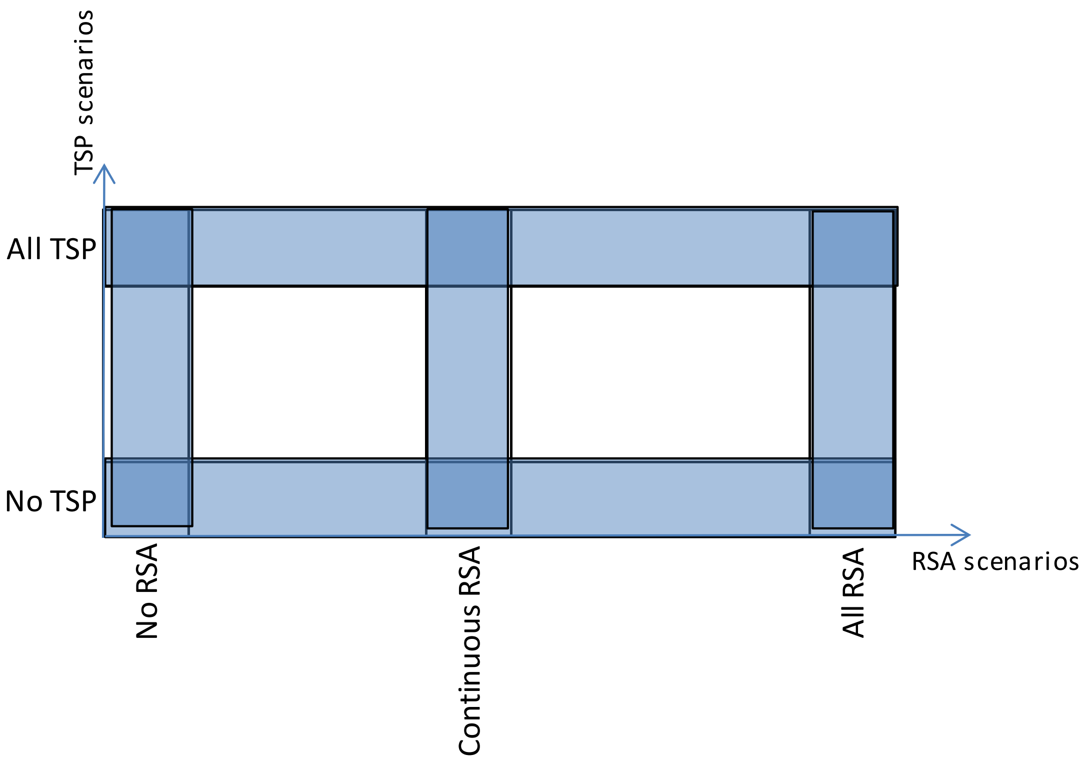


Figure 8-10 Decomposed searching space for TSP-TPL locating optimization

A depth-first search algorithm (Cormen et al., 2001) was implemented to generate all feasible scenarios and the decomposed ones in two different files. The selected scenarios were then loaded as the candidate solutions that were evaluated using the VISUM software. In this example, a constant demand of 250 vph was assumed for each OD pair, reflecting near saturation condition of the network. Transit demand was also assumed to be equal to OD pair demand, as it is not changing the transit travel time (the implemented system assignment module is independent from passenger load and capacity). The weighting parameters were defined to intensify the transit demand and delays against passenger cars.

Figure 8-11 summarizes the results of the greedy search over the critical searching spaces. All the defined scenarios were evaluated using the developed VISUM based procedure. The output of this procedure is the link travel time and demand for both private and public modes. Optimum scenario for each weighting parameter were then obtained through a post-calculation process. It can be seen that with an increase in the weight of PT, optimum solution tends to introduce scenarios with lower transit delay and higher delay for passenger cars. For the given level of congestion, TSP implementation were suggested for all the intersections, regardless the PT weight. However, while no dedicated lane was suggested for the buses when β =1 and β =2, with the increase of the PT weight (β = *12*), the number of dedicated lanes was increased to 12 lines (i.e. making dedicated lanes along all the routes), reaching maximum prioritization for the transit service.

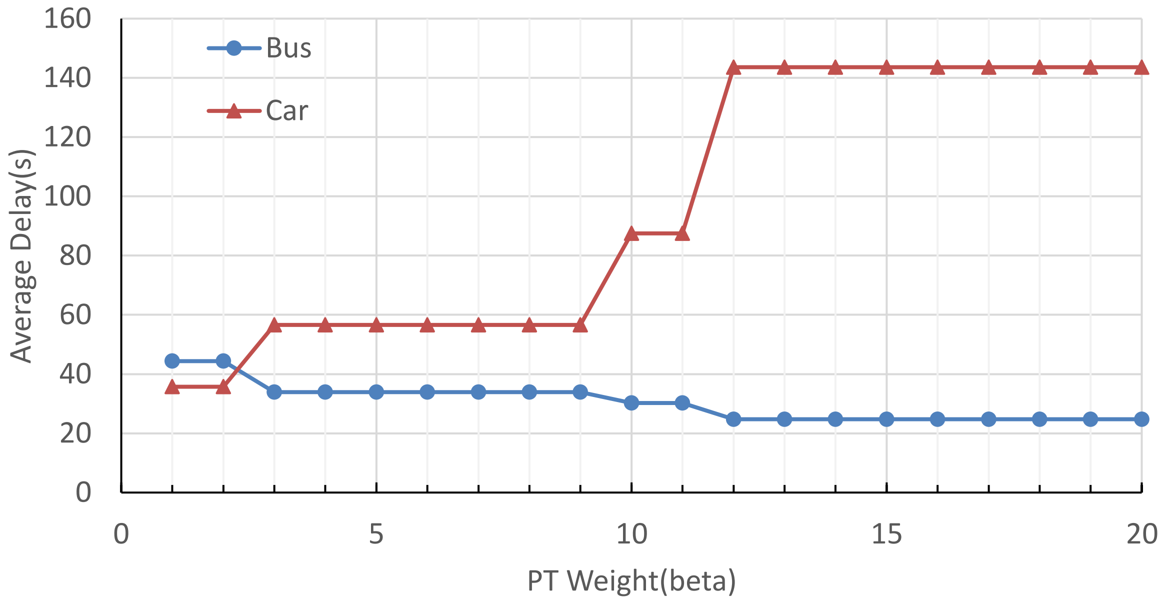


Figure 8-11 Optimum result of TSP-TPL locating problem for different level of transit priority

Optimization Results in Uncongested Regime

The same experiment was performed by reducing the level of demand to *100vph* for each OD pair which represent an uncongested conditions(*v/c<0.6*) throughout the network. It was observed that in this regime, introducing dedicated lanes did not cause a significant improvement in bus operation. Indeed, the developed tool suggested to implement dedicated lanes for all the feasible links. Nevertheless, analysis of the results confirmed that the savings from dedicate lanes consideration is marginal. Figure 8-12 shows the comparison of the objective functions between different demand levels. It can be seen that on the contrary of the former congestion level (OD demand=250 vph), in an uncongested condition, the changes in travel times are almost negligible. Considering the noticeable capital costs of introducing bus dedicated lanes and their potential safety concerns, it can be justified that when the improvements are marginal, dedicated lanes may not be useful.

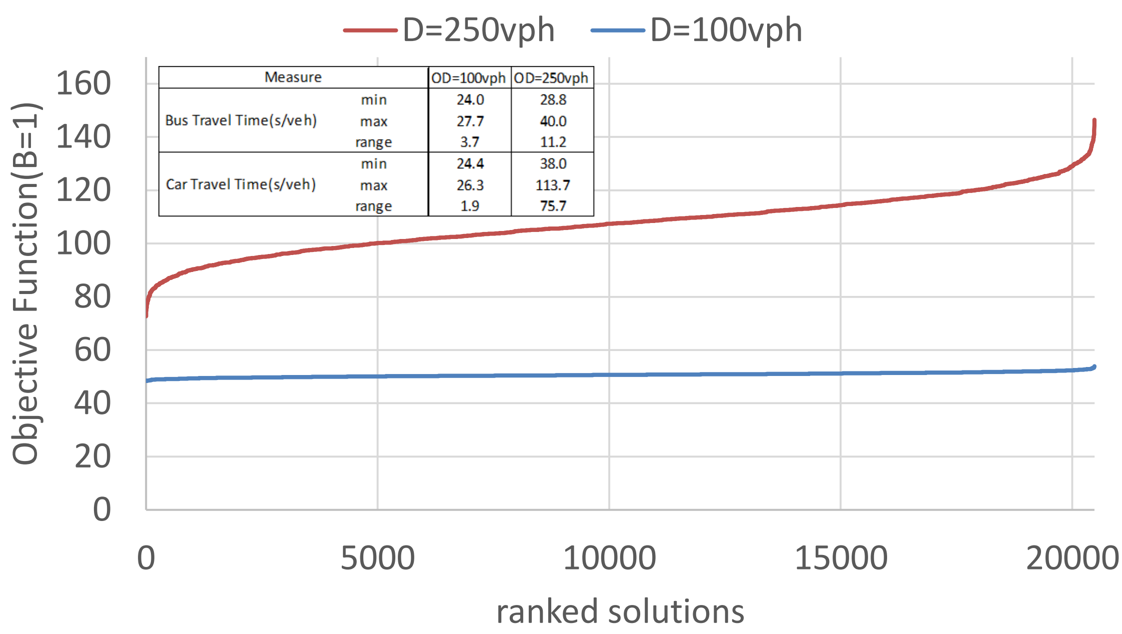


Figure 8-12 The changes in objective function based on demand

The results for this scenario suggests TSP implementation for all the intersections. This output is consistent with the former studies on TSP performance (e.g. Smith et al., 2005) which have shown that TSP has the highest performance in low levels of congestion.

Using BPSO as the Searching Method

The enumeration method used in former section was replaced by a BPSO algorithm (presented in chapter 8.1.1), aiming at improvement in searching performance.

Figure 8-13 shows the converging trend of BPSO over successive generations for TPL-TSP implementation problem. Using the tuned BPSO parameters (C1=1, C2=4 and Swarm Size=30), the algorithm was integrated to VISUM to find optimum location of TPL-TSP locations. Having ten replications with different random seeds, it was observed that in eight scenarios the optimal solution was found using BPSO algorithm. In all of the searching procedures, however, after at most 26 iterations (see Figure 8-13) the best 'found best' solution had less than 4% deviation from the 'global best' solution(f(x)=72.65). In two of the experiments, the algorithm had a premature convergence behaviour in two other scenarios and were trapped in sub-optimal solution (75.47). This is actually one of the disadvantages of the solutions obtained through metaheuristic optimizations (Engelbrecht, 2007).

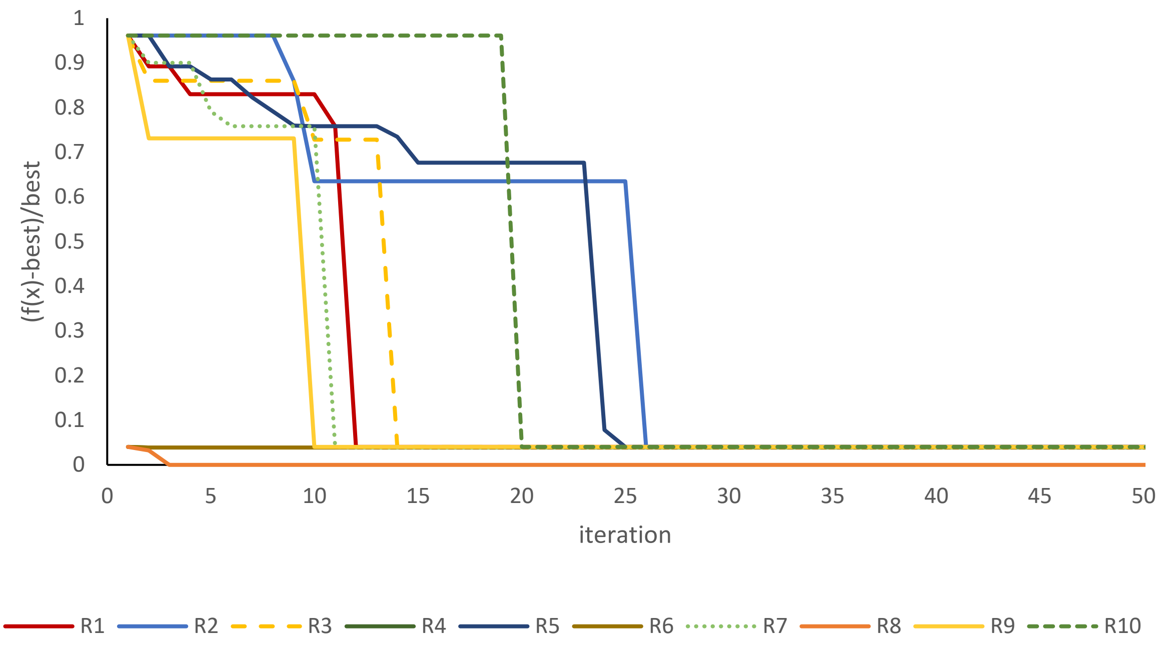


Figure 8-13 Convergence behaviour of BPSO algorithm for TSP-TPL locating problem

Remarks on Analytical Optimization of TSP-TPL Scenarios

In this section, a new analytical approach is presented to evaluate preferential strategies. In this method, TSP effect was modelled using a set of adjustment factors for every single approaching link in the network, obtained from either observations or simulation based studies. The effect of bus dedicated lanes was also modelled by applying an adjustment factor in the selected link's capacity, aiming at separating the buses from the other modes to avoid congestion along the link. Considering the total travel time or delay as the objective function a method to integrate the evaluation module to searching algorithms was presented. This method is used to search for optimal location of priority strategies for a given network and targeted prioritizing weight. The route choice module that is implemented to find minimum car travel time in equilibrium condition could adjust the car routes for every road space allocation along the network. It is shown that the method can find the optimal location of the preferential strategies with a significant amount of saving in computational costs than simulation based method, with the expense of having aggregated measures of travel time values.

8.3. Chapter Summary

Confirming the necessity of a systematic approach to locate priority strategies, this chapter presented the developed optimization framework to assist decision-makers in selecting the best potential locations for deploying priority strategies in a network. To this end, two approaches, namely the simulation-based and analytical ones were presented. The simulation-based approach was developed through an integration of VISSIM microsimulation package and a binary version of particle swarm optimization (BPSO) algorithm, aiming at minimizing travel time value and variability of public and private vehicles. It was shown that despite the detailed results and validity of the searching algorithm, computational cost of the model was raised as the main concern of network-wide simulation-based optimization of priority strategies. Consequently, the simulation core was replaced by analytical tools to expedite the speed in evaluation process. In addition, the objective function was to minimize total bus and car travel time values. The significant amount of saving in computational costs of the model empowered us to expand the priority strategies to integrated signal priority and transit priority lanes. Promising results confirm that the suggested framework can be implemented by a decision maker to introduce priority strategies to their analysis and locate the priority strategies in the network.

9. Conclusions and Future Research

The main goal of this research was to develop and validate a planning tool to evaluate and design priority schemes at the network level. Developing the evaluation, and design modules, the tool can help practitioners and planners to find the best strategy considering all the system-wide impacts of TSP implementation at intersections. Furthermore, this tool would be able to reflect TSP deployment when it is combined with planning-level solutions such as exclusive bus lanes. The summary of the thesis, its contributions to the existing knowledge and suggestions for future research in this area are presented here. Figure 9-1 depicts the relationship of this section to the entire study.

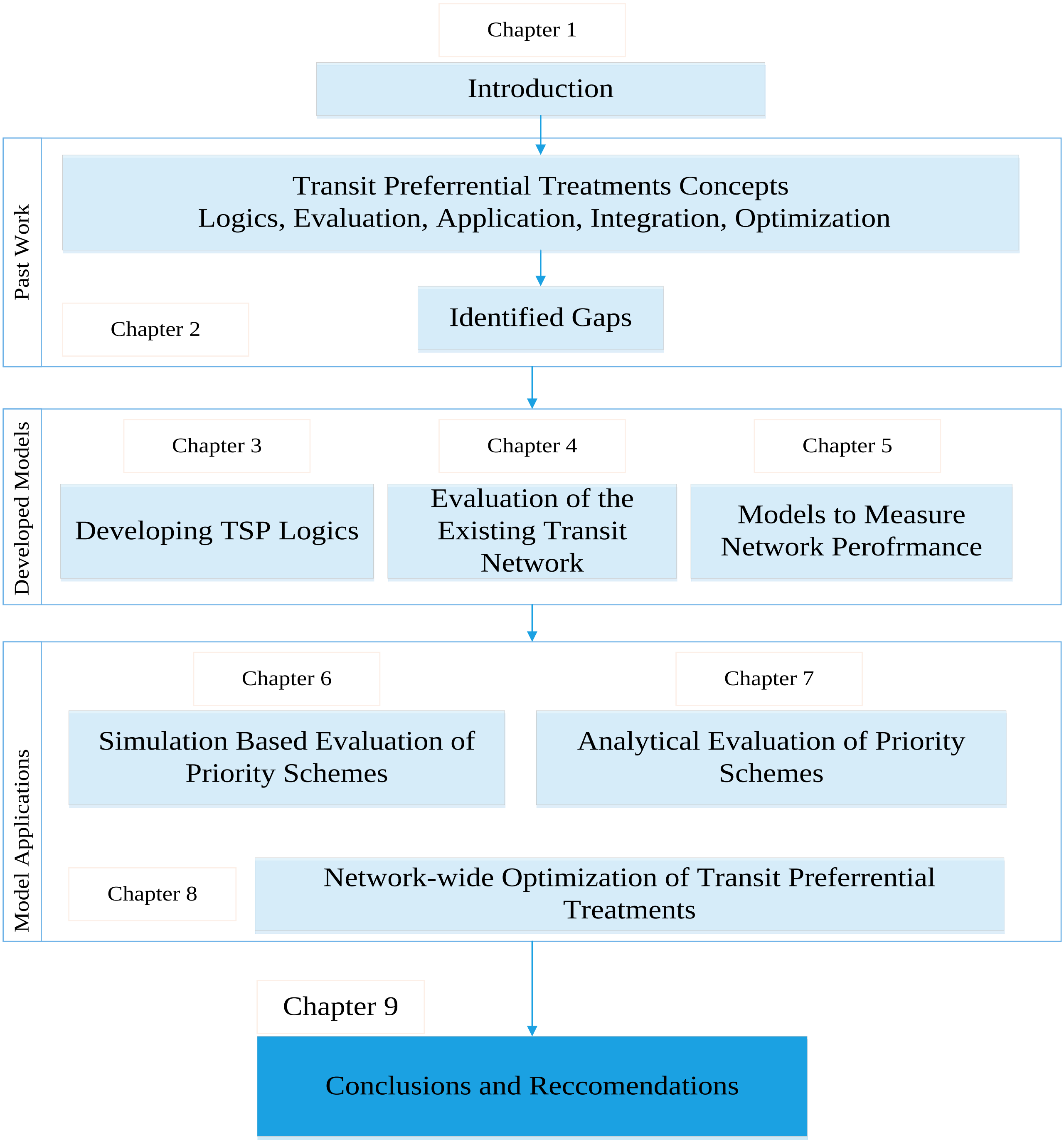


Figure 9-1 Research structure and the thesis chapters

9.1. Summary of the Research

The first part of this research (Chapter 2) was allocated to review the literature and identify the gaps in the existing practices on transit priority concepts. After a review on the existing preferential treatments, logics, measures of their performance, and their design and optimization approaches, a set of gaps were identified for possible further research. The identified gaps were potential improvements on the development of the existing TSP logics, a need to develop a measure of performance to reflect bus and car travel time value and reliability simultaneously, a need to explore the network status and identify candidate segments and services for prioritization, when to introduce efficient method to perform a network-wide analysis and design of priority schemes, and more importantly integrate TSP and TPL in macro-level studies.

Through the second part of this study (presented in Chapters 3-5), the fundamental models in this realm were developed. Firstly, logics and methodologies to integrate TSP into simulation models were developed (Chapter 3). In this chapter, the developed and implemented preferential treatments at intersections were introduced and validated. Following a review, the method to develop TSP logics was introduced, followed by validation of a set of TSP.A V2I based logic was also developed whose aim is to reduce bus fuel consumption by coordinating bus dwell time and signal timings.

In Chapter 4, measures of performance were developed to evaluate the effect of deploying priority schemes. The developed metrics to measure the performance of different preferential treatments was reviewed. These measures were categorized into simulation based and analytical approaches. In this regard, simulation based methods rely on available disaggregated data of vehicles, and thusreflect the changes in variability of travel times. On the other hand, an analytical tool was developed to capture the delay in planning studies. Furthermore, the model was implemented to estimate the amount of fuel consumptions.

One of the key tasks was to identify the services with unexpected delays and the segments along their route for possible application of priority strategies. To answer this need, a practical approach to observe the network condition and identify prone areas to transit priority deployment was presented in Chapter 5 of this study. A comprehensive tool to estimate the passenger-oriented measure of transit service reliability was presented. This method included two metrics to reflect both predictability and punctuality of the network in the selected spatial-temporal window, measured at the passenger journey level. The methodology was presented along with the data analytics procedures. It was shown how transport agencies and operators can identify the locations and times where maximum person-delay may occur so as to deploy transit priority schemes effectively.

The main contributions of this research was achieved by utilizing the developed fundamental models to develop a set of tools to evaluate, design and optimize priority schemes in different levels of studies. This part of the research was presented through Chapters 6-8. Simulation based tools to evaluate transit priority networks were discussed in Chapter 6 where the model structure was proposed and validated. Firstly, the TSP treatments were applied to a set of scenarios in three different levels (isolated intersection, a corridor, and a grid network) and the performance of prioritization scenarios were evaluated and discussed by examples. It was shown that depending on the signal setting parameters, network structure, deployed logic, and congestion level, a wide range of performances can be achieved by TSP schemes. A network wide analysis of priority schemes revealed that a special attention should be paid on a systematic approach for preferential treatment deployment so that maximum efficacy can be achieved with tolerable negative impacts on competent modes. Computational cost of using simulation based methods was observed to be the key challenge to utilize them for large network level studies and as planning tools.

In order to have a network wide evaluation of priority schemes, a set of analytical approaches were developed as presented in Chapter 7. Firstly, a delay function was proposed, reflecting the signal settings and the deployed priority scheme at an intersection. This function has a set of parameters to be calibrated and implemented in transport modelling studies. Secondly, adjustment factors were presented where TSP impacts can be evaluated in network level studies without updating the delay function type and parameters. The latter was then implemented to integrate TSP and TPL strategies so as to evaluate the effect of their combination in network level studies.

Confirming the necessity of a systematic approach to locate priority schemes, the final part of the study was dedicated to developing optimization framework to assist decision-makers to select the best potential locations for deploying priority schemes in a network (Chapter 8). To this end, two approaches, namely the simulation-based and analytical ones were presented. The simulation-based approach was developed through an integration of VISSIM microsimulation package and a Discrete version of Particle Swarm Optimization (DPSO) algorithm, aiming at minimizing travel time value and variability of public and private vehicles. It was shown that despite the detailed results and validity of the searching algorithm, computational cost of the model was raised as the main concern of network-wide simulation-based optimization of priority schemes. Consequently, the simulation core was replaced by analytical tools to expedite the evaluation process, aiming at minimizing total bus and car travel time values. The significant amount of saving in computational costs of the model empowered the proposed method to expand the priority schemes to integrated signal priority and transit priority lanes. Promising results confirm that the suggested framework can be implemented to introduce priority schemes to locate the priority schemes in the network.

9.2. Contributions to New Knowledge

This thesis contributes to the existing knowledge in the transit priority area. The main contribution is the development of an optimization framework to find the optimum location of priority schemes in the network. In this regard, a set of methodologies were developed for finding the location of transit priority schemes. These methods are relying on either simulation-based or analytical evaluation tools that are integrated into an optimization algorithm.

The research also presented a methodology to evaluate effect of priority schemes through a set of analytical tools. Moreover, a tool was developed to account for the passenger oriented delay and service variability as well as a tool to utilize Vehicle-to-Infrastructure (V2I) coordination. The followings are the major contributions of this research:

1. A simulation based network-wide optimization framework for Transit Signal Priority (TSP) schemes, presented in Chapter 8.
2. Analytical evaluation and optimization of integrated TSP and Transit Priority Lanes (TPL) at a network level (Chapters 7 and 8)

In addition, a range of other contributions are made in this study as shown below:

3. Two novel analytical approaches to evaluate the performance of priority schemes, presented in Chapter 7.
4. A tool and two passenger oriented delay and variability metrics to identify prone areas for possible treatments using smart card data (Chapter 5).
5. Using V2I communication to reduce bus fuel consumption at intersections, developed and implemented in Chapters 3 and 6, respectively.
6. An integrated Transit Signal Priority (TSP) and V2I communication to reduce bus fuel consumption with minimum delay at intersections(Chapter 6)
7. Using Particle Swarm Optimization (PSO) algorithm for finding optimum location of priority schemes (Chapter 8)
8. A set of developed measures of performance, considering travel time value and reliability and bus fuel consumption value, discussed in Chapter 4.

9.3. Future Research

This thesis has provided a detailed methodology for modelling, evaluating and designing priority schemes in a network. Several areas can be suggested as future research directions to expand this work:

Chapter 3 of this dissertation was allocated to the implemented and developed TSP logics. Future research can be directed to improve the performance of V2I based treatments. Firstly, connected vehicles technology may better estimate traffic state and arrival times which could be introduced into the model in future. This method could also be extended to evaluate the effect of other parameters such as bus cruising speed on potential savings. Also, the developed integrated V2I-TSP treatment can be extended to improve service performance measures such as service variability with marginal negative impacts on non-prioritized approaches. Finally, the developed method only targeted the portion of total bus fuel consumption at the intersections. The methods can be scaled to a corridor level or a small grid network so as to minimize fuel consumption throughout a route.

In Chapter 4 we presented the mathematical formulations to measure the performance of transit preferential treatments. These measures can further be improved by extending the models and encompassing further costs and benefits into the model. Considering the impacts of transit priority schemes on urban texture and safety indexes is a promising area of research. Furthermore, a detailed analysis of the actual project's costs and benefits can help to estimate appropriate weighting parameters for the developed objective functions.

Chapter 5 introduced a tool and two passenger oriented delay and variability metrics to identify prone areas for possible treatments using smart card data. Passenger-oriented reliability metrics can lead to a paradigm shift in managing transit services from planning to operations. The introduction of incentives based on passenger reliability metrics(instead of vehicle-based performance measures) will assist service providers in focusing on remedies such as preferential treatments, rescheduling the services, and transfer points coordination where and when such remedies most needed in terms of their consequences for passengers. Monitoring passenger reliability in real-time can facilitate steering operations towards passengers' experience. Research into passengers' perception of service reliability will enable differentiating between journey components and account for their contribution to the overall passenger experience. Future research will also further improve the reports and visualizations produced by the tool. Different networks and transit services can be assessed to allow the analysis of performance evolution by comparing with past performance as well as benchmarking by comparing with peer networks.

Chapter 6 presented a simulation based network-wide optimization framework of TSP schemes. Future research can improve the performance of the framework. Firstly, the computational costs of the evaluation model could be improved by optimizing and tuning simulation parameters, to mitigate the computational cost of the process. Finally, similar to the developed analytical methods, other preferential treatments (reviewed in section 2.2) as well as different TSP logics could be introduced as the variables of the problem, thereby pursuing maximum efficiency of TSP for the whole transportation system. To this end, an increase in computational power is crucial.

In Chapter 7, two analytical approaches were developed based on the delay functions and adjustment factors. The models can be further improved to have better estimation of TSP effectiveness in various conditions such as different transit facility characteristics. In this regard, one can suggest consideration of the effects of TSP on service variability and can propose a generalized function reflecting TSP impacts. Furthermore, in this study a non-linear regression method was used to obtain optimal parameters of the function. A comprehensive study on parameters for different cases is the next step to expand this study. Finally, real time data from different TSP and TPL application can provide more realistic adjustment factors for different network layouts.

Finally, Chapter 8 was dedicated to the optimization of transit priority schemes in a network, highlighting the findings and potential challenges. As the computational cost of performing network-wide optimization process was the main concern of the developed models, enhancing the performance of the process can provide the opportunity of testing larger networks. An efficient independent simulation-based core model is recommended to enhance the capability of both simulation-based and analytical tools. Furthermore, the performance of the searching algorithms can further be improved by testing other metaheuristic and optimization methods.

10. References

AASHTIANI, H. & IRAVANI, H. *Use of Intersection Delay Functions to Improve Reliability of Traffic Assignment Model*. 14th annual international EMME/2 conference, Chicago, Illinois, 1999. 1-6.

ABDY, Z. R. 2010. *A Method for Evaluating and Prioritizing Candidate Intersections for Transit Signal Priority Implementation*. University of Waterloo.

ABDY, Z. R. & HELLINGA, B. R. 2011. *Analytical Method for Estimating the Impact of Transit Signal Priority on Vehicle Delay*. Journal of Transportation Engineering, 137**,** 589-600.

AHN, K. & RAKHA, H. *System-Wide Impacts of Green Extension Transit Signal Priority*. Intelligent Transportation Systems Conference, . ITSC06. IEEE, 2006. 91-96.

AKCELIK, R. 1991. *Travel Time Functions for Transport Planning Purposes: Davidson's Function, Its Time Dependent Form and Alternative Travel Time Function*. Australian Road Research, 21.

BABAZADEH, A., POORZAHEDY, H. & NIKOOSOKHAN, S. 2011. *Application of Particle Swarm Optimization to Transportation Network Design Problem*. Journal of King Saud University - Science, 23**,** 293-300.

BAGHERIAN, M., MASSAH, S. & KERMANSHAHI, S. *A Swarm Based Method for Solving Transit Network Design Problem*. Australasian Transport Research Forum (ATRF), 36th, 2013, Brisbane, Queensland, Australia, 2013.

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. 2014a. *Using Delay Functions to Evaluate Transit Priority at Signals*. Public Transport, 7**,** 61-75.

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. *An Integrated Transit Signal Priority and Vehicle-to-Infrastructure Communication to Reduce Bus Fuel Consumption*. World Conference on Transport Research - WCTR 2016a Shanghai.

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. *An Integrated Transit Signal Priority and Vehicle-to-Infrastructure Communication to Reduce Bus Fuel Consumption*. World Conference on Transport Research - WCTR 2016a Shanghai, 2016b.

BAGHERIAN, M., MESBAH, M. & FERREIRA, L. 2016c. *Using Vehicle to Infrastructure Communication to Reduce Bus Fuel Consumption at Intersections*. 95td Annual Meeting for Transport Research Board (TRB). Washington, D.C., USA.

BAGHERIAN, M., MESBAH, M., FERREIRA, L. & CHARLES, P. 2017. *An Analytical Approach to Evaluate and Design Integrated Transit Priority Treatments in a Network*.

BAGHERIAN, M., MESBAH, M., FERREIRA, L., CHARLES, P. & KHALILIKHAH, M. 2014b. *Network-Wide Optimization of Transit Signal Priority*. 94td Annual Meeting for Transport Research Board (TRB). Washington, D.C., USA.

BAKER, R. J., COLLURA, J., DALE, J., GREENOUGH, J., HEAD, L., HEMILY, B., IVANOVIC, M., JARZAB, J., MCCORMICK, D. & OBENBERGER, J. 2004. *An Overview of Transit Signal Priority-Revised and Updated*. Washington DC, USA: ITS America.

BALKE, K., DUDEK, C. & URBANIK II, T. 2000. *Development and Evaluation of Intelligent Bus Priority Concept*. Transportation Research Record: Journal of the Transportation Research Board, 1727**,** 12-19.

BARCELÓ, J. 2010. *Fundamentals of Traffic Simulation*, Springer.

BISHOP, J. M. 2007. *Stochastic Diffusion Search*. Scholarpedia, 2**,** 3101.

CATALA, M., DOWLING, S. & HAYWARD, D. 2011. *Expanding the Google Transit Feed Specification to Support Operations and Planning*.

CATS, O. 2014. *Regularity-Driven Bus Operation: Principles, Implementation and Business Models*. Transport Policy, 36**,** 223-230.

CHAKRABARTI, S. & GIULIANO, G. 2015. *Does Service Reliability Determine Transit Patronage? Insights from the Los Angeles Metro Bus System*. Transport Policy, 42**,** 12-20.

CHAN, J. 2007. *Rail Transit Od Matrix Estimation and Journey Time Reliability Metrics Using Automated Fare Data*. Massachusetts Institute of Technology.

CHANG, J., COLLURA, J., DION, F. & RAKHA, H. 2003. *Evaluation of Service Reliability Impacts of Traffic Signal Priority Strategies for Bus Transit*. Transportation Research Record: Journal of the Transportation Research Board, 1841**,** 23-31.

CHRISTOFA, E. 2012. *Traffic Signal Optimization with Transit Priority: A Person-Based Approach*.

CHRISTOFA, E., ABOUDOLAS, K. & SKABARDONIS, A. *Arterial Traffic Signal Optimization: A Person-Based Approach*. Transportation Research Board 92nd Annual Meeting, 2013.

CHRISTOFA, E., PAPAMICHAIL, I. & SKABARDONIS, A. *Person-Based Traffic Signal Optimization for Real-Time Applications*. Transportation Research Board 91st Annual Meeting, 2012.

CHRISTOFA, E. & SKABARDONIS, A. 2011a. *Traffic Signal Optimization with Application of Transit Signal Priority to an Isolated Intersection*. Transportation Research Record: Journal of the Transportation Research Board, 2259**,** 192-201.

CHRISTOFA, E. & SKABARDONIS, A. 2011b. *Traffic Signal Optimization with Transit Signal Priority*. Transportation Research Board 90nd Annual Meeting. Washington DC,USA.

CORMEN, T. H., LEISERSON, C. E., RIVEST, R. L. & STEIN, C. 2001. *Introduction to Algorithms*, MIT press Cambridge.

COUNCIL, N. R. 1985. *Hcm 1985 Highway Capacity Manual*, Washington, D.C, Transportation Research Board.

CUI, C.-Y., SHIN, J.-S., MIYAZAKI, M. & LEE, H.-H. 2013. *Real-Time Traffic Signal Control for Optimization of Traffic Jam Probability*. Electronics and Communications in Japan, 96**,** 1-13.

DANAHER, A., LEVINSON, H. & ZIMMERMAN, S. 2007. *Bus Rapid Transit: Practitioner's Guide*. Transit Cooperation Research Program Report, 118.

DANAHER, A. R. 2010. *Bus and Rail Transit Preferential Treatments in Mixed Traffic*, Transportation Research Board, Washington, D.C.

DIAB, E. I., BADAMI, M. G. & EL-GENEIDY, A. M. 2015. *Bus Transit Service Reliability and Improvement Strategies: Integrating the Perspectives of Passengers and Transit Agencies in North America*. Transport Reviews, 35**,** 292-328.

DORIGO, M., BIRATTARI, M. & STÜTZLE, T. 2006. *Ant Colony Optimization*. Computational Intelligence Magazine, IEEE, 1**,** 28-39.

EBERHART, R., SIMPSON, P. & DOBBINS, R. 1996. *Computational Intelligence Pc Tools*, Academic Press Professional, Inc.

EKEILA, W., SAYED, T. & EL ESAWEY, M. 2009. *Development of Dynamic Transit Signal Priority Strategy*. Transportation Research Record: Journal of the Transportation Research Board, 2111**,** 1-9.

ENGELBRECHT, A. P. 2007. *Computational Intelligence: An Introduction*, John Wiley & Sons.

ESTRADA, M., TRAPOTE, C., ROCA-RIU, M. & ROBUSTÉ, F. 2009. *Improving Bus Travel Times with Passive Traffic Signal Coordination*. Transportation Research Record: Journal of the Transportation Research Board, 2111**,** 68-75.

FERREIRA, L. 2009. *Redland Bay Rd Upgrade: Microsimulation Model (Vissim)*. UniQuest, the University of Queensland. Australia.

FLORIAN, M., MAHUT, M. & TREMBLAY, N. 2008. *Application of a Simulation-Based Dynamic Traffic Assignment Model*. European Journal of Operational Research, 189**,** 1381-1392.

FREY, H. C. 2007. *Comparing Real-World Fuel Consumption for Diesel- and Hydrogen-Fueled Transit Buses and Implication for Emissions*. Transportation research. Part D, Transport and environment, 12**,** 281-291.

FRIMAN, M., EDVARDSSON, B. & GÄRLING, T. 2001. *Frequency of Negative Critical Incidents and Satisfaction with Public Transport Services. I*. Journal of Retailing and Consumer Services, 8**,** 95-104.

FURTH, P., CESME, B. & RIMA, T. 2010. *Signal Priority near Major Bus Terminal*. Transportation Research Record: Journal of the Transportation Research Board, 2192**,** 89-96.

FURTH, P. & MULLER, T. H. 2000. *Conditional Bus Priority at Signalized Intersections: Better Service with Less Traffic Disruption*. Transportation Research Record: Journal of the Transportation Research Board, 1731**,** 23-30.

GARROW, M. & MACHEMEHL, R. B. 1997. *Development and Evaluation of Transit Signal Priority Strategies*. University of Texas at Austin.

GITTENS, A. & SHALABY, A. 2015. *Evaluation of Bus Reliability Measures and Development of a New Composite Indicator*. Transportation Research Record: Journal of the Transportation Research Board, 2533**,** 91-99.

GOLDBERG, D. & HOLLAND, J. 1988. *Genetic Algorithms and Machine Learning*. Machine Learning, 3**,** 95-99.

HE, J. & HOU, Z. 2012. *Ant Colony Algorithm for Traffic Signal Timing Optimization*. Advances in Engineering Software, 43**,** 14-18.

HE, Q., HEAD, K. & DING, J. 2011. *Heuristic Algorithm for Priority Traffic Signal Control*. Transportation Research Record: Journal of the Transportation Research Board, 2259**,** 1-7.

HE, Q., HEAD, K. L. & DING, J. 2014. *Multi-Modal Traffic Signal Control with Priority, Signal Actuation and Coordination*. Transportation Research Part C: Emerging Technologies, 46**,** 65-82.

HEAD, L., GETTMAN, D. & WEI, Z. 2006. *Decision Model for Priority Control of Traffic Signals*. Transportation Research Record: Journal of the Transportation Research Board, 1978**,** 169-177.

HEASLIP, K., BOSWORTH, R., BARNES, R., SOBH, A. S., THOMAS, M. & SONG, Z. 2014. *Effects of Natural Gas Vehicles and Fuel Prices on Key Transportation Economic Metrics*.

HENDREN, P., ANTOS, J., CARNEY, Y. & HARCUM, R. *Transit Travel Time Reliability: 2 Shifting the Focus from Vehicles to Customers 3*. Transportation Research Board 94th Annual Meeting, 2015.

HU, J. 2014. *Transit Signal Priority with Connected Vehicle Technology*. Transportation research record, 2418**,** 20-29.

HU, J., PARK, B. B. & LEE, Y.-J. 2015. *Coordinated Transit Signal Priority Supporting Transit Progression under Connected Vehicle Technology*. Transportation Research Part C: Emerging Technologies.

JIN, X., HOSSAN, M. S. & ASGARI, H. 2015. *Investigating the Value of Time and Value of Reliability for Managed Lanes*.

JORDAN, C. A. & CETIN, M. *Signal Preemption Strategy for Emergency Vehicles Using Vehicle to Infrastructure Communication*. Transportation Research Board 94th Annual Meeting, 2015.

KENNEDY, J. & EBERHART, R. C. *A Discrete Binary Version of the Particle Swarm Algorithm*. Systems, Man, and Cybernetics, 1997. Computational Cybernetics and Simulation., 1997 IEEE International Conference on, 12-15 Oct 1997 1997. 4104-4108 vol.5.

KENNEDY, J. F., KENNEDY, J. & EBERHART, R. C. 2001. *Swarm Intelligence*, Morgan Kaufmann.

KERMANSHAHI, S., SHAFAHI, Y. & BAGHERIAN, M. 2015. *Application of a New Rapid Transit Network Design Model to Bus Rapid Transit Network Design: Case Study Isfahan Metropolitan Area*. Transport, 30**,** 93-102.

KHALIGHI, F. & CHRISTOFA, E. Emission-Based Signal Timing Optimization for Isolated Intersections. Transportation Research Board 94th Annual Meeting, 2015.

KHALILIKHAH, M., HABIBIAN, M. & HEASLIP, K. 2016. *Acceptability of Increasing Petrol Price as a Tdm Pricing Policy: A Case Study in Tehran*. Transport Policy, 45**,** 136-144.

KIM, W. & RILETT, L. 2005. *Improved Transit Signal Priority System for Networks with Nearside Bus Stops*. Transportation Research Record: Journal of the Transportation Research Board, 1925**,** 205-214.

KIMPEL, T., STRATHMAN, J., BERTINI, R. & CALLAS, S. 2005. *Analysis of Transit Signal Priority Using Archived Trimet Bus Dispatch System Data*. Transportation Research Record: Journal of the Transportation Research Board, 1925**,** 156-166.

LAHON, D. *Modeling Transit Signal Priority and Queue Jumpers for Brt*. ITE 2009 Annual Meeting and Exhibit, 2009.

LEE, A., VAN OORT, N. & VAN NES, R. 2014. *Service Reliability in a Network Context: Impacts of Synchronizing Schedules in Long Headway Services*. Transportation Research Record: Journal of the Transportation Research Board**,** 18-26.

LI, Y., KOONCE, P., LI, M., ZHOU, K., LI, Y., BEAIRD, S., ZHANG, W.-B., HEGEN, L., HU, K. & SKABARDONIS, A. 2008. *Transit Signal Priority Research Tools*, Federal Transit Administration.

LIU, H.-C., SKABARDONIS, A. & ZHANG, W.-B. 2003. *A Dynamic Model for Adaptive Bus Signal Priority*. Transportation Research Board 82nd Annual Meeting. Washington D.C.

LIU, H., SKABARDONIS, A., ZHANG, W.-B. & LI, M. 2004. *Optimal Detector Location for Bus Signal Priority*. Transportation Research Record: Journal of the Transportation Research Board, 1867**,** 144-150.

LIU, H., ZHANG, J. & CHENG, D. 2008. *Analytical Approach to Evaluating Transit Signal Priority*. Journal of Transportation Systems Engineering and Information Technology, 8**,** 48-57.

LIU, Z. P., LI, K. P. & NI, Y. *Isolated Transit Signal Priority Control Strategy Based on Demand Degree of Green*. 2012 London.

LV, N., YAN, X., RAN, B., WU, C. & ZHONG, M. 2012. *Optimization of Dynamic Parking Guidance Information for Special Events*. Transportation Research Record: Journal of the Transportation Research Board, 2324**,** 71-80.

MA, W., LIU, Y. & YANG, X.-G. *A Dynamic Programming Model for Bus Signal Priority with Multiple Requests*. Transportation Research Board 90th Annual Meeting, 2011.

MA, W., YANG, X. & LIU, Y. 2010. *Development and Evaluation of a Coordinated and Conditional Bus Priority Approach*. Transportation Research Record: Journal of the Transportation Research Board, 2145**,** 49-58.

MA, X., WU, Y.-J., WANG, Y., CHEN, F. & LIU, J. 2013. *Mining Smart Card Data for Transit Riders' Travel Patterns*. Transportation Research Part C: Emerging Technologies, 36**,** 1-12.

MAHFOUD, S. W. 1995. *Niching Methods for Genetic Algorithms*. Urbana, 51**,** 61801.

MAZLOUMI, E., MESBAH, M., CEDER, A., MORIDPOUR, S. & CURRIE, G. 2012. *Efficient Transit Schedule Design of Timing Points: A Comparison of Ant Colony and Genetic Algorithms*. Transportation Research Part B: Methodological, 46**,** 217-234.

MESBAH, M., SARVI, M. & CURRIE, G. 2011. *Optimization of Transit Priority in the Transportation Network Using a Genetic Algorithm*. IEEE Transactions on Intelligent Transportation Systems, 12**,** 908-919.

MESBAH, M., SARVI, M., CURRIE, G. & SAFFARZADEH, M. 2010. *Policy-Making Tool for Optimization of Transit Priority Lanes in Urban Network*. Transportation Research Record: Journal of the Transportation Research Board, 2197**,** 54-62.

MORENCY, C., TRÉPANIER, M. & AGARD, B. 2007. *Measuring Transit Use Variability with Smart-Card Data*. Transport Policy, 14**,** 193-203.

NASSIR, N., HICKMAN, M. & MA, Z.-L. 2015. *Activity Detection and Transfer Identification for Public Transit Fare Card Data*. Transportation, 42**,** 683-705.

NATIONAL RESEARCH COUNCIL . TRANSPORTATION RESEARCH, B. 2010. *Hcm 2010: Highway Capacity Manual*, Washington, D.C, Transportation Research Board.

NGAN, V., SAYED, T. & ABDELFATAH, A. 2004. *Impacts of Various Traffic Parameters on Transit Signal Priority Effectiveness*. Journal of public Transportation, 7**,** 71-93.

OZKAN, M., OZENER, O. & YAVASLIOL, I. *Optimization of Fuel Consumption of a Bus Used in City Line with Regulation of Driving Characteristics*. Proceedings of World Academy of

Science, Engineering and Technology, 2012. World Academy of Science, Engineering and Technology.
PARK, B., MESSER, C. & URBANIK, T. 1999. *Traffic Signal Optimization Program for Oversaturated Conditions: Genetic Algorithm Approach*. Transportation Research Record: Journal of the Transportation Research Board, 1683**,** 133-142.
PARSOPOULOS, K. E. 2010. *Particle Swarm Optimization and Intelligence: Advances and Applications: Advances and Applications*, IGI Global.
PELLETIER, M.-P., TRÉPANIER, M. & MORENCY, C. 2011. *Smart Card Data Use in Public Transit: A Literature Review*. Transportation Research Part C: Emerging Technologies, 19**,** 557-568.
PTV 2013. *Vissim 6 Manual*. Planung Transport Verkehr AG, Karlsruhe, Germany.
RAKHA, H. & DING, Y. 2003. *Impact of Stops on Vehicle Fuel Consumption and Emissions*. Journal of Transportation Engineering, 129**,** 23-32.
REKLAITIS, G. V., RAVINDRAN, A. & RAGSDELL, K. M. 2006. *Engineering Optimization: Methods and Applications*, Hoboken, N.J, John Wiley & Sons.
ROUPHAIL, N. M. & HUNTSINGER, L. F. 2011. *Bottleneck and Queuing Analysis*. Transportation Research Record: Journal of the Transportation Research Board, 2255**,** 117-124.
SAYED, T. & ABDELFATAH, A. 2004. *Impacts of Various Parameters on Transit Signal Priority Effectiveness*. Journal of Public Transportation, 7.
SHAFAHI, Y. & BAGHERIAN, M. 2013. *A Customized Particle Swarm Method to Solve Highway Alignment Optimization Problem*. Computer-Aided Civil and Infrastructure Engineering, 28**,** 52-67.
SHI, Y. & EBERHART, R. *A Modified Particle Swarm Optimizer*. Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on, 1998. IEEE, 69-73.
SKABARDONIS, A. 2000. *Control Strategies for Transit Priority*. Transportation Research Record: Journal of the Transportation Research Board, 1727**,** 20-26.
SKABARDONIS, A. & CHRISTOFA, E. 2011. *Impact of Transit Signal Priority on Level of Service at Signalized Intersections*. Procedia - Social and Behavioral Sciences, 16**,** 612-619.
SKABARDONIS, A. & DOWLING, R. 1997. *Improved Speed-Flow Relationships for Planning Applications*. Transportation Research Record: Journal of the Transportation Research Board, 1572**,** 18-23.
SMITH, H. R., HEMILY, B. & IVANOVIC, M. 2005. *Transit Signal Priority (Tsp): A Planning and Implementation Handbook*, US, U.S. Federal Transit Administration(FTA).
SOBH, A. S. 2015. *Transportation Economics and Energy*.
SOLTANI-SOBH, A., HEASLIP, K., BOSWORTH, R. & BARNES, R. 2015. *Effect of Improving Vehicle Fuel Efficiency on Fuel Tax Revenue and Greenhouse Gas Emissions*. Transportation Research Record: Journal of the Transportation Research Board**,** 71-79.
STEVANOVIC, A., MARTIN, P. & STEVANOVIC, J. 2007. *Vissim-Based Genetic Algorithm Optimization of Signal Timings*. Transportation Research Record: Journal of the Transportation Research Board, 2035**,** 59-68.
STEVANOVIC, A., STEVANOVIC, J., KERGAYE, C. & MARTIN, P. *Traffic Control Optimization for Multi-Modal Operations in a Large-Scale Urban Network*. 2011 Vienna. 146-151.
STEVANOVIC, A., STEVANOVIC, J., ZHANG, K. & BATTERMAN, S. 2009. *Optimizing Traffic Control to Reduce Fuel Consumption and Vehicular Emissions*. Transportation Research Record: Journal of the Transportation Research Board, 2128**,** 105-113.
STEVANOVIC, J., STEVANOVIC, A., MARTIN, P. T. & BAUER, T. 2008. *Stochastic Optimization of Traffic Control and Transit Priority Settings in Vissim*. Transportation Research Part C: Emerging Technologies, 16**,** 332-349.

SUN, D., BENEKOHAL, R. F. & WALLER, S. T. 2006. *Bi-Level Programming Formulation and Heuristic Solution Approach for Dynamic Traffic Signal Optimization*. Computer-Aided Civil and Infrastructure Engineering, 21**,** 321-333.

SUNKARI, S. R., BEASLEY, P. S., URBANIK, T. & FAMBRO, D. B. 1995. *Model to Evaluate the Impacts of Bus Priority on Signalized Intersections*. Transportation Research Record**,** 117-123.

TEODOROVIĆ, D. 2008. *Swarm Intelligence Systems for Transportation Engineering: Principles and Applications*. Transportation Research Part C: Emerging Technologies, 16**,** 651-667.

UBIERGO, G. A. & JIN, W.-L. *Mobility and Environment Improvement of Signalized Networks through Vehicle-to-Infrastructure (V2i) Communications*. Transportation Research Board 94th Annual Meeting, 2015.

UNIMAN, D., ATTANUCCI, J., MISHALANI, R. & WILSON, N. 2010. *Service Reliability Measurement Using Automated Fare Card Data*. Transportation Research Record: Journal of the Transportation Research Board, 2143**,** 92-99.

VAN OORT, N. 2014. *Incorporating Service Reliability in Public Transport Design and Performance Requirements: International Survey Results and Recommendations*. Research in Transportation Economics, 48**,** 92-100.

VAN OORT, N. 2016. *Incorporating Enhanced Service Reliability of Public Transport in Cost-Benefit Analyses*. Public Transport**,** 1-18.

VAN OORT, N., BRANDS, T. & DE ROMPH, E. 2015. *Short Term Ridership Prediction in Public Transport by Processing Smart Card Data*. Transportation Research Record.

WANG, Y. & NORTHWEST, T. 2007. *Comprehensive Evaluation on Transit Signal Priority System Impacts Using Field Observed Traffic Data*. Transportation Northwest, Department of Civil and Environmental Engineering, University of Washington.

WANJING, M. & XIAOGUANG, Y. *A Passive Transit Signal Priority Approach for Bus Rapid Transit System*. Intelligent Transportation Systems Conference, 2007. ITSC 2007. IEEE, Sept. 30 2007-Oct. 3 2007 2007. 413-418.

WILLUMSEN, L. G. & ORTÚZAR, J. D. D. 2011. *Modelling Transport*, Oxford, Wiley-Blackwell.

WOOD, D. A. 2015. *A Framework for Measuring Passenger-Experienced Transit Reliability Using Automated Data*. Massachusetts Institute of Technology.

XU, Z., JIN, P. J., JIANG, X. & RAN, B. *Macroscopic Fundamental Diagram (Mfd) Based on Vehicle-to-Infrastructure (V2i) Connected Vehicle Data*. Transportation Research Board 94th Annual Meeting, 2015.

YU, B., LAM, W. H. K. & TAM, M. L. 2011. *Bus Arrival Time Prediction at Bus Stop with Multiple Routes*. Transportation Research Part C: Emerging Technologies, 19**,** 1157-1170.

ZARKADOULA, M., ZOIDIS, G. & TRITOPOULOU, E. 2007. *Training Urban Bus Drivers to Promote Smart Driving: A Note on a Greek Eco-Driving Pilot Program*. Transportation Research Part D: Transport and Environment, 12**,** 449-451.

ZHAI, H., FREY, H. C. & ROUPHAIL, N. M. 2008. *A Vehicle-Specific Power Approach to Speed- and Facility-Specific Emissions Estimates for Diesel Transit Buses*. Environmental Science & Technology, 42**,** 7985-7991.

ZHAO, J., FRUMIN, M., WILSON, N. & ZHAO, Z. 2013. *Unified Estimator for Excess Journey Time under Heterogeneous Passenger Incidence Behavior Using Smartcard Data*. Transportation Research Part C: Emerging Technologies, 34**,** 70-88.

ZHENG, F. & VAN ZUYLEN, H. 2013. *Urban Link Travel Time Estimation Based on Sparse Probe Vehicle Data*. Transportation Research Part C: Emerging Technologies, 31**,** 145-157.

ZHOU, G. & GAN, A. 2005. *Performance of Transit Signal Priority with Queue Jumper Lanes*. Transportation Research Record: Journal of the Transportation Research Board, 1925**,** 265-271.

ZHOU, G., GAN, A. & SHEN, L. D. 2007. *Optimization of Adaptive Transit Signal Priority Using Parallel Genetic Algorithm*. Tsinghua Science & Technology, 12**,** 131-140.

ZHOU, G., GAN, A. & ZHU, X. 2006. *Determination of Optimal Detector Location for Transit Signal Priority with Queue Jumper Lanes*. Transportation Research Record: Journal of the Transportation Research Board, 1978**,** 123-129.

ZLATKOVIC, M., STEVANOVIC, A., CEVALLOS, F. & JOHNSON, H. R. 2010. *35m Max: The First Bus Rapid Transit System in Salt Lake County*. World Review of Intermodal Transportation Research, 3**,** 103-120.

ZLATKOVIC, M., STEVANOVIC, A. & MARTIN, P. 2012a. *Development and Evaluation of Algorithm for Resolution of Conflicting Transit Signal Priority Requests*. Transportation Research Record: Journal of the Transportation Research Board, 2311**,** 167-175.

ZLATKOVIC, M., STEVANOVIC, A., MARTIN, P. & TASIC, I. 2012b. *Evaluation of Transit Signal Priority Options for Future Bus Rapid Transit Line in West Valley City, Utah*. Transportation Research Record: Journal of the Transportation Research Board, 2311**,** 176-185.

ZLATKOVIC, M., STEVANOVIC, A. & R. M. ZAHID , R. 2013. *Effects of Queue Jumpers and Transit Signal Priority on Bus Rapid Transit*. In Proceedings of the 92nd annual meeting of the Transportation Research Board. Washington DC.