UTILISING BIG TRANSIT DATA FOR TRANSFER COORDINATION

THESIS BY PUBLICATION

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Abstract

Transfer is an inevitable activity in transit journeys. Providing seamless coordinated transfer is an effective solution to enhance the transit quality of service and attract ridership. The problem of transfer coordination in public transit is sophisticated due to (1) the stochasticity of public transport travel time variability, and (2) the unavailability of passenger transfer plan. However, the transit operators are now currently in a critical transition from manual data collections to Big Data where vehicle and passenger data are automatically collected in high volumes and details. The proliferation of these modern technologies provides a tremendous opportunity to solve the two aforementioned problems of transit transfer coordination.

This dissertation has two primary objectives and is divided into 2 stages in which each stage pursue a primary objective. Stage 1 focuses on improving offline transfer coordination in strategic planning. It obtains the knowledge of Public Transport Travel time Variability (PTTV) through probability distribution modelling, and utilises that knowledge to investigate the offline transfer coordination planning by an Event-based Multi Agent Simulation model. Stage 2 focuses on providing online transfer coordination in real-time from the knowledge of passenger travel pattern and segmentation. It develops algorithms for travel pattern analysis and then develops simple to sophisticated online transfer coordination strategies to enable seamless coordinated transfer in real-time.

The transfer coordination strategies significantly improve the transfer quality. Offline transfer coordination optimises transit schedule to reduce the mean transfer time by up to 20% and probability of missing a transfer by 80%. Online transfer coordination provides seamless transfer by coordinating transit vehicle arrivals at transfer stop in real-time. The most prediction-enabled online transfer coordination reduces the mean transfer time by up to 16% and probability of missing a transfer by 99%.

In terms of publication, this thesis by publication has resulted in 5 published/under review journal articles and 4 conference proceeding papers.

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List of Abbreviations

AFC	Automatic Fare Collection
ANN	Artificial Neural Network
APC	Automatic Passenger Counting
AVI	Automatic Vehicle Identification
AVL	Automatic Vehicle Location
BIC	Bayesian Information Creation
CBD	Central Business District
CCNN	Cascade Correlation Neural Network
CDF	Cumulative Density Function
CV	Coefficient of Variation
DBSCAN	Density Based SCanning Algorithm with Noise
EDF	Empirical Density Function
EMAS	Event-based Multi Agent Simulation
EWT	Extra Waiting Time
FV	Feeding Vehicle
GPS	Global Positioning System
IMMPH	Interactive Multiple Model-based Pattern Hybrid
INAR	Integer-Valued Auto Regressive
KS	Kolmogorov-Smirnov
LS-SVM	Least Squares Support Vector Machine
MAC address	Media Access Control address
MH	Maximum Holding time
MLE	Maximum Likelihood Estimation
MLP	Multi-Layered Perceptron
MTUNN	Multiple Temporal Units Neural Network
OD	Origin-Destination
OLS	Ordinary Least Square
ONTF	Online transfer coordination
PA	Passenger Agent

PDF	Probability Density Function
PMT	Probability of missing a transfer
PP	Predicting Power
PTT	Planned Transfer Time
PTTV	Public transport Travel time Variability
RFID	Radio Frequency IDentification system
RMSE	Root Mean Squared Error
RV	Receiving Vehicle
SA	Simple Analytical
SC	Smart Card
SEQ	South-East Queensland
TCQSM	Transit Capacity and Quality of Service Manual
TS	Timetable Synchronisation
TTC	Timed Transfer Coordination
TTV	Travel Time Variability
TTV_{d2d}	Day-to-day Travel Time Variability
TTV_{p2p}	Period-to-period Travel Time Variability
TTV_{v2v}	Vehicle-to-vehicle Travel Time Variability
VA	Vehicle Agent
VID	Vehicle IDentification
WS-DBSCAN	Weighted-Stop DBSCAN
ZINB	Zero-Inflated Negative Binomial Regression
ZIP	Zero-Inflated Poisson Regression

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Le Minh KIEU

21th July 2015

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1 Introduction

1.1 Background

Transit demand in metropolitan area is usually widespread over space and time. It is not cost-effective to provide door-to-door transit service for every origin-destination (OD) pairs. The transit system is then designed by a network of intersecting lines and modes, requiring one or more transfers within a multimodal transit network to complete a journey. On the one hand, transfer extends the transit service coverage by omnidirectional connections of routes and reduces the needs for transit vehicles. On the other hand, poorly coordinated transfer would significantly increase passenger waiting time; especially when there is a missed connection.

Transfer time is usually perceived as time lost for passengers (Creutzig and He, 2009). Mohring et al. (1987) found that passenger usually perceive transfer time as twice as much as the actual value. Guo & Wilson (2011) quantified the significant cost imposed by transfers and suggested that an improvement of transfer coordination would benefit transit services. They found that from passenger perspective the number of transfer is associated with much higher cost than other sources of unreliability such as initial waiting time and in-vehicle travel time. Compared with private transport as almost a door-to-door service, a poorly coordinated transfer could be the decisive factor to discourage people to switch to public transport. Conversely, synchronised timetable and seamlessly coordination between transit trips are much desired by passengers and could significantly enhance the transit quality of service.

In South East Queensland (SEQ), transfer is an important part of public transportation system. Analysing the Smart Card AFC data, we found that transfers were involved in 18.5% of all public transport journeys from March to June 2012. Many geographical areas do not have direct access to the city CBD due to the limitation of network connectivity. Figure 1.1-1 illustrates the total travel and transfer time of a random 250,000 passengers travelled from outside city CBD to the Roma St Train Station, one of the largest transit centre in Brisbane CBD, Australia. The sizes of the red and black circles represent the total time spent for travel time (including transfer) and only the transfer time, respectively. The location of the circle illustrates the origin location of the passenger. If multiple passengers started their journeys from the same location, the lowest travel and transfer time among them is used for plotting.

Figure 1.1-1 clearly shows the accessibility variation to the CBD of different areas using data from Go card data. Among the journeys with high travel time, transfer is one of the major contributors of total travel time. This feature is further investigated by looking at the empirical cumulative density function (CDF) of the ratio between transfer time and total travel time in Figure 1.1-2 of the trips illustrated in Figure 1.1-1.

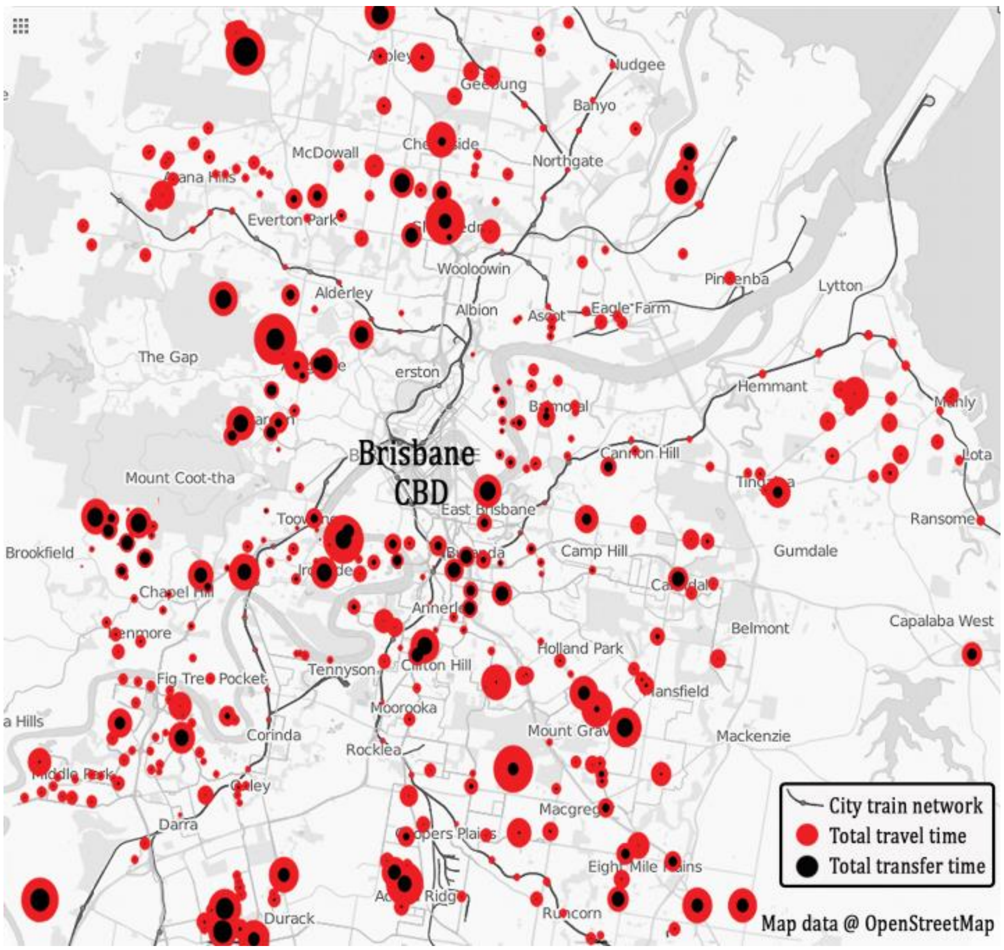


Figure 1.1-1. Accessibility to Roma St train station, Brisbane CBD

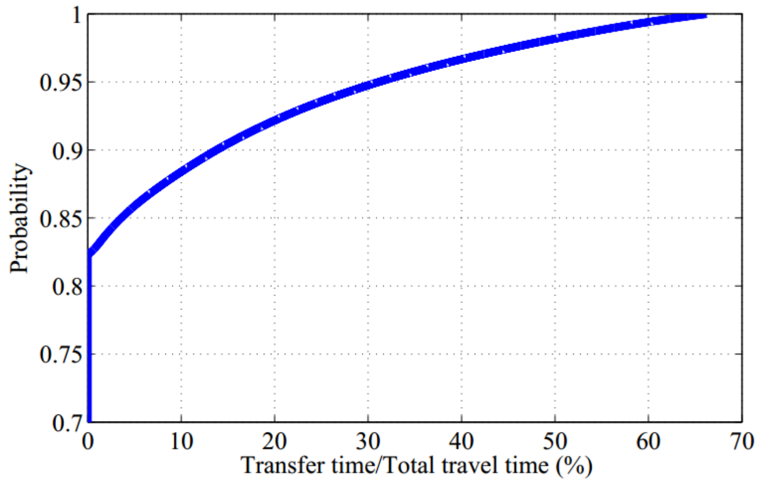


Figure 1.1-2. CDF of the ratio between transfer and total travel time to the Roma St Train Station, SEQ, Australia.

Although approximately 82% of passenger journeys do not require any transfer, the time spent on transfer could go up to 65% of the total travel time. The figure demonstrates that at certain areas in the system, passengers are required to make lengthy transfers, which may discourage them to use more public transport. Regarding to the transfer pattern in time, Figure 1.1-3 shows the average number of legs per journey at different time of day

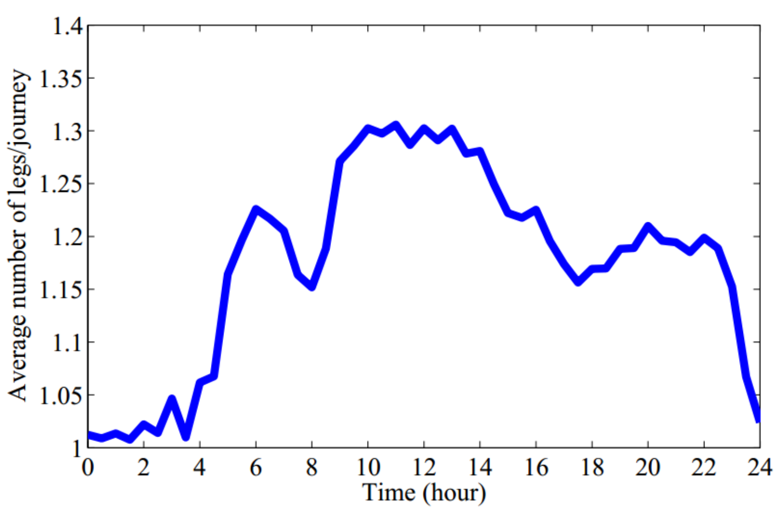


Figure 1.1-3. Average number of legs per journey at different time-of-the-day

At midday off-peak period, approximately 30% of all journeys in SEQ are associated with at least one transfer due to the reduction in service frequency provided. Many bus services in SEQ are operated only during the peak periods, forcing passengers to take other indirect alternatives requiring transfers. The situation is worsen because service during off-peak are operating with low frequency. A number of studies in the literature suggested a frequency of six service per hour (every ten minutes) is the minimum requirement for avoiding transfer coordination, whereas twelve services per hour is preferred (Mees, 2010; Nielsen, 2005). However on the SEQ network there are only 26 high frequency lines (equal or less than 15 minutes per vehicle, recently increased from 19 routes in 2012) over the total 230 bus lines (Translink, 2012).

1.2 **Motivation**

A seamless interconnected transit system is essential to attract ridership for major metropolitan areas (Chen, 2010; Lee and Schonfeld, 1991). The idea of public transport transfer coordination is similar to the very successful *hub-and-spoke* system of air transportation. In *hub-and-spoke*, a hub is a central airport where different routes are servicing and spokes are the routes through the hub airport. Compared to the direct-flight or point-to-point system, *hub-and-spoke* provides much larger service coverage and maintain high occupancy on each flight (Young and Wells, 2011).

A *hub-and-spoke* system consists of two principal components: Offline transfer coordination (or schedule coordination) and Online transfer coordination (or dispatching control for coordinated operation) (Chen, 2010).

- Offline transfer coordination designs route and synchronises timetable to minimise passenger transfer time. It is a scheduling problem of multiple lines to coordinate schedules.
- Online transfer coordination is a real-time problem which focuses on dispatching control from transfer terminals. When an incoming vehicle is delayed, the online transfer coordination model will decide through an optimisation process if the outgoing vehicle should be delayed at the transfer terminal to wait for the incoming vehicle, so that passengers can make transfers.

The success of transfer coordination in air transportation strongly depends on three principal factors (Dessouky et al., 1999): (1) the delay of the incoming flight, (2) the number of transferring passengers, and (3) the frequency of the outgoing flight.

Existing studies in literature have explored the applicability of offline transfer coordination (Domschke, 1989; Knoppers and Muller, 1995; Lee and Schonfeld, 1991; Nachtigall and Voget, 1996; Teodorović and Lučić, 2005) and online transfer coordination (Chowdhury and Chien, 2001; Chung and Shalaby, 2007; Dessouky et al., 1999; Dessouky et al., 2003; Hadas and Ceder, 2010a) in public transit. However, transfer coordination in public transit is not as popular and successful as air transportation (Dessouky et al., 1999), mainly because of the complexities in the first two factors among the three aforementioned ones.

(1) Public transport travel time, especially **bus travel time is more stochastic** compared to air transportation due to travel time variability, which makes **offline transfer coordination** in scheduling more difficult.
(2) The **passenger transfer plan is unknown** during **online transfer coordination** in real-time. It is then not possible to optimise the cost induced by the transfer decision to transferring and non-transferring passengers.

Therefore, the motivation of this PhD research is to enhance the public transit transfer coordination to as close as possible to the quality of air transportation by solving these two problems.

1.3 Research problem

This research has been developed to address the 2 aforementioned problems from Section 1.2. It enhances offline transfer coordination by solving the problem of stochastic travel time and online transfer coordination by solving the problem of unknown passenger transfer plan.

1.3.1 Scope of research

Transfers in public transport are mainly used to (1) eliminating direct routes between all origin-destination pairs, (2) concentrating passengers on major routes with better quality of service, (3) enhancing the utilisation of existing infrastructures, (4) reducing negative impacts of transit vehicles such as congestions, fuel consumption and emissions. Transfer coordination is a transit scheduling and operation problem in which two or more transit vehicles simultaneously or nearly simultaneously arrive at transfer terminals to enhance passenger transfer activities. The procedure may be as complex as multiple transit routes with multiple vehicles at multiple transfer terminals to as simple as two transit routes at a single transfer stop. This research focuses on the transfer coordination problem between a receiving with a feeding transit route at a single transfer stop. Figure 1.3-1 demonstrates the problem addressed in this research.

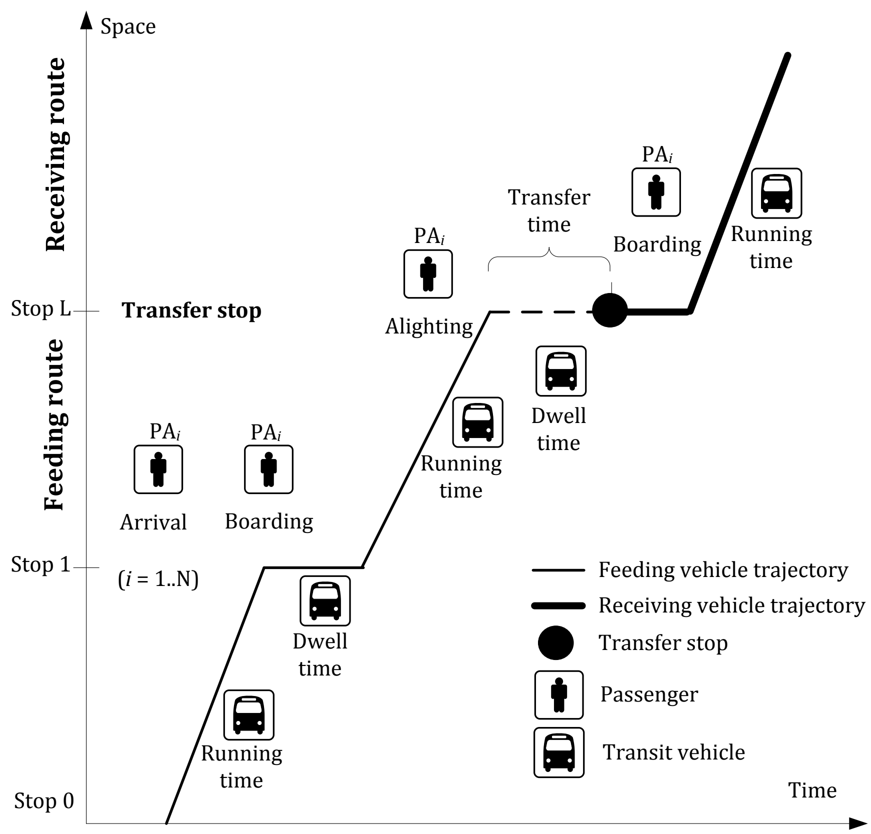


Figure 1.3-1 Transfer coordination problem

While this research aims to solve transfer coordination at the simple set-up illustrated in Figure 1.3-1, it is applicable to the case of a single feeding line and multiple receiving lines because transfer coordination planning and control only apply to the receiving lines. The following assumptions define the scope of this research to: (1) coordination is at a single stop with control is restricted to this transfer stop (no dynamic control upstream); (2) transfer is uni-directional (connection between a feeder service to a receiver service); (3) the transfer stop is a time point stop (schedule regulation).

This research aims to reduce transfer time by transfer coordination using the knowledge of the causality interactions between transit passengers and vehicles. Passengers arrive, board and alight the feeding route and then board the receiving route. The time gap between their alighting (from the feeding route) and boarding (to the receiving route) is the transfer time. Meanwhile, transit vehicle operates in a dynamic environment where various factors could affect its operations. Variability (of travel time and dispatch time) is an inevitable part of transit operations from dispatch to the end stop of a service. Any model to represent the transit system should sufficiently integrate dispatch time variability and travel time variability in the model.

The interaction between passenger demand and bus operations also significantly affects the transfer time. More passenger means longer dwell time and more stopping at stops. High transfer demand also requires a well-planned transfer schedule. This research therefore focuses on theses distributed and interacting entities under dynamic behaviours and phenomena of transit passengers and transit vehicles in a simple set-up of two transit routes connecting at a single transfer terminal. We divide the transfer coordination procedure into offline and online transfer coordination problem.

1.3.2 **Offline transfer coordination problem**

Offline transfer coordination is a scheduling problem. The literature of offline transfer coordination could be divided into *timetable synchronisation* (TS) and *timed transfer coordination (*TTC*)*. TS coordinates multiple schedules to reduce passenger transfer time. TTC focuses on a narrower problem compared to TS. TTC defines a value of Planned Transfer Time between transit schedules so that passengers can make successful transfers. While the value of Planned Transfer Time should not be too small to accommodate all the randomness in vehicle arrival time to the transfer stop, it also should not be too large because it increases total travel time. In a deterministic world without travel time variability, Planned Transfer Time would simply be the time needed for passenger to alight a transit vehicle and board another vehicle. However, because of travel time variability, transit vehicles dispatch from the depot and arrive to the transfer stop earlier or later than their schedule.

The existing studies in literature are based on the same fundamental assumption that the randomness in vehicle arrival time is anticipated because coordinated timetable should accommodate all the variability in transit travel time. However, existing offline transfer coordination models have two main problems: (1) public transport travel time variability has not been thoroughly understood, as the common definition of travel time variability has been established for private transport; and (2) the passenger demand has not been comprehensively considered in offline transfer coordination models.

1.3.3 Online transfer coordination

This research defines the online transfer coordination as a real-time problem to dynamically coordinate two transit vehicles of two routes at a single transfer stop. These two transit vehicles are hereafter referred as the receiving vehicle (RV) and the feeding vehicle (FV), in which passengers are transferring from FV to RV. In operation if FV arrives earlier to the transfer stop than RV there would be no transfer coordination needed, because passengers would simply alight from FV to wait for the coming RV. However, if RV arrives earlier than FV, there would be a binary operational problem of whether RV should be held at the transfer stop to wait for FV so that passengers can make transfers, or should RV leave as scheduled.

The fundamental difference between air transportation and public transit in online transfer coordination is the availability of passenger transfer plan. In air transportation, the passenger itineraries are widely available, so that air traffic controller can easily devise timely decision on transfer coordination by considering the cost to both transferring and non-transferring passengers. In public transit, passenger transfer plan is generally not available. Most of the existing online transfer coordination models in the literature assume a transfer demand at the studied transfer stop (Chowdhury and Chien, 2001; Chung and Shalaby, 2007; Dessouky et al., 1999; Dessouky et al., 2003). In order to implement these models in the practical world, predicting the transfer demand in an arriving bus is essential. However, most of the existing studies in the literature have not described a methodology to predict the transfer demand in real-time.

As mentioned in Section 1.3.1, this research focuses on the problem of a single transfer stop. This simple study case is consistent with the majority of existing studies in online transfer coordination (Abkowitz et al., 1987; Chung and Shalaby, 2007; Dessouky et al., 1999; Dessouky et al., 2003; Lee and Schonfeld, 1991). While the multiple transfer stops case is also an interesting transfer coordination problem, it is outside the scope of this research.

1.3.4 Availability of Big Transit Data

One of the dominant factors originating these problems is the unavailability of data. Traditional transit data includes manual observations and transit user surveys are generally expensive and limited in size & coverage. Transit Agencies are at a critical transition in data collection technology from Manual Data Collection toward Big Data where data are automatically collected in large volume and density. Manual Data Collection with low capital cost, but high marginal cost, small sample size and sometimes unreliable accuracy is being replaced by little marginal cost, large sample size and disaggregated Big Data. Public transport Big Data is the data of transit vehicles and passengers that have massive volume and are automatically collected. Only recently those Big Data system such as Automatic Vehicle Location (AVL), Automatic Passenger Counter (APC), Automatic Vehicle Identification (AVI) and Automatic Fare Collection (AFC) System have become widely popular for collection and analysis. The proliferation of these modern technologies provides a tremendous opportunity to solve the two aforementioned research problems. Interested readers can refer to Appendix A for more detailed descriptions of Public transport Big Data.

1.4 Research Objective and Questions

This research aims to develop a comprehensive and effective transfer coordination framework that optimises both offline and online transfer coordination, so that public transit transfer quality would be as close as possible to the quality of air transportation transfers. Under that motivation, this dissertation has two primary objectives: (1) to enhance offline, and (2) to improve online transfer coordination.

To pursue these primary objectives, this research also defines three secondary objectives to develop the required knowledge to meet the primary objectives. Offline transfer coordination primary objective requires travel time variability knowledge, while online transfer coordination primary objective requires the knowledge on passenger travel pattern and segmentation. Therefore, understanding travel time variability and understanding passenger travel pattern and segmentation are the secondary objectives of this dissertation. **As this is a thesis by publication, both primary and secondary objectives are investigated in comprehensive stand-alone studies and integrated in journal articles.**

Figure 1.4-1 illustrates the primary and secondary objectives, as well as the research questions that those objectives are answering.

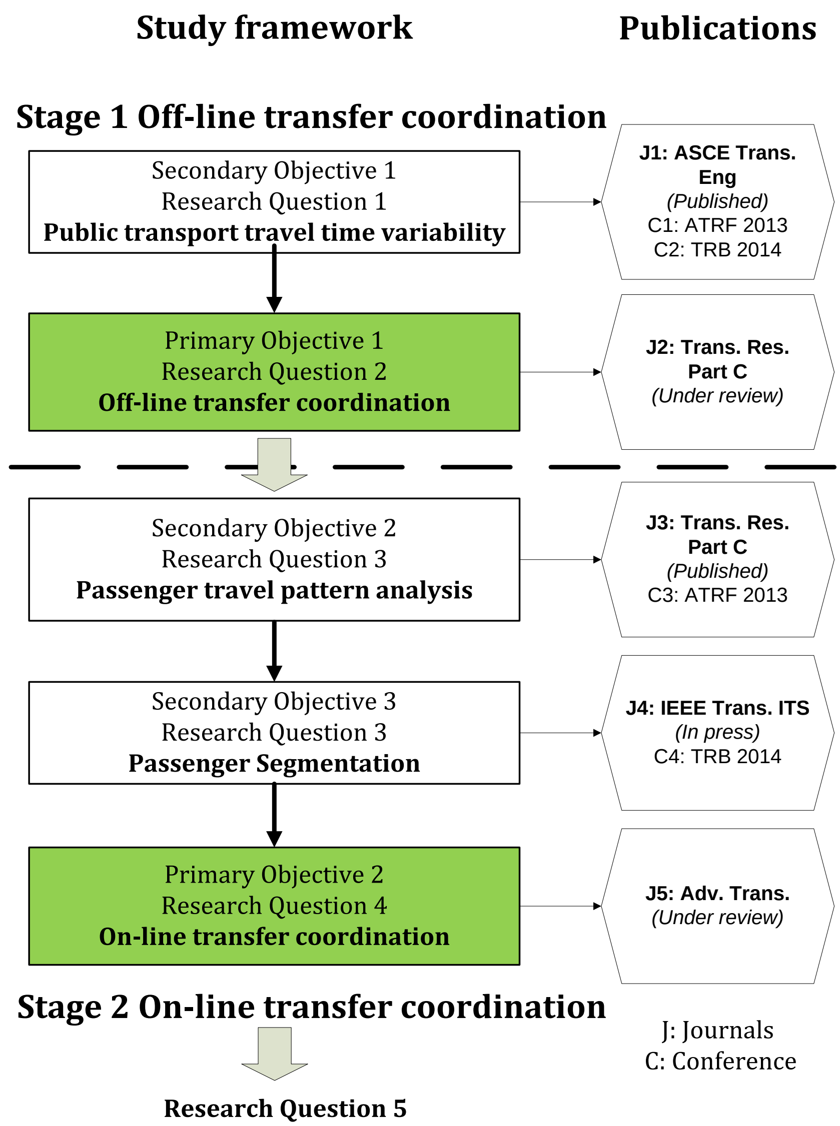


Figure 1.4-1 Thesis stages, objectives, questions and publications

1.4.1 Stage 1: Offline transfer coordination

Stage 1 solves the problem of offline transfer coordination in public transit. As offline transfer coordination is a scheduling problem, it requires knowledge of travel time variability. Therefore to pursue this primary objective, a secondary objective needs to be achieved.

Secondary Objective 1: Understand public transport travel time variability

Public transport travel time variability shows the variation in transit vehicle operations, which facilitates the optimisation of Planned Transfer Time. The following steps will be done to achieve this Secondary Objective

1) Establish the public transport-oriented definitions of travel time variability
2) Propose a 7 step parametric bootstrapping method to investigate the probability distribution of travel time
3) Propose a probabilistic indicator of public transport travel time variability

Primary Objective 1: Enhance offline transfer coordination

Based on the understanding of travel time variability, the problem of TTC is investigated. The investigation will have the following steps

1) Integration of travel time variability and real passenger demand into an Event-Based Multi Agent Simulation (EMAS) model
2) Investigation of transfer time and probability of missing a transfer at different value Planned Transfer Time, dispatching strategies and travel time values

Research questions answered in Stage 1

The Stage 1 of this dissertation answers the following research questions

- Research Question 1: How to characterise and model public transport travel time variability?
- Research Question 2: How to improve transfer coordination in offline strategic planning?

1.4.2 Stage 2: Online transfer coordination

The main research problem in Stage 2: online transfer coordination is the unavailability of passenger transfer plan. To anticipate the passenger transfer plan or predict the number of transferring passengers, this research firstly analyses individual passenger travel pattern (Secondary Objective 2) and passenger segmentation (Secondary Objective 3) to develop the knowledge required to the final online transfer coordination strategies.

Secondary Objective 2: Analyse passenger travel pattern

Passenger travel pattern shows the regular times and places of individual passenger travels. It reveals passenger travel behaviour and facilitates the anticipation of passenger transfer plan for online transfer coordination. This thesis proposes a comprehensive method to mine travel pattern from Smart Card AFC data using the following steps

1) Reconstructing full travel itineraries from Smart Card transactions
2) Mine travel pattern from the historical travel itineraries
3) Provide a sensitivity analysis of parameters for the mining algorithm
4) Propose a new algorithm to detect and update the daily changes in travel pattern

Secondary Objective 3: Passenger segmentation

The next secondary objective is to perform passenger segmentation. This step augments passenger characterisation and profiling. This step also enables the transfer demand prediction in online transfer coordination by separating passengers who follows regular behaviours with those who are randomly using public transport, so that the confidence in individual travel pattern is known and increased. This is done using the following steps

1) *A priori* market segmentation analysis
2) Analysis of each passenger segment

Primary Objective 2: Improve online transfer coordination

This dissertation proposes a new transfer coordination framework in real-time that utilises the knowledge of individual travel pattern. The understanding of travel pattern and passenger segmentation enables us to predict the number of transferring passengers, which in turn is an essential component of online transfer coordination strategies. The knowledge of transfer demand facilitates the estimation of the cost induced by a coordinated transfer decision to dynamically compare with the cost induced by not issuing a coordinated transfer decision. The following steps will be reached to pursue this primary objective

1) Predict the transfer demand
2) Predict the non-transferring demand
3) Predict transit vehicle travel time
4) Propose and compare 6 strategies of online transfer coordination

5) Sensitivity analysis of passenger demand and travel time

Research questions answered in Stage 2

To accomplish the objectives, we have to address the following research questions:

- Research Question 3: How to mine individual passenger travel pattern?
- Research Question 4: What strategies could enhance online transfer coordination in transit operational control?

1.4.3 The integration of Stages 1 and 2

While Stage 1 provides a method to coordinate two transit schedules for transfer coordination in offline strategic planning, Stage 2 provides a dynamic model to ensure simultaneous vehicles dwelling in real-time so that passenger transfers are possible. By solving different problems of public transport transfer coordination, the Stages are not overlapped but cooperated. Stage 1 optimises the transit schedule so that passengers in general would have smaller mean transfer time and probability of missing a transfer. However, there will be still some occasions where RV arrives to the transfer stop earlier than FV. Stage 2 is developed to provide an optimal solution for these occasions.

The Stage 1 and Stage 2 of this dissertation together answer a final research question

- Research Question 5: What are the benefits of transfer coordination?

1.4.4 Publication plan

Table 1.4-1 presents the publication plan of this thesis by publication.

Table 1.4-1 Publication list

ID	Journal articles	Objective	Status
J1	**Kieu, L. M.,** Bhaskar, A. & Chung, E. 2015. Public transport travel time variability definitions and monitoring. *ASCE Journal of Transportation Engineering*. Vol. 141, Issue 1, Jan 2015. DOI: 10.1061/(ASCE)TE.1943-5436.0000724.	Secondary objective 1	Published
J2	**Kieu, L. M.,** Bhaskar, A. & Chung, E. TBA. An evaluation of timed transfer coordination using Event-based Multi Agent Simulation. *Transportation Research Part C.*	Primary objective 1	Under review

J3	**Kieu, L. M.,** Bhaskar, A. & Chung, E. 2015. A Modified Density-Based Scanning Algorithm with Noise for spatial travel pattern analysis. *Transportation Research Part C.* DOI: 10.1016/j.trc.2015.03.033.	Secondary objective 2	In Press
J4	**Kieu, L. M.,** Bhaskar, A. & Chung, E. 2015. Passenger Segmentation using Smart Card data. *IEEE Transactions on Intelligent Transport System*. Vol 16, Issue 3, June 2015. DOI: 10.1109/TITS.2014.2368998.	Secondary objective 3	Published
J5	**Kieu, L. M.,** Bhaskar, A. & Chung, E. TBA. Transferring demand prediction for timed transfer coordination in public transport operational control. *Journal of Advanced Transportation*.	Primary objective 2	Under review
ID	**Conference proceeding papers**	**Objective**	**Status**
C1	**Kieu, L. M.,** Bhaskar, A. & Chung, E. Empirical Evaluation of Public Transport Travel time Variability. Australasian Transport Research Forum, 2013 2-4 October, Brisbane Australia.	Secondary objective 1	Presented
C2	**Kieu, L. M.,** Bhaskar, A. & Chung, E. 2014. Establishing the Definitions and Modeling the Public Transport Travel time Variability. 93rd Annual Meeting of the Transportation Research Board. 12-16 January, Washington DC, US.	Secondary objective 1	Presented
C3	**Kieu, L. M.,** Bhaskar, A. & Chung, E. 2013. Mining temporal and spatial travel regularities for transit planning. Australasian Transport Research Forum. 2-4 October, Brisbane, Australia.	Secondary objective 2	Presented
C4	**Kieu, L. M.,** Bhaskar, A. & Chung, E. 2014. Transit passenger classification by temporal and spatial travel regularity mined from Smart Card data. 93rd Annual Meeting of the Transportation Research Board. 12-16 January, Washington DC, US.	Secondary objective 3	Presented
ID	**Out-of-the-scope journal articles**	**Objective**	**Status**
J6	**Kieu, L. M.,** Bhaskar, A. & Chung, E. 2015. Empirical modelling of the relationship between bus and car speeds on signalised urban networks. *Transportation Planning and Technology.* Vol 38 no 4. DOI: 10.1080/03081060.2015.1026104	Understand the data	Published
J7	Bhaskar, A., **Kieu, L. M.,** Qu, M., Nantes, A., Miska, M. &	Understand	Published

	Chung, E. 2014. Is bus overrepresented in Bluetooth MAC Scanner data? Is MAC-ID really unique? *International Journal of Intelligent Transport System*. 1-12 Apr 2014. DOI: 10.1007/s13177-014-0089-9.	the data	
J8	Bhaskar, A., Tsubota,T., **Kieu, L. M.** & Chung, E. 2014. Urban traffic state estimation: Fusing point and zone based data. *Transportation Research Part C*. Volume 48, November 2014, Pages 120–142. DOI: 10.1016/j.trc.2014.08.015.	Understand the data	Published

1.5 **Thesis outline**

Chapter 1 introduces the research problem and Chapter 2 reviews the state-of-the-art in transfer coordination and passenger travel pattern analysis. To answer the 5 research questions, the research has been divided into 2 Stages.

Stage 1 consists of Chapter 3 and 4 aiming to understand the public transport travel time variability to answer research question 1-2 and enhance offline transfer coordination. Chapter 3 establishes the definitions of public transport travel time variability (PTTV) and models it to augment the understanding of public transport operational characteristic. Chapter 4 demonstrates the proposed strategies to improve the offline transfer coordination of transit vehicles.

Stage 2 consists of Chapter 5, 6 and 7 aiming to understand individual passenger travel pattern to answer research questions 3-4 and provide online transfer coordination control. Chapter 5 enhances the understanding of individual transit passenger by travel pattern analysis, before further augmented by the study on passenger segmentation in Chapter 6. Employing the knowledge gained from Chapter 5 and 6, chapter 7 proposes strategies for transfer coordination by a incorporating a series of real-time predictive control models.

Finally, the main contributions of this research, the response for the aforementioned research questions and recommendations for future research are concluded in Chapter 8.

2 Literature review

This chapter reviews the latest developments in transit transfer coordination methodologies. The review firstly focuses on the state-of-the-art on transfer control (Section 2.1), followed by the challenges in providing a coordinated transfer (Section 2.2). Finally, the chapter is concluded with the discussion on the gaps in literature (Section 2.3).

2.1 Transfer coordination improvements in literature

Poor on-time performance leads to the problem of transfer coordination, where the passenger might have to catch the next transfer trip, instead of the planned one. Hadas and Ceder (2010b) showed that missed transfer is one of the main determinants of service unreliability. Guo & Wilson (2011) suggested that an improvement of transfer coordination would significantly improve the service reliability. The author showed that from passenger perspective the number of transfer actually have much higher cost than other sources of unreliability such as initial waiting time, in-vehicle travel time, transfer waiting time and transfer walking time. Sharaby and Shiftan (2012) found that the implementation of free transfers policy in Haifa, Israel contributed to an increase in passenger trips by 7.7%. Transfer coordination becomes an essential problem to enhance the transit service reliability in comparison with private transport, which is beyond dispute a nearly door-to-door service without connections. According to Ceder (2007), coordinated transfer is one of the special service with the possibility of attracting transit ridership from private transport.

To alleviate the inconvenience of travelling multi-legged trips, various transfer coordination strategies have been proposed in literature. Transfer coordination improvements strategies aim to reduce the transfer time by either adjusting the timetables in offline strategic planning or dynamically adjusting the vehicle departure time in online operational strategy. The literature has evolved from transfer coordination using: (1) synchronised timetable (Section 2.1.1) to (2) timed transfer coordination (Section 2.1.2) and finally to (3) online transfer coordination in real-time (Section 2.1.3).

2.1.1 Transfer coordination by timetable synchronisation in offline planning phase

The offline transfer coordination approach aims to synchronise multiple route schedule to maximise the probability of passenger transfer. Most of the authors in literature developed an optimisation-based solution approach to minimise the sum of transfer times of all passengers involved in the connection**. Early researches assumed deterministic headways and travel times** to solve the transfer optimisation model using either mathematical programming model or heuristic approaches. Multiple timetables are synchronised to minimise the passengers transfer time.

Rapp and Gehner (1967) proposed a transfer optimization tool to minimize the total passenger transfer waiting time assuming deterministic travel time and passenger arrival process. The objective of their optimisation model was an automated adjustment of departure times, which was solved by a heuristic search method. The data of Switzerland validates their method, with the passenger transfer time reduced by 20%. Domschke (1989) used several heuristic and branch-and-bound solutions to minimise the total waiting times for all passengers who want to transfer from one route to another. Daduna and Voss (1995) formulated a programming problem as a quadratic semi-assignment problem. A heuristic is proposed to find the initial solution, and tabu search and simulated annealing are used to find the final solution. A few other studies aimed to investigate the impacts of transfer coordination by simulation. Abkowitz et al. (1987) analysed the simple case of two interconnected bus routes in a simulation study of four transfer strategies: no coordination, coordination transfers without vehicle waiting, coordination with holding one route, and coordination with holding both routes. The simulation results revealed the situations where each of the transfer coordination type is suitable. Ceder et al. (2001) synchronised multiple bus timetables with the objective of maximising the number of simultaneous bus arrivals at transfer stops. The deterministic optimisation model was formulated as a mixed integer programing problem and solved with a heuristic.

In the practical world, transit vehicles generally cannot run exactly as planned due to the variability of travel time and demand. **More recent studies in literature have considered some stochasticity in their transfer coordination model**. Bookbinder and Desilets (1992) was one of the first studies that explicitly considered the vehicle arrival time as a random variable, assumed as a truncated exponential distributed variable. A heuristic search algorithm similar to the one in Rapp and Gehner (1967) was developed to minimise the passenger expected waiting time. The authors emphasized the importance of considering stochasticity in coordinated timetable. They believed that timetable synchronisation could even be worse than the original timetable if deterministic variables had been used. Nachtigall and Voget (1996) showed that waiting times for transferring passengers can be reduced to departure time variability. The authors developed a genetic algorithm combined with a greedy heuristic and a local improvement approach to find the solution for timetable synchronisation that minimise passenger waiting time. Wong et al. (2008) proposed a mixed integer programming optimisation model for the train schedule synchronisation problem. The stochasticity of transit operation is modelled by the range of travel time between its upper and lower bound. Cevallos and Zhao (2006) optimised the transfer time in bus transit system by shifting current timetables. The model was solved using a genetic algorithm using the schedule and ridership data. The developed method was tested using the data in Florida, US and showed 10% reduction of transfer time per day. Ibarra-Rojas & Rios-Solis (2012) formulated their optimisation model of bus timetable synchronisation based on Ceder et al. (2001) but focused on a much more complicated network in terms of size, density, orientation and structure. Stochasticity in vehicle departure time was considered by formulating a feasible departure time window.

Timetable synchronisation method is a systematic approach where multiple transit line timetables are coordinated, and total passenger transfer time is minimized. Its drawback is the assumption of deterministic in early studies. Recent studies have added stochasticity in travel time, dwell time and passenger demand into the timetable synchronisation model. However, in a global problem of multiple lines aiming at long-term effective timetable, the integrated stochasticity might not reflect the level of variability in the practical world.

2.1.2 Transfer coordination by timed transfer in offline planning phase

In order to take into account more randomness in vehicle arrival times, dwell times and passenger demand, existing studies in the literature have also been addressing transfer coordination in a narrower problem: timed transfer of two or several lines. The objective of timed transfer coordination is to develop a transit schedule so that vehicle would arrive simultaneously at transfer stops. An amount of slack for transfer coordination is added to account for variability of vehicle arrival time.

Hall (1985) aimed at finding an optimal slack time to minimise the expected passenger waiting time when transit vehicles were delayed for transit coordination to an exponential distributed amount of time. This study is the first attempts in timed transfer, where the author emphasized its importance when the headway was large. Hall et al. (2001) extended the original work of Hall (1985) by developing a dynamic dispatching model where RV was either dispatched immediately or held until a predetermined time to wait for a connecting FV. An objective function of several variables such as the number of on-board passengers, expected transferring passengers, next service departure time and lateness distribution was proposed to minimise the passenger expected waiting time. Lee and Schonfeld (1991) proposed two models to choose the best slack time for a transfer interchange between bus and train. The models assumed bus and train travel time from a probability function. The authors showed that transfer coordination is only effective when the standard deviation of arrivals is less than a certain value. A similar statement was also found in Knoppers and Muller (1995). This study analysed the benefits and limitations of transfer coordination in public transport (Knoppers and Muller, 1995). The empirical study in this research showed a significant reduction in transfer waiting time by adjusting the departure time of connecting vehicle. Ngamchai and Lovell (2003) further investigate the possibilities of transfer coordination in reducing passenger transfer time. The objective of this study was to optimise the route configurations, frequencies and coordinated headway at transfer stops by a deterministic optimisation model. The solution was found by a genetic algorithm showing around 10% reduction in transfer waiting time. The authors also found that passenger transfer time in the worst coordinated scenario was similar to the best scenario without coordination. Shafahi & Kani (2010) formulated two deterministic mixed integer programing models of timetable synchronisation and timed transfer coordination which can be solved by CPLEX in small to medium-sized network and by genetic algorithm in large-sized network. The methodology proposed is highly practical and significantly reduces the passenger transfer waiting time at transfer stops.

Timed transfer is generally an optimisation problem of minimising passenger transfer time in a narrower scope than the timetable synchronisation problem. The existing timed transfer coordination studies share same fundamental assumption that travel time variability is adequately considered in the transfer coordination models. Although the randomness in vehicle travel time and dwell time are better considered than the timetable synchronisation studies, the added slack time may not be enough to accumulate the variability in vehicle arrival time. The connection vehicle may have to wait for a full slack time period without a successful transfer, if the feeding vehicle is late for even more than the planned time for transfer coordination.

2.1.3 Transfer coordination by online operational strategies

Transfer coordination studies in offline planning phase share a similar draw-back of under estimating the variability of vehicle arrival time. The transit system is operating in a dynamic environment where various factors affect the transit vehicle travel time. A timetable will be the optimal schedule for a certain time period, but might not still be the best when the operating condition has changed. There is a need for a more dynamic method with high adaptability for better considering the stochasticity of vehicle arrival times.

Recently, the availability of Big Data has opened a new avenue to enhance the transfer coordination in real-time. The primary idea of online transfer coordination is to predict the arrival time of the first transit vehicle and the number of transferring passengers to decide if the second transit vehicle should be held for passenger interchange. The idea is similar to the "hub-and-spoke" system at some major connecting airports, where air controller may delay an outcoming flight to allow passengers transfer in case their incoming flight has been delayed for a certain amount of time. The availability of AVL in real-time facilitates the implementation of these online strategies in public transit. Dessouky et al. (1999) was the first attempt in online transfer coordination. The impacts of the real-time AVL data to a proposed timed connection model for high frequency bus lines are explored. The arrival time is predicted with the presence of real-time AVL data and vehicle holding decision is issued accordingly, whereas without real-time AVL the connecting bus would sometimes have to delay up to the predetermined holding time. The results from the simulation in this study showed that AVL has the potential to reduce passenger transfer time. Dessouky et al. (2003) followed the same approach as in Dessouky et al. (1999), but depended heavily on predictions of arrival time, number of transferring and boarding passengers. The authors again concluded that the strategy with most data available would perform best in reducing passenger waiting time. Chowdhury and Chien (2001) developed a model for dynamic dispatching of vehicle for maximising transfer opportunities. A cost function consisted of the cost for holding vehicle, delay cost and passenger missed connection cost is minimised. The authors showed that dynamic vehicle dispatching noticeably enhanced the transfer efficiency and reduced total cost. In Chung and Shalaby (2007), the cost function was the combination of transfer time, in-vehicle passenger waiting time and downstream passenger waiting time. The aim of that study was to find the best of the trade-off between these costs. The author also emphasised that an online control was essential to maintain coordinated transfer due to unexpected delays of transit vehicles. Hadas and Ceder (2010a) proposed the use of operational tactics such as hold, skip stop and short-turn to enhance the probability of transfer coordination in real-time. The authors developed a dynamic-programming optimisation model to reduce total travel time by 10% and increase the number of direct transfer by 200%.

The transfer demand is one of the most important factors in these existing online transfer coordination cost functions (Chowdhury and Chien, 2001; Chung and Shalaby, 2007; Dessouky et al., 1999; Dessouky et al., 2003). The transfer demand shows the balance between the trade-off between the cost induced by the transfer decision to transferring and non-transferring passengers. While the non-transferring demand is the passengers who physically walk to transit stations and a few existing studies have successfully predicted this demand in the literature (FHWA, 2006), the nature of the transfer demand is very stochastic. In an operational bus arriving to the transfer stop, there may be none or only several passengers who will transfer. Analysing the transfer demand using observed Smart Card AFC data in SEQ in 2012, we found that in an arriving bus of Route 555 to the transfer stop, there is on average only 1.25 passenger who will transfer and the probability of no transferring passenger is 40%. The fact that this variable is discrete and usually very small makes it complicated to predict in real-time. However, to the best of the author's knowledge, none of the existing studies have described a method to forecast the transfer demand in real-time.

There is a trend of study from offline transfer coordination using synchronised timetable to online transfer coordination using operational strategies. While the literature still continues to acknowledge the importance of synchronised timetable, the majority of studies have emphasised the vital role of real-time control. The success of timed transfer relies heavily firstly on schedule adherence to ensure that transit vehicles would arrive on-time, and secondly on real-time strategies to adjust transit trajectories to maximise the number of simultaneous arrivals at connection stops (Ceder et al., 2009). However, similarly to the connection activities at airports, the online transfer coordination decision needs the following information: (1) arrival time of the feeding vehicle, (2) number of connecting passengers, and (3) number of passengers using the receiving vehicle that would be affected by the coordination strategy. While this information is widely available in air transport, it must be estimated in public transport because passenger trips are not preregistered. Most of the online existing transfer coordination studies had a travel time prediction model, whereas the number of transfer passenger was assumed as known and constant (Chung and Shalaby, 2007; Dessouky et al., 1999) or was estimated (Dessouky et al., 2003).

2.2 **Complexities in transfer coordination**

Transfer coordination has been one of the essential components in air transportation "hub-and-spoke" system. Flight schedule are synchronised to grant sufficient time for passenger transfers. Air controller also delays outcoming flight for a certain amount of time to allow passenger interchange if the feeding flight arrives late. The delay of the incoming flight, the number of transferring passengers, and the frequency of the outgoing flight are the three most crucial factors for transfer coordination in air transportation. Transfer coordination in public transportation follows the same principal. Offline transfer coordination minimises the total passenger transfer time during transit planning by schedule synchronisation. Online transfer coordination takes advantage of real-time Big Public transport data to dynamically synchronise transit vehicle trajectories to maximise the probability of simultaneous arrivals at transfer stops.

However, transfer coordination in public transit is not as widely applied as in air transportation due to two major challenges in connecting multiple transit lines. Firstly, compared to airplane travel time, the travel time variability in transit vehicles, especially buses, is much higher and complicated. Timetable synchronisation and timed transfer strategies can provide an optimal plan for transfer coordination in offline planning phase, but poor on-time performance due to high TTV could completely devastate the plan. Secondly, transit authorities have limited knowledge about their customers, preventing them from understanding their transferring behaviour and predicting the number of transferring passengers. Without an accurate estimation of the number of passengers willing and not willing to transfer, online transfer coordination could fail to find the optimal transfer strategy in real-time. This following section reviews the latest advances in public transport travel time variability (PTTV) and passenger travel pattern analysis to understand these complexities.

2.2.1 Public transport travel time variability in literature

TTV has been defined in the literature as having three main types (Bates et al., 1987; Noland and Polak, 2002):

Vehicle-to-vehicle (or inter-vehicle) variability (TTV_{v2v}) is the difference between travel times experienced by different vehicles travelling similar trips within the same time period. Factors contributing to TTV_{v2v} includes signal delay, driver behavior and flow impedance from bikes and pedestrians.

Period-to-period (inter-period or within-day) (TTV_{p2p}) is the variability between the travel times of vehicles travelling similar trips at different times on the same day. Factors contributing to TTV_{p2p} includes temporal variations in traffic demand, incidents, weather conditions or level of daylight.

Day-to-day (or inter-day) (TTV_{d2d}) is the variability between similar trips on different days within the same time period. It is attributed to the day-to-day fluctuations in traffic demand, weather, driver behaviors, and incidents. TTV_{d2d} is independent to the recurrent congestion effects. Within the same time period, a high demand transit system has low day-to-day TTV if congestions are recurrent.

For transfer coordination, the variability of travel time of the same service or route on multiple days is more important than the TTV_{v2v} or TTV_{p2p}. Day-to-day TTV provides a complete picture of transit performance on multiple days and facilitates the modelling of TTV for transfer coordination.

The literature on day-to-day PTTV is limited. Abkowitz and Engelstein (1983) predicted the running time and running time deviation by using linear regression. Their model revealed that only the link length has significant impact on the day-to-day PTTV. Mazloumi et al. (2010) explored the day-to-day PTTV in Melbourne, Australia using GPS data. The nature and pattern of variability were explored by fitting bus travel time to Normal and Lognormal distribution, followed by a linear regression analysis to investigate the impacts of different factors to PTTV. Moghaddam et al. (2011) proposed a procedure and empirical models for predicting the Standard Deviation (SD) of travel time based on the average bus travel time, number of signalized intersection and a ratio between volume and capacity for an origin-destination path.

Abkowitz and Engelstein (1983), Mazloumi et al. (2010) and Moghaddam et al. (2011) have defined PTTV as deviation or SD of travel time using individual bus travel time samples from multiple days at the same time period. Their definitions were based on the common definition of TTV_{d2d} by Bates et al. (1987) and Noland&Polack (2002), where "similar trips" means vehicles of the same route travelling within the same time period.

The estimation of day to day PPTV based on the individual vehicle travel values does not provide true actual daily variations. The calculated PTTV could be sourced from multiple days or multiple vehicles travel time variation because on each day multiple samples are collected. The problem can be explained with the help of an example: Given two days with exactly the same individual vehicle travel times, in which *day1* has *n* buses for a given period. There is TTV_{v2v} during that period if not all travel time values are same. Assuming, *day2* be exactly the same as *day1*, if all the individual vehicle travel time samples from *day1* and *day2* are used to calculate TTV_{d2d} then estimated TTV_{d2d} will be equal to TTV_{v2v}. However, in this example the TTV_{d2d} should be zero because the two days are exactly the same.

In public transport, PTTV is closely related to the on-time performance of transit services. When PTTV is high, the on-time performance is worse and vice versa. On-time performance of transit vehicle is essential for the success of transfer coordination. It has been long considered as one of the most important characteristics of any transit system and extensively studied in the literature, where authors have explored the on-time performance by one of two major approaches.

The first approach is to investigate the determinants of service on-time performance. Various factors' impacts to the key indicators of service reliability such as running time, headway variation or schedule deviation are measured and modelled. Abkowitz and Engelstein (1983) predicted the running time and running time deviation by using linear regression. Their model revealed that only the link length has significant impact on the service reliability. The authors also revealed that the schedule adherence at earlier stop on the bus route had a significant influence on the bus travel time variance at downstream of the bus route. Strathman and Hopper (1993) quantified the negative impacts of the number of alighting passengers, the location of transit stop, headways and time-of-the-day to the probability of on-time arrival. Driver's behaviour is also one of the determinant factors of on-time performance. Dueker et al. (2004) conclude that drivers tried to stay on the schedule by speeding up. The authors also found out that the dwell time tended to be less for buses which were behind the schedule. The advantage of this approach is the ability to explore the determinants of service reliability. However, a large variety of data sources should be analysed to investigate the combination and interaction between different determinants of service reliability. Moreover, most of the studies employed *an ex post* approach which does not facilitate the reliability monitoring and control.

The second approach to understand the on-time performance is to explore the travel time distribution or schedule deviation distribution. While travel time and schedule deviation could follow two different types of distribution, the exploration of these two distributions both shows the nature and shape of on-time performance because schedule travel time is deterministic for a specific study period. A short-tailed distribution of travel time usually denotes good on-time performance, while a long tail skewed distribution shows high schedule deviation. Bates et al. (2001) showed that the median and distribution of travel time are better performance indicator than the mean travel time Skewed types of distribution are often used as the descriptor of the schedule deviation: Log-normal (Turnquist, 1978), Gamma (Guenthner and Hamat, 1988) and Exponential distribution (Talley and Becker, 1987). The travel time has conversely described by both symmetrical (Taylor, 1982) and screwed distribution (Andersson et al., 1979) or both of them (Mazloumi et al., 2010). The distribution exploration approach facilitates the understanding of the pattern of travel time and the probability of on-time. However, the data sample size and distribution fitting approach significantly affects the resulting distribution type, which could be the reason why the distribution of travel time and schedule deviation is inconsistent among different studies.

Existing studies have also proposed various on-time performance enhancement strategies. These remedies can be characterised as either short term or long term approach.

The short term approach aims to return service to the schedule in either occasional incidents or to keep the service always on schedule and often involves in transit operation. These strategies are classified into bus holding – where buses are held at time points if they are ahead of the schedule and stop skipping – where buses skip some stops to "catch up" with the schedule. Eberlein et al. (2001) formulated the bus holding problem as deterministic quadratic programing problem based on the rolling horizon scheme. An iterative heuristic optimisation problem with deterministic passenger arrival rate and running time was formulated to determine the optimal holding strategy. Hickman (2001) solved the bus holding problem by an analytic optimisation model considering stochastic vehicle running time and passenger arrival. The convex quadratic program model optimised the holding time of single bus at a single control point. Recently, several authors have also solved the bus holding problem using control strategies, where the authors delay (or slow down) the bus dynamically based on real-time headway information to keep a regular headway between multiple vehicles (Bartholdi III and Eisenstein, 2012; Daganzo, 2009; Daganzo and Pilachowski, 2011; Xuan et al., 2011). The stop skipping strategies can be formulated into four categories: zone scheduling, short turning, deadheading and expressing. Zone scheduling is the category of strategies in which each transit vehicle only serves a limited zone within the whole route (Furth, 1986; Jordan and Turnquist, 1979; Turnquist, 1981). Short turning strategies allow transit vehicles to cover only the high-demand zone, and then skip the remaining part of the route by making an U-turn and start the reverse direction service (Ceder, 1989; Furth, 1987). Deadheading strategies allow transit vehicles to skip a number of stops at the beginning of the route to reduce the total dwelling time (Cortés et al., 2011; Furth, 1985). Expressing involves skipping a set of stops to keep up with the schedule and increase transit operating speed if the bus is behind the schedule (Liu et al., 2013; Sun and Hickman, 2005).

The long term approach focuses on systematic on-time performance and often involves in transit schedule and route design. Seneviratne (1990) used Monte Carlo simulation to analyse the impacts of multiple operating strategies to service reliability. The author found either under or over presents of time points would lead to an undesirable impact to on-time performance. Zhao et al. (2013) proposed a stochastic optimisation model to solve the slack time setting problem that considering spatial equity, drivers and transit operators risk taking attitude. The authors believed that both TTV and bus frequency can affect the slack time setting. Wirasinghe and Liu (1995) developed a cost-based approach to transit schedule design for a simple bus route with a single time point. Various cost components such as passenger waiting time, passenger schedule delay and operating cost were included in the objective function. The timetabling problem is usually considered straight forward in the literature, but timetable design to facilitate transfer coordination is undoubtedly complex (Desaulniers and Hickman, 2003).

2.2.2 Passenger travel pattern analysis in literature

Passenger travel pattern has been traditionally analysed using stated preference or travel diaries survey data (Adler and Ben-Akiva, 1979; Goulias, 1999). Recently Smart Card (SC) AFC system has been increasingly popular in public transport, providing a massive quantity of continuous and dynamic data on passenger temporal and spatial movements. It enables continuous analysis of multiday travel patterns on a much larger population than the traditional travel survey method.

The literature review in this section will cover the state-of-the-art on travel pattern analysis using Big Public transport data, in particular AFC data to understand passenger behaviours and facilitate transit planning. There are two trends that could be identified from the literature of travel pattern analysis from AFC data. The existing studies in the literature have explored travel pattern by different level of discretisation on passenger and spatial/temporal travel pattern.

Existing passenger aggregation approaches for travel pattern analysis

An emerging number of publications have recently analysed transit passenger travel pattern by different level of aggregation from whole aggregated dataset to each individual SC user. Utsunomiya et al. (2006) is an example of aggregated dataset analysis. The authors described the data possessing and analysis methods to mine meaningful information from SC data. Jang (2010) demonstrated the use of SC data in travel time and transfer locations analysis. The method facilitates the comparison between different transit modes and the identification of passenger transfer choices. Hasan et al. (2013) exploited SC data to observe both spatial and temporal passenger travel pattern. The authors modelled two important passenger decisions: (a) which place to visit (by assuming a fixed probability of visit to each regular place) and (b) how long to stay (by a hazard based duration modelling). The whole dataset analysis explores general travel patterns from transit passengers.

Some other authors emphasized the similarity of travel pattern by subgroup. Their analyses are based on the aggregation of several similar characteristics of the transit trip and passenger. Morency et al. (2007) aggregated the SC into five classes according to the card type and the privilege of route usage. The travel profile of each card type could be well observed by investigating the indicators of spatial and temporal travel pattern. Chu (2009) proposed a new framework to mine spatial-temporal distribution of transit demand by different aggregation level such as stop, route, link, node and card type. Lee and Hickman (2014) developed a heuristic rules algorithm and a classification decision tree to group SC users into multiple classes and infer their trip purposes.

Although aggregated travel pattern analysis provides insights into the travel pattern of general user, it fails to capture the individuality of travel behaviour and does not facilitate the inference of passenger behaviours. Moreover, the typologies of trips and passengers are predefined which might not reflect the similarity of passengers between the same class, and the difference between classes.

Several studies have recently enriched the travel pattern comprehension by individually analysing each SC user. Chu (2010) described a disaggregated travel pattern analysis framework for multi-day SC data. "Anchor points" or repeated travel locations are mined from each SC user and then assigned to known spatial coordinates. Ma et al. (2013) and Kieu et al. (2015c) used the classical DBSCAN algorithm, originally proposed in Ester et al. (1996), to mine spatial and temporal travel patterns from SC data. While individual analysis of travel behaviour enables oriented service provision, the classical DBSCAN algorithm has high quadratic computation complexity.

Existing spatial and temporal pattern aggregation approaches for travel pattern analysis

Spatial travel pattern analysis often spatially breaks down to stop-to-stop repeated trips. However, the limitation of this method has been identified by several authors (Lee and Hickman, 2013). A transit stop is usually linked with only a single direction or route, while transit passengers normally have several route choices options within their origin destination locations. Any stops within the immediate vicinity that provide the same access should be considered in the same travel pattern, because transit passengers might choose them randomly or just by the first arriving schedule. In literature different stop aggregation approaches are proposed to group spatially close stops into the same travel pattern. Chu (2010) aggregated stops within 50m of each other to form a new node. Similarly, Ma et al. (2013) allowed a radius of 200m to consider in the same travel pattern.

Lee et al. (2012b) and Lee & Hickman (2013) proposed a model named "Stop aggregation model" to group stops according to the proximity, stop description and catchment area.

The problem of temporal travel pattern analysis has not received much attention as spatial travel pattern. The existing discretization of time usually breaks down to the aggregation of time to either a number of predefined time window (e.g 1-hour period in (Morency et al., 2007)) or time-of-the-day (e.g. am peak, midday, pm peak in (Chu and Chapleau, 2010; Lee and Hickman, 2014)). A temporal pattern is defined if the passenger repeatedly made multiple trips within a time period. It is strenuous to discretise the temporal pattern for individual passenger because different people would have different regular behaviour. For instance, a 1-hour time window may segregate the journeys at 9:59AM to the ones at 10:01AM, while these journeys come from the same temporal behaviour. Recently, Ma et al. (2013) allowed a 1h time window between the first journey and the last one to be considered in the same travel pattern. Table 2.2-1 summarizes the aforementioned review of the existing advances in travel pattern analysis using SC data.

Table 2.2-1 Comparative overview of the literature on travel pattern analysis using Smart Card (SC) data.

Paper	SC data type*	Passenger aggregation	Spatial pattern discretization	Temporal pattern discretization	Method	Aim
Utsunomiya et al. (2006)	Entry only	Dataset	N/A	N/A	Statistic	Investigate the potential of SC in transit planning
Jang (2010)	Entry-Exit	Dataset	N/A	N/A	Statistic	Travel time and transfer analysis
Hasan et al. (2013)	Entry only	Dataset	N/A	N/A	Simulation	Spatial-temporal analysis
Morency et al. (2007)	Entry only	Group	N/A	Time window	Data mining	Spatial-temporal transit use variability
Chu et al. (2009)	Entry only	Group	N/A	Time-of-the-day	Data mining	Passive survey from SC data
Lee & Hickman (2014)	Entry only	Group	Stop aggregation model	Time-of-the-day	Rules-based heuristic and data mining	Trip purpose inference
Chu & Chapleau (2010)	Entry only	Individual	50m	Time-of-the-day	Data mining	Multiday spatial-temporal analysis
Ma et al. (2013)	Entry only	Individual	200m	Flexible time window	Data mining	Multiday spatial-temporal analysis

* Entry only: Boarding data is available; Entry-Exit: Both Boarding and Alighting data are available

2.3 **Critical overview**

The literature in transfer coordination could be broadly classified into 2 main approaches: offline transfer coordination in strategic planning and online transfer coordination in operational strategy. Although different studies have different objectives and scope of studies, the literature of transfer coordination has generally evolved through 4 main steps:

(1) The earlier researches in offline transfer coordination assumed deterministic vehicle arrival time or headway, and ignored the impacts of stochastic factors in transfer coordination. Most of studies in this category developed optimisation models to minimise the total transfer wait time of transit passengers by timetable synchronisation during route and schedule planning phase. Examples of these studies are Rapp and Gehner (1967) , Domschke (1989) and Daduna and Voss (1995). This approach aims at providing an systematic method to align the schedule of multiple transit lines in a network to minimise passenger transfer time. However, the lack of randomness may limit their applicability in practice.

(2) More recent studies incorporated the impacts of randomness in headway or vehicle arrival time in coordinated transfer models. These studies emphasized the importance of the stochastic factors in finding the optimal connection strategy. The variability of vehicle arrival time, travel time or headway was considered as the main cause for failed transfer. Timetable synchronisation model was still solved by optimisation models, but with vehicle arrival time followed a distribution function (Bookbinder and Desilets, 1992; Cevallos and Zhao, 2006; Nachtigall and Voget, 1996), or as a random variable with an upper bound and a lower bound (Wong et al., 2008). However, the arrival time variability varies at different transit lines and time periods. It is challenging to include all these variations in a global timetable synchronisation solution.

(3) Some other studies solved the coordinated transfer problem by a narrower approach: timed connection of two or several transit lines. Most of studies in this category added an amount of slack time at the schedule to account for variability of vehicle arrival time. Slack time allows the receiving transit vehicle to stay at the transfer stop to wait in case the feeding vehicle is behind its schedule. Examples these studied include Hall (1985), Lee and Schonfeld (1991), Knoppers and Muller (1995), and Ngamchai and Lovell (2003). However, without real-time updates and

predictions of the vehicle arrival time, the receiving vehicle may have to wait for a full slack time period without a successful transfer.

(4) Taking advantage of the newly available Big data, online transfer coordination has recently been developed for real-time operational strategies. The idea is to decide if the receiving vehicle should wait for the feeding vehicle or not, given a prediction of transferring passengers, non-transferring passenger and vehicle arrival time. Examples of these studies include Dessouky et al. (1999), Dessouky et al. (2003), Chowdhury & Chien (2001), Chung & Shalaby (2007) and Hadas & Ceder (2010a). However, without an effective method to estimate the number of transferring and non-transferring passengers, the applicability of these studies in the practical world could be questionable.

The state-of-the-art has been developed from offline to online transfer coordination strategy, from considering deterministic to stochastic factors, and from not using to using real-time Big public transport data. Two major challenges hinder the feasibility of seamlessly transfer in practical. Firstly, the variability of travel time causes poor on-time performance and complicates the transfer coordination. Secondly, the unavailability of the number of transferring passengers due to the lack of knowledge on passenger travel pattern. These challenges precipitate the following gaps in the literature of transfer coordination:

1) In offline transfer coordination, the existing studies have developed multiple algorithms for the optimal coordinated timetable or slack time for minimising the passenger transfer time. These models would only be effective if the randomness in vehicle arrival time is anticipated. In other words, the PTTV of transit vehicle travel time should be well considered in the models. However, to the best of the author knowledge, **a transit-oriented definition of PTTV has not yet been established and modelled.** The knowledge of PTTV would facilitate the modelling of on-time performance, which is the basis of all offline transfer coordination models.
2) The principal reason for the unsuccessful of public transportation in online transfer coordination compared to air transport is the lack of passenger transfer plan. In air transportation, the passenger itineraries are widely available, so that air traffic controller can easily devise timely decision on transfer delay by taking into consideration the cost/benefit to both transferring and non-transferring

passengers. However, **there is not yet any online transfer coordination model in public transportation which examines the possibility of using passenger travel pattern for anticipating the passenger transfer plan.** There is a need for a method to take into account the passenger travel pattern/behaviour in online transit coordinated transfer.

The next chapters of this dissertation aim to smartly exploit the advanced Big transit data sources to augment offline and online transfer coordination by addressing these two gaps in the literature. This research contains two main stages, each stage solves a research problem. Stage 1 involves with enhancing the offline transfer coordination, while Stage 2 solves the online coordination problem in real-time.

STAGE 1

Enhancing Offline Transfer Coordination by Establishing Fundamental Knowledge of Public Transport Travel Time Variability

3 Travel time variability definitions and modelling

This chapter describes how travel time variability are defined and modelled. It contributes to the understanding of the transit operation by travel time variability metrics.

The contents of this chapter have been published in the following publications

Journal articles

J1 Kieu, L. M., Bhaskar, A. & Chung, E. 2015. Public transport travel time variability definitions and monitoring. *ASCE Journal of Transportation Engineering.* Vol. 141, Issue 1, Jan 2015. DOI: 10.1061/(ASCE)TE.1943-5436.0000724.

Conference proceeding papers

C1 Kieu, L. M., Bhaskar, A. & Chung, E. Empirical Evaluation of Public Transport Travel time Variability. Australasian Transport Research Forum, 2013 2-4 October, Brisbane Australia.

C2 Kieu, L. M., Bhaskar, A. & Chung, E. 2014. Establishing the Definitions and Modeling the Public Transport Travel time Variability. 93rd Annual Meeting of the Transportation Research Board. 12-16 January, Washington DC, US.

3.1 Introduction

Public Transport Travel Time Variability (PTTV) is essential for transit operators. It facilitates investigating the deteriorations of travel time reliability and explaining the reliability index. Knowledge of PTTV also simplifies the optimization of slack time, which is the added time to the schedule running time, to account for both travel time variation and a short break before the next departure. In transfer coordination, PTTV is crucial, because timetable synchronisation and timed transfer strategies will be devastated if the on-time performance is poor due to high TTV. A too short slack time between the arrivals of the feeding vehicle to the departures of the receiving vehicle may lead to missed transfers, whereas a too long slack time would lead to reduced commercial speed of transit services.

Travel Time Variability (TTV) has been defined in literature as the variance in travel times of vehicles travelling similar trips (Bates et al., 1987; Noland and Polak, 2002). However, the definition is better suited for measuring private rather than public transport, as confusion arises in the definition of "similar trips". While private transport vehicles are treated as homogenous to some extent, public transport vehicles are noticeably different. By stopping at only selected stops, express routes are significantly faster than local routes, questioning the definition of "similar trips" particularly for practical purposes. Conversely, the availability of individual travel time data of each transit vehicle will provide new approaches to better define PTTV.

This chapter exploits Vehicle Identification (VID) Data to establish PTTV's definitions and investigate its statistical characteristics. Compared to the existing studies in the literature, this chapter proposes a comprehensive methodology to model the TTV and its probabilistic indicator. This is also the first systematic attempt to establish the transit-oriented definitions of TTV. The findings of this chapter will provide the fundamental understanding for on-time performance improvements and offline transfer coordination. This chapter advances the conceptual understanding of travel time variability by the 7-step approach to comprehensively examine the distribution of travel time from limited sample size. The 7-step approach is a hybrid of Monte Carlo simulation and Maximum Likelihood Estimation to find and test any type of distribution to a variable with limited samples (Kieu et al., 2015d).

The chapter contains 5 sections. Section 3.2 establishes oriented definitions of PTTV, which is based on and also distinct from the common definitions used in private transport. Secondly, Section 3.3 proposes a comprehensive hybrid approach to investigate the distribution of public transport travel time, considering all types of continuous distribution types to explore the nature and shape of public transport travel time. Section 3.4 develops a probabilistic indicator of the PTTV, which facilitates the calculation of slack time/recovery time and statistical studies of travel time. Finally, Section 3.5 sums up the findings, knowledge gained, as well as the scientific and practical contributions of the chapter.

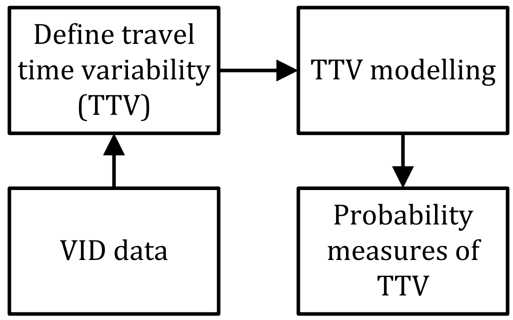


Figure 3.1-1 Study framework of Chapter 3

3.2 **Public Transport Travel time Variability definitions**

3.2.1 **Dataset**

This chapter exploits the VID Data for PTTV definitions and modelling investigation. The reason to use VID is the availability of data. VID data has been collected from the Transit Signal Priority (TSP) system in SEQ, Australia over a year period (1st July 2011 to 30th Jun 2012). TSP gives bus extra green light at signalised intersection and identifies all buses passing TSP-enabled intersections in SEQ. VID data is the only source of data that provides the timestamps of each and every bus passing an arterial corridor over a long time period. By using a rich data source such as VID, we can develop a comprehensive methodology to define and model PTTV.

The TSP sensors act as an automatic vehicle monitoring system to identify the unique vehicle identification number, route, timestamps and service scheduled start times of each passing bus. The difference between observed timestamps at upstream and downstream intersections is the travel time between the two intersections. Figure 3.2-1 shows 4 major arterial corridors in SEQ along with their operating bus routes and lengths. The Coronation Drive corridor (from High Street to Cribb Street) is the case study site for PTTV definition establishment and analysis in this chapter. The study site is highly congested on both morning and afternoon peak periods. The other three corridors and their bus routes are used at the final sub-section of the analysis for validation.

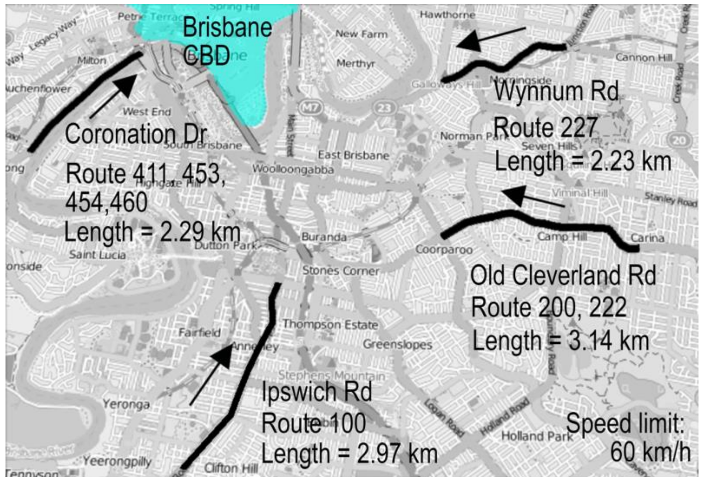


Figure 3.2-1 Study site (Map data @ OpenStreetMap)

The analysis has been carried out on inbound traffic. The analysis performed in this chapter is on the recurrent variability of bus travel time during working days (weekdays excluding Public Holidays and School Holidays). Public transport data is integrated with incident records to filter out travel time values during incidents. Service scheduled start time is the scheduled departure time from the depot, which is defined as a “service” in this chapter.

Buses started earlier or later than the predetermined scheduled start time are also not considered, since different stop skipping, bus holding or priority strategies could have been applied exclusively on them.

3.2.2 Day-to-day public transport travel time variability definitions

This section establishes two key definitions of PTTV to measure only the day-to-day variation of travel time, considering multiple bus routes. While the first definition is an extension from the common TTV definition used for private transport, the second definition is specially established for measuring PTTV of each bus service (Kieu et al., 2014a).

Day-to-day PTTV definition derived from private transport TTV

TTV is commonly calculated from the average travel time values of multiple days within a certain time window, or using the floating car travel time on the same study sites (Chien and Liu, 2012; Oh and Chung, 2006). This section extends this common definition of TTV to define PTTV, where the term “similar trips” means vehicle traversing on the same road section and within the same time period. We measure the variability of travel time using the Coefficient of Variation (CV) of travel time, the well-accepted measure of travel time variability in literature. CV is chosen as a meaningful comparison between two or more magnitude of variations. The TTV can be calculated as CV_p in Equation (1)

$$CV_p = \frac{\sqrt{\frac{1}{D}\sum_{d=1}^{D}(TT_{d,p} - \overline{TT}_p)^2}}{\overline{TT}_p} \quad (1)$$

Here,

CV_p = CV of travel time (%) within time window *p* during *D* days,

$TT_{d,p}$ = mean travel time (s) of the vehicles traversing during time window *p* on day *d,*

$\overline{TT_p}$ = the average value of all $TT_{d,p}$ (s) within time window *p* during D days,

$$\overline{TT}_p = \frac{\sum_{d=1}^{D} TT_{d,p}}{D} \quad (2)$$

The common definition of TTV can be extended to accommodate PTTV, in which PTTV is measured by the Equation (2). Each mean value $TT_{d,p}$ includes *all buses of all routes* passing the study corridor within a 30 minutes study time window on a working day. This definition of PTTV is illustrated in Figure 3.2-2. Although individual vehicle travel time is available, the first definition of PTTV uses the mean travel time obtained from each day and period ($TT_{d,p}$) to measure only the day-to-day PTTV. This chapter terms this variability as ***day-to-day PTTV on corridor level*** **(**$PTTV_c$).

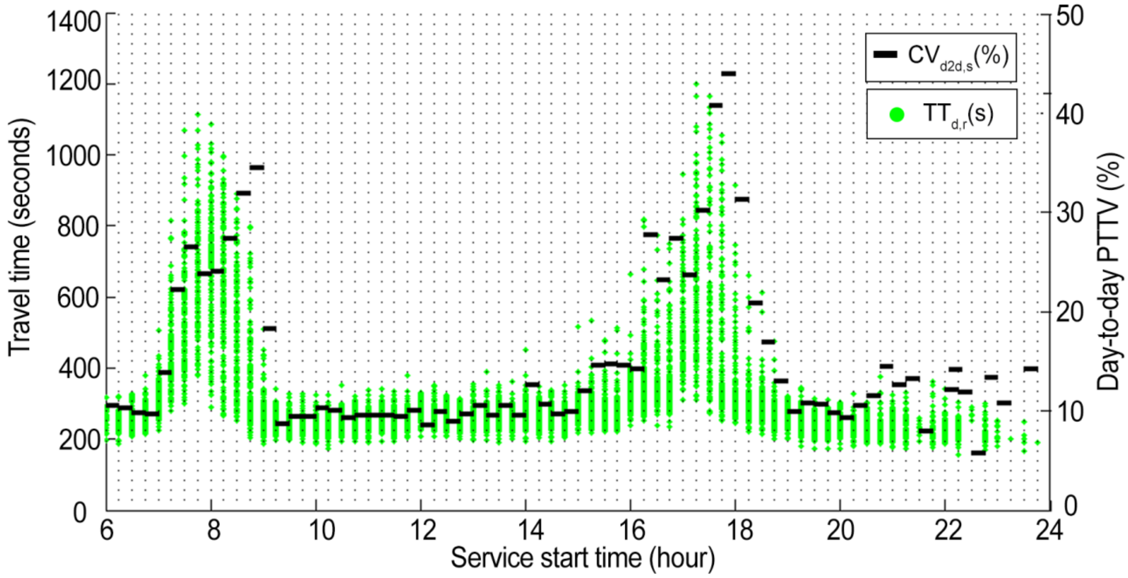


Figure 3.2-2 Observed PTTV$_c$ on Coronation Drive, Brisbane, SEQ

PTTV$_c$ definition is useful for traffic managers in monitoring the day-to-day variability of bus travel time in general. Having the same method to calculate TTV enables effective comparison of the variability between different modes of transport, for instance between public and private transport.

Day-to-day PTTV definition using additional data of transit vehicles

Public transport often allows tracking of each individual vehicle on a specific service. This sub-section establishes another definition of *day-to-day PTTV* to take advantage of the additional information. The definition aims for monitoring transit performance and facilitating timetable adjustments. The term “similar trips” refers to the buses on the *same route* and *service*, because these buses are scheduled to travel time similarly.

$$CV_{r,s} = \frac{\sqrt{\frac{1}{D}\sum_{d=1}^{D}(TT_{d,r,s} - \overline{TT}_{r,s})^2}}{\overline{TT}_{r,s}} \qquad (3)$$

Here

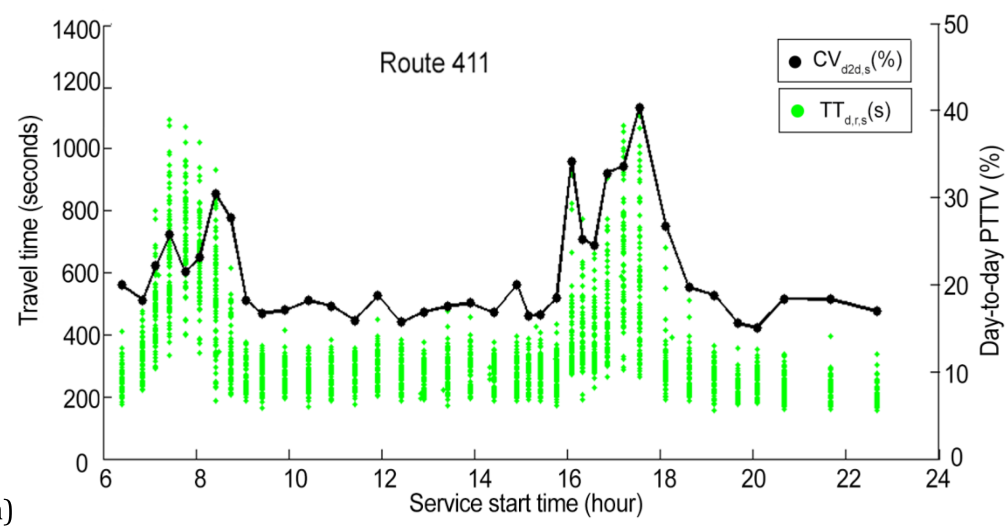
$CV_{r,s}$ = CV of travel time (%) of route *r* and service *s* during *D* days,

$TT_{d,r,s}$ = d^{th} individual travel time sample (s) of the bus of route *r* and service *s* on day *d,*

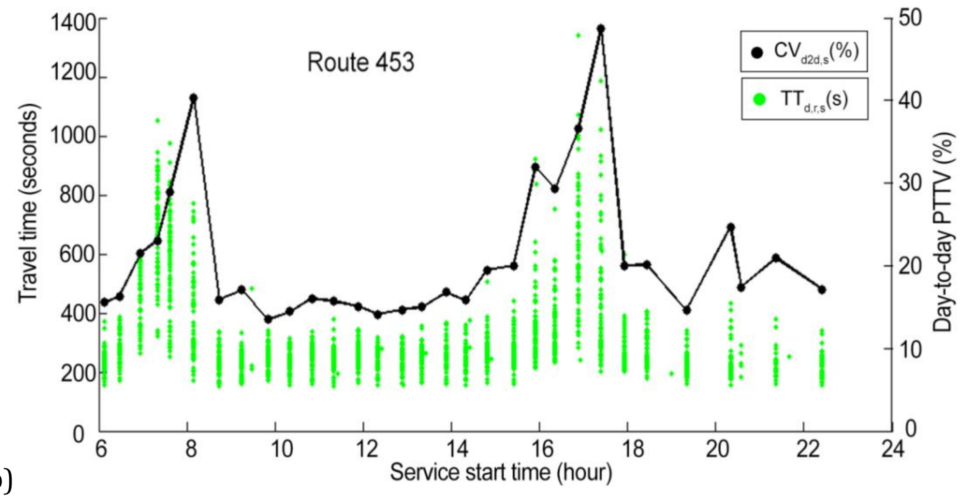
$\overline{TT_{r,s}}$ = the average value of all $TT_{d,r,s}$ (s) of route *r* and service *s* on all day,

$$\overline{TT}_{r,s} = \frac{\sum_{d=1}^{D} TT_{d,r,s}}{D} \quad (4)$$

This definition separates from the common measurement of private transport TTV by making use of the additional data of public transport. Each value of $TT_{d,r,s}$ includes only an individual bus of the specific service on a specific route. Figure 3.2-3 illustrates the definition using the four routes running along the Coronation Drive where day-to-day PTTV (%) is measured by the CV of travel time (%). Figure 3.2-3 shows the day-to-day PTTV of services during off-peak periods are relatively low, indicating high reliability. The variability follows the same pattern as the congestion increases and reduces. Afternoon congestion shows a small peak of $CV_{r,s}$ before the main peak congestion at the school-off time when secondary school students are traveling home. This chapter terms this variability as ***day-to-day PTTV on service level*** **(**PTTV$_s$).This second established definition of PTTV is useful for transit operators in scheduling, particularly in deciding the timetable and recovery time along with discovering the multiple day reliability performance of each service because it is defined by individual bus travel time.



(a)



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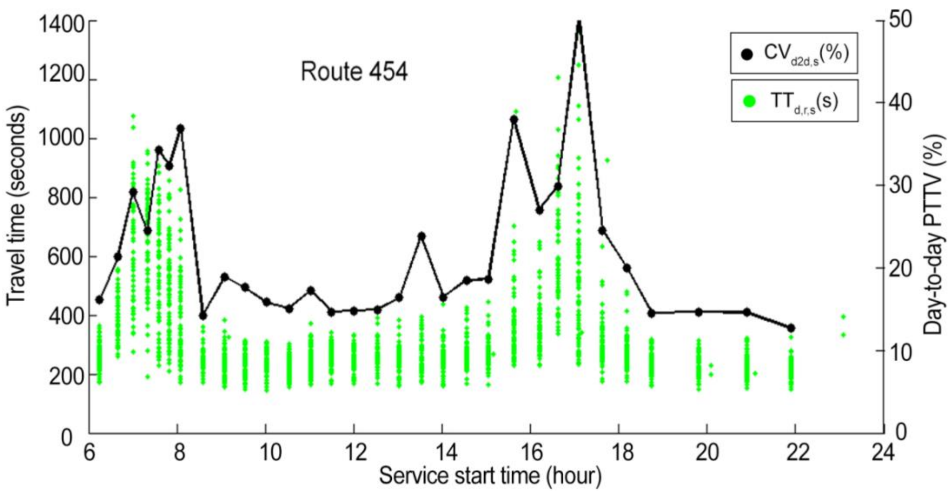
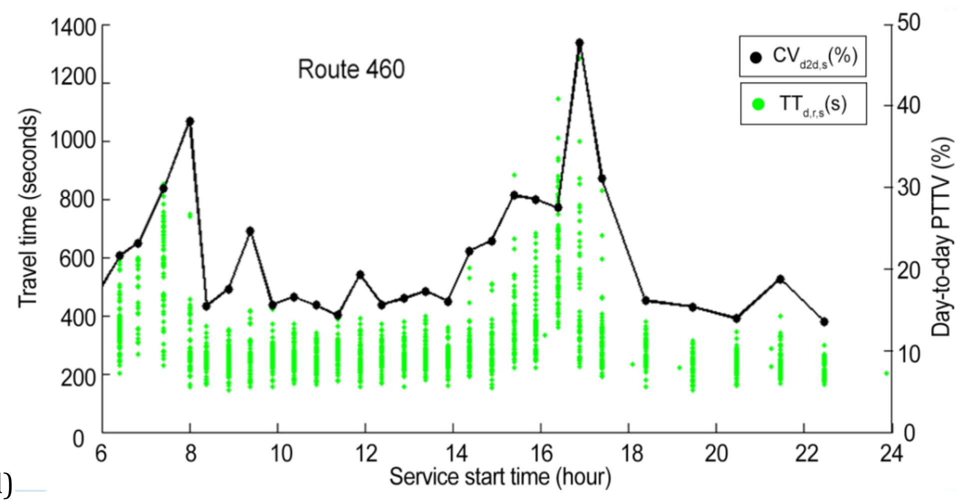


(c)



(d)

Figure 3.2-3 Observed $PTTV_s$ on Route: (a) 411, (b) 453, (c) 454 and (d) 460 where day-to-day PTTV (%) is measured by the CV of travel time (%)

Figure 3.2-4 further demonstrates the $PTTV_s$ on Route 411, 453,454 and 460 by the value of Buffer time index, which represents the extra time that must be added to the average travel time to ensure on-time arrival of transit vehicle. Buffer time index could be calculated by the following equation (FHWA, 2006)

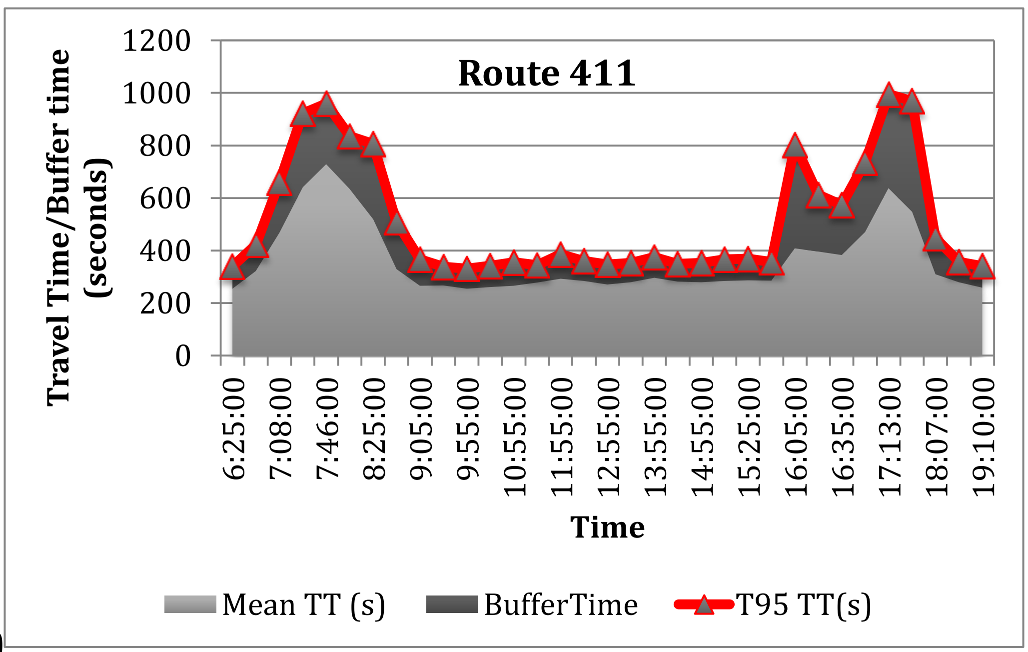
BufferTime = T95TT – MeanTT (5)

Where:

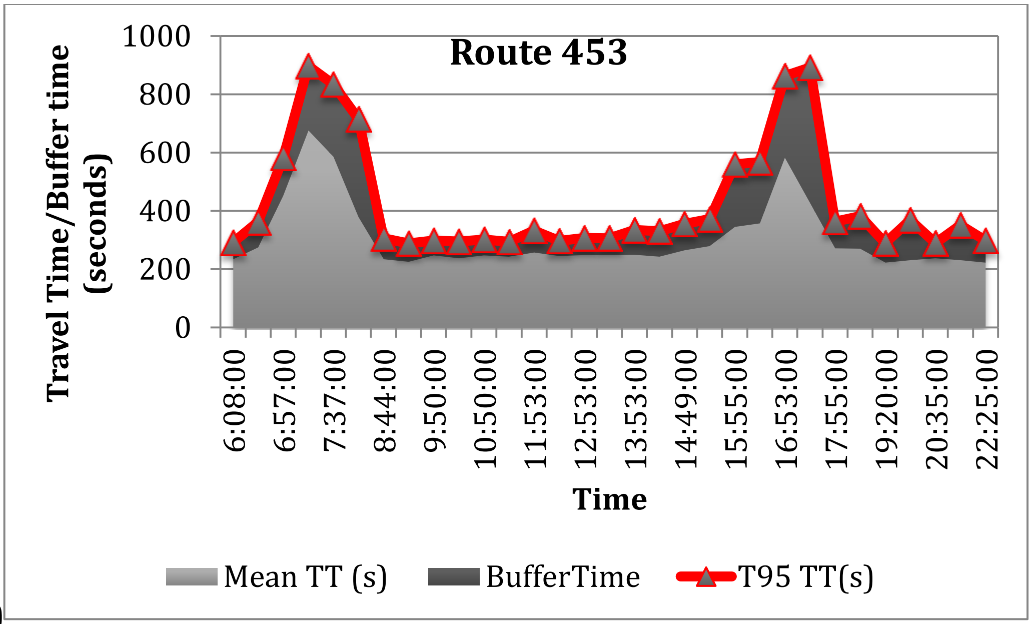
BufferTime (s) is the time gap between the 95th percentile of travel time and the mean travel time

T95TT is the 95th percentile of travel time (s)

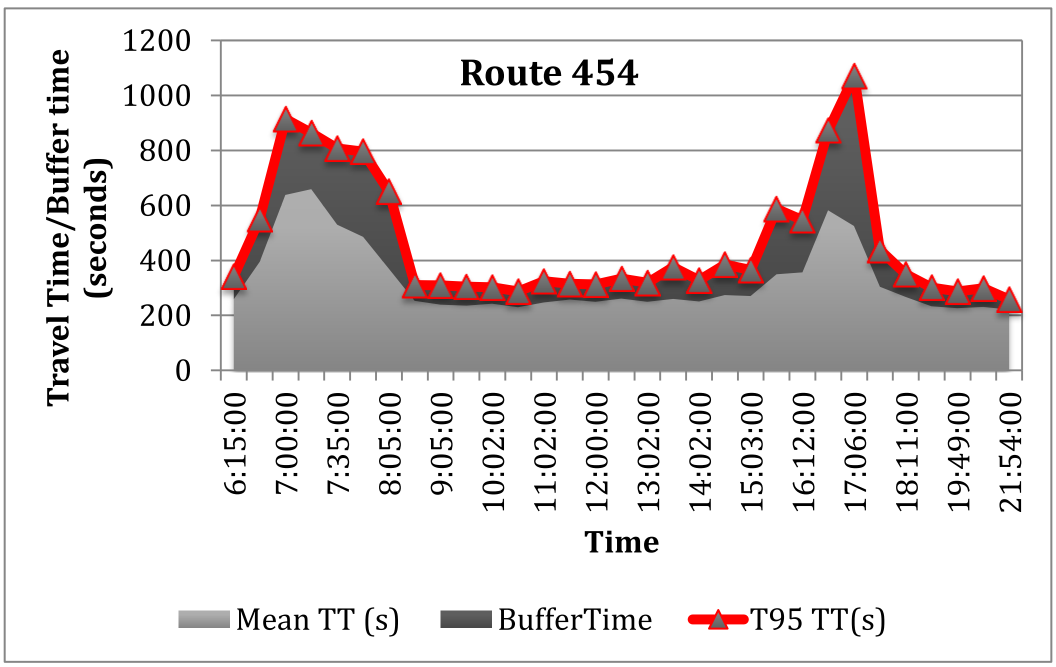
MeanTT is the mean travel time (s)



(a)


Route 453
Travel Time/Buffer time (seconds)
1000
800
600
400
200
0
6:08:00
6:57:00
7:37:00
8:44:00
9:50:00
10:50:00
11:53:00
12:53:00
13:53:00
14:49:00
15:55:00
16:53:00
17:55:00
19:20:00
20:35:00
22:25:00
Time
Mean TT (s)
BufferTime
T95 TT(s)

(b)


Route 454
Travel Time/Buffer time (seconds)
1200
1000
800
600
400
200
0
6:15:00
7:00:00
7:35:00
8:05:00
9:05:00
10:02:00
11:02:00
12:00:00
13:02:00
14:02:00
15:03:00
16:12:00
17:06:00
18:11:00
19:49:00
21:54:00
Time
Mean TT (s)
BufferTime
T95 TT(s)

(c)

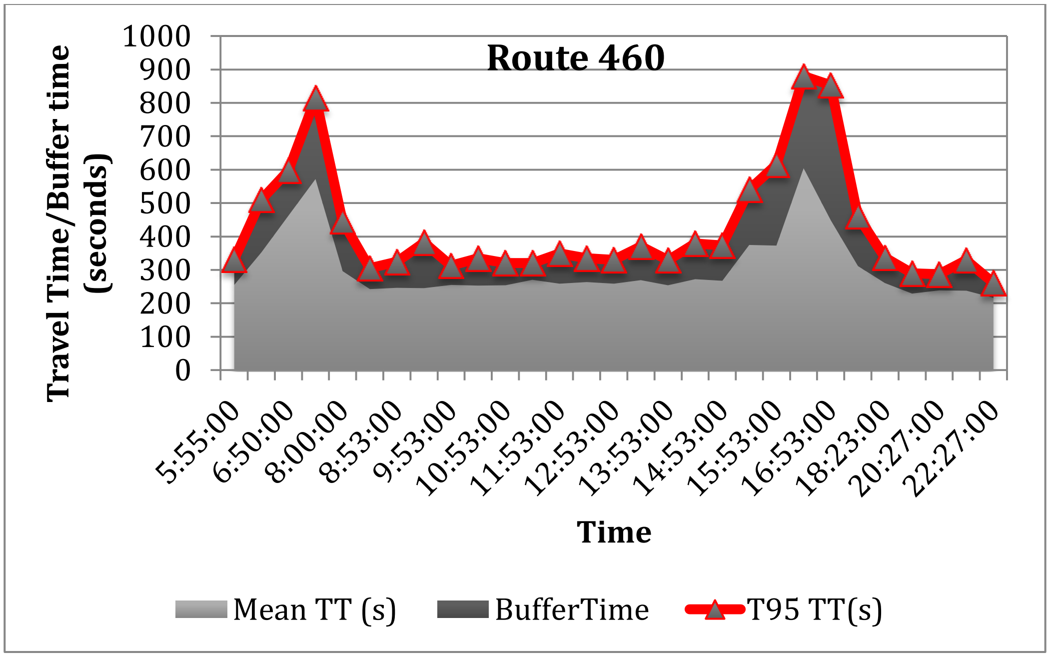
(d)


Figure 3.2-4 Observed Buffer time Index on Route: (a) 411, (b) 453, (c) 454 and (d) 460

The aforementioned two definitions are further discussed as below:

Day-to-day PTTV on corridor level ($PTTV_c$) is the extension of the widely used definition of TTV to public transport. The definition reflects the PTTV in general by considering all passing buses, which enables meaningful comparison with other modes of transport. For instance, $PTTV_c$ provides insights on how the consistency and dependency of public transport modes are compared to private counterparts.

Day-to-day PTTV on service level ($PTTV_s$) measures TTV of a specified route service. The individual bus travel time samples on multiple days are used for TTV calculation. These individual buses are planned to travel similarly as they are on the same route and service. The variations in their travel times show the patterns of TTV and indicate service performance. Significantly, as it is a more focused scale compared to the first definition. $PTTV_s$ facilitates investigating the sources of unreliability and optimizing the timetables. The definition of $PTTV_s$ is more useful as it provides more information on individual vehicle performances, which can be used on more transit planning purposes.

3.3 Public Transport Travel time Variability modelling methodology

The previous section established definitions of PTTV and identified $PTTV_s$ *as* the most useful definition. This section analyses the probability distribution of travel time to investigate *the nature and shape of* $PTTV_s$. For instance, a uniform distribution denotes no variability, while a long tail skewed distribution shows the bus could experience long and unreliable travel time. Travel time distribution is also essential in public transport planning. Resource allocations such as recovery time and timetable optimization are not often planned on the basis of average travel time, but on minimizing the opportunity that any journey would exceed the scheduled time (Moghaddam et al., 2011). However, the literature on public transport travel time distribution is still limited and inconsistent, exploring only common distributions at limited time-of-the-day, and revealing symmetric types of distribution (Taylor, 1982), skewed distribution (Andersson et al., 1979) or both of them (Mazloumi et al., 2010) as the descriptor of public transport travel time.

For the analyses on $PTTV_s$ a comprehensive seven-step approach is applied to all services of Route 411 – the busiest bus route on the Coronation Dr. The analysis aims to test all types of probability distribution which neglects only the discrete types of distribution (e.g. Binominal, Negative binominal, Poisson) as well as Uniform and limited samples distributions (Triangular, Rectangular) because the nature of travel time is continuous (Bhaskar et al., 2011). The list of 23 fitted distribution types includes: Beta, Birnbaum-Saunders, Burr, Chi-Squared, Dagum, Erlang, Error, Exponential, Frechet, Gamma, Generalized Pareto, Inverse Gaussian, Levy, Logistic, Log-logistic, Lognormal, Nakagami, Normal, Rayleigh, Rician, Pareto, t location-scale and Weibull.

3.3.1 Seven-step approach for public transport travel time distribution analysis

Travel time samples of each service are fitted by the Maximum Likelihood Estimation (MLE) method to estimate the parameters of each distribution. Most existing studies of travel time distribution analysis performed one of the three common goodness-of-fit tests named Chi-Squared; Kolmogorov-Smirnov (KS); and Anderson-Darling to find whether the data follows the specified distribution (hypothesis H0). Any p-value larger than the significance level (α) fails to reject H0 and the distribution is considered as significantly fitted with the data. However, this method has two key drawbacks (Durbin, 1973). Chi-squared requires large sample size, while the original critical values of KS and Anderson-Darling tests are not valid if parameters are directly estimated from the data.

Literature offers other approaches which solve the aforementioned problems, but they also have their own disadvantages. First, the information creation technique such as Bayesian Information Creation (BIC) (Schwarz, 1978) measures the relative quality of a statistical model by trading off the complexity (by considering the number of parameters) and goodness-of-fit of the fitted distribution (by considering the maximized value of the log-Likelihood). However, the BIC statistic is difficult to interpret. The fitted distribution with the lowest BIC is the "best" descriptor of the data, without a hypothesis testing to validate the goodness-of-fit. Second, the best fitted distribution could be examined graphically by using the probability plot, histogram, stem & leaf plots, scatter plot, or box & whisker plots. This graphical approach does not provide a reference point so that multiple distributions can be compared within multiple time periods. Third, recent goodness-of-fit tests such as Lilliefors test (Lilliefors, 1967) extends the KS test by determining the critical value by a Monte Carlo simulation, which enables estimating the distribution parameters from the data. However, the critical values table supports only a few limited types of distributions, restricting the study to a few selected distributions.

To overcome the limitation of the existing approaches in travel time distribution analysis, this thesis extends the Liliefors test to support all types of distribution. Instead of using any tables from Liliefors, KS or Anderson-Darling, we use parametric bootstrapping – a Monte Carlo simulation method (D'Agostino and Stephens, 1986) for calculating KS critical value of each distribution type at each service. Parametric bootstrapping is chosen because of these two following reasons

- It does not depend on any predefined critical value table
- It supports probability distribution analysis with various low to high sample size

However, the parametric bootstrapping KS test identifies the list of distribution types that passed the KS, but does not provide a measure to compare the fitness of each distribution type if multiple types are accepted. A hybrid approach is then used, in which the top five distribution types in the number of passed KS tests are chosen as the five candidates for the descriptor of bus travel time. BIC statistic (Schwarz, 1978) is then calculated to compare the goodness-of-fit of the five candidates where the one with lowest BIC has the best fitness to the bus travel time data. The descriptor of bus travel time will then pass the most number of KS test, while having the lowest BIC statistic value. The hybrid method could be described in 7 steps.

(1) *Step 1:* Consider each type of distribution. MLE method is employed to estimate distribution parameter(s) from bus travel time data.
(2) *Step 2:* Generates random data samples from the studied distribution using the parameter(s) from Step 1.
(3) *Step 3:* Use MLE to re-estimate distribution parameter(s) from the generated data. The parameter(s) is used to build theoretical cumulative distribution function (c.d.f) *F(x)*
(4) *Step 4:* Calculate the KS statistics D_N^*, i.e., maximum difference between the empirical distribution function (e.d.f.) $S_N(x)$ from the generated data (Step 2) and the theoretical c.d.f. *F(x)* (Step 3)

$$D_N^* = \max\left|S_N(x) - F(x)\right| \qquad (6)$$

(5) *Step 5:* Repeat Step 2 to Step 4 a large number of time (say 10000) to gather the set of D_N^*. Since significance level (α) equals 0.05, the 95th percentile of the set is chosen as the critical value D_C.
(6) *Step 6:* Compute the observed KS statistic D_N between the e.d.f. from the bus travel time data and the c.d.f. using the parameter(s) from Step 1, and compare it to the simulated critical value. If $D_N < D_C$, the test fails to reject the null hypothesis that the distribution could describe bus travel time data.
(7) *Step 7:* BIC statistics are calculated for each candidate distribution from Step 6.

The BIC can be formulated as follows (Schwarz, 1978)

$$BIC = k \ln n - 2 \ln L_{max} \qquad (7)$$

Where:

n = number of observations

k = number of parameters to be estimated

L_{max} = maximized value of the likelihood function of the estimated distribution

This seven-step approach investigates the best descriptor of public transport travel time.

3.3.2 **Analysis results and discussion**

The Step 6 of the seven-step approach reveals five candidates of bus travel time distribution: Burr, Gamma, Lognormal, Normal and Weibull. While Normal and Lognormal are commonly used in public transport studies, the other three are relatively new in the area. The KS test results and histogram of each distribution type, along with the lowest 2 distribution types in BIC statistics are presented in Table 3.3.1. The following presents each aforementioned candidate to justify its overall goodness-of-fit to the bus travel time data.

Table 3.3-1 Descriptive statistic of travel time distribution analysis

Service	Observations	Skewness	Kurtorsis	KS test with bootstrap resampling (1 for Accepted, 0 for rejected)					Hatigan Dip test		Lowest BIC	2nd lowest BIC
				Burr	Normal	Log-normal	Wei-bull	Gam-ma	Dip stat	p-value		
6:51	103	1.2	7.05	0	1	1	0	1	0.04	0.38	Lognormal	Gamma
7:08	93	0.8	3.81	1	1	1	1	1	0.06	**0.02**	Lognormal	Gamma
7:26	104	0.4	2.68	1	0	1	0	1	0.05	0.06	Gamma	Lognormal
7:46	95	0.2	4.03	0	0	0	0	0	0.03	0.97	Normal	Burr
8:05	91	-0.6	3.84	1	1	1	1	0	0.03	0.77	Weibull	Normal
8:25	91	0.2	2.57	0	1	0	1	1	0.04	0.21	Weibull	Gamma
8:45	92	1.0	3.39	1	0	1	1	1	0.03	0.70	Lognormal	Burr
9:05	79	0.6	2.25	1	1	1	1	1	0.02	0.99	Lognormal	Gamma
9:25	120	0.0	1.94	0	1	1	1	1	0.05	**0.04**	Normal	Gamma
9:55	109	0.8	3.11	1	1	1	1	1	0.03	0.55	Burr	Lognormal
10:12	93	0.2	2.03	1	1	1	1	1	0.04	0.28	Gamma	Lognormal
10:55	109	0.5	2.56	1	0	1	1	1	0.04	0.14	Lognormal	Gamma
11:25	96	-0.2	2.18	0	0	0	0	0	0.04	0.44	Weibull	Normal
11:55	94	0.2	2.55	0	1	1	0	1	0.04	0.55	Gamma	Lognormal
12:25	108	0.0	2.23	0	0	0	0	0	0.03	0.82	Normal	Gamma
12:55	110	0.2	2.48	1	0	1	0	1	0.03	0.46	Gamma	Lognormal
13:25	113	0.1	2.66	0	0	0	0	0	0.04	0.31	Normal	Gamma
13:55	102	0.0	2.26	1	1	0	1	1	0.04	0.13	Normal	Gamma
14:25	99	-0.2	1.98	0	1	1	1	1	0.04	0.31	Weibull	Normal
14:55	97	1.4	8.40	1	0	1	0	1	0.05	0.06	Lognormal	Gamma
15:10	102	-0.1	2.50	0	1	0	1	0	0.02	0.97	Normal	Weibull
15:25	100	0.0	2.70	0	1	0	0	1	0.03	0.82	Normal	Gamma
15:46	90	-0.1	2.61	1	1	1	1	0	0.03	0.97	Normal	Weibull
16:05	105	2.1	9.68	1	1	1	1	1	0.02	0.96	Burr	Lognormal
16:20	97	1.1	4.99	1	1	1	1	1	0.04	0.38	Burr	Lognormal
16:35	88	1.1	3.88	1	1	1	1	1	0.04	0.49	Burr	Lognormal
16:51	89	1.8	7.76	1	0	1	1	1	0.04	0.39	Lognormal	Burr
17:13	91	1.0	4.62	0	0	1	0	1	0.03	0.71	Lognormal	Burr
17:33	101	1.0	3.21	0	0	1	1	1	0.03	0.80	Lognormal	Burr
18:07	72	2.2	9.54	1	1	1	1	1	0.03	0.86	Burr	Lognormal
18:37	93	1.3	6.30	1	0	1	0	1	0.03	0.61	Lognormal	Burr
19:10	77	0.2	2.21	0	0	1	0	1	0.04	0.51	Gamma	Lognormal
19:40	98	1.0	4.44	0	0	1	0	1	0.03	0.95	Lognormal	Gamma
20:05	106	0.2	2.56	0	0	1	0	1	0.03	0.78	Gamma	Lognormal
20:40	105	0.6	2.65	0	0	1	0	1	0.03	0.84	Lognormal	Gamma
21:40	85	1.2	5.53	0	1	1	1	1	0.02	0.99	Lognormal	Gamma
22:40	79	0.7	3.37	0	1	1	0	1	0.04	0.72	Lognormal	Gamma

The *Burr distribution* has been recently used in traffic engineering to model urban road travel time (Susilawati et al., 2011). Burr distribution is described as a heavy-tailed, highly-skewed distribution. Table 3.3.1 shows that while the Burr distribution only passed the KS test at 18/37 services, it is the best fitted distribution where bus travel time is high left skewed and long tailed, especially with a range of travel time with very high occurrences. However, this travel time pattern appears in only a few services.

The *Weibull distribution* has been widely used to represent travel time on arterial roads (Al-Deek and Emam, 2006) and especially on duration-related studies such as traffic delay durations (Mannering et al., 1994) and waiting time at unsignalised intersections (Hamed et al., 1997). Weibull distribution has been described as flexible representing right-skew, left-skew and also symmetric data. The BIC results show that Weibull is almost always within the top 2 in negative skewed travel time patterns. As the services with negatively skewed distribution are limited in the dataset, Weibull distribution has the lowest BIC statistic value in only 3 services.

The *Normal distribution* has been suggested as the descriptor of bus travel time in a number of studies (Mazloumi et al., 2010; Taylor, 1982). It has a symmetric shape and its characteristics are thoroughly studied in statistics, which facilitates theoretical research. Normal distribution is still a strong candidate as the descriptor of bus travel time in this study by passing the KS test in 20/37 services and having the lowest BIC statistics in 8 services, most of which are in mid-peak period.

The tests results indicate the *Gamma* and *Lognormal distributions* to be superior. The *Gamma distribution* has been long considered one of the first candidates for distribution of travel time. Polus (1979) believed that travel time on arterial road would "closely follow" a Gamma distribution, and for this reason Dandy and McBean (1984) suggested Gamma distribution as the descriptor for in-vehicle travel time. *Lognormal distribution* is extensively used to represent bus travel time (Andersson et al., 1979; Mazloumi et al., 2010) due to the flexibility and ability to accommodate skewed data.

While the Gamma distribution passes the KS test in 30/37 service, the Lognormal distribution passes in only one less services (29/37 services). Both of them are the optimal descriptors of bus travel time with moderate skewness and kurtosis (i.e. absolute value of skewness smaller than 1 and kurtosis smaller than 3). This type of travel time pattern is dominant in the dataset, which is why Gamma and Lognormal passed most KS tests.

Both Lognormal and Gamma distribution are capable of modelling both heavy and light tailed data, but the Lognormal is better in representing higher skewed and longer tailed data, as it came with the Burr distribution in the top 2 lowest BIC statistic in several services. The BIC statistics also indicate that Lognormal is the best fitted distribution in more services than any other distribution types (14/37 services).

Another advantage of the Lognormal distribution is its mathematical characteristics that facilitate TTV studies. Lognormal distribution allows direct calculation of CV from its parameter.

$$\mathrm{CV} = \sqrt{e^{\sigma^2} - 1} \qquad (8)$$

The $(p \times 100)^{\text{th}}$ percentile θ, commonly used in many variability and reliability indicators, can be computed using the lognormal quartile function as in Equation (9)

$$\theta = F_X^{-1}(p) = e^{\mu - \sqrt{2}erfcinv(2p)\sigma},\ 0 \le p \le 1 \qquad (9)$$

where $erfcinv(x)$ is the inverse complementary error function. While there is no known closed form expression, the value of $erfcinv(x)$ can be approximated to the method described in Blair et al. (1976). Equation (9) also denotes that if the data is Lognormally distributed, the Lognormal parameters μ and σ can be easily estimated from the value of two percentile values ($p_1 \times 100$)-th percentile θ_1, and the ($p_2 \times 100$)-th percentile θ_2, which means the following equations can be obtained.

$$\begin{cases} p_1 = \dfrac{1}{2}erfc\left(-\dfrac{\ln(\theta_1)-\mu}{\sqrt{2}\sigma}\right) \\ p_2 = \dfrac{1}{2}erfc\left(-\dfrac{\ln(\theta_2)-\mu}{\sqrt{2}\sigma}\right) \end{cases} \qquad (10)$$

The parameters of Lognormal can be calculated by solving Equation (10)

$$\begin{cases} \sigma = \dfrac{\ln(\theta_2) - \ln(\theta_1)}{\sqrt{2}\left[erfcinv(2p_1) - erfcinv(2p_2)\right]} \\ \mu = \ln(\theta_1) + \sqrt{2}erfcinv(2p_1)\sigma \end{cases} \tag{11}$$

Overall, Lognormal distribution provides excellent representation of the public transport travel time. It is recommended as the descriptor of public transport travel time variation due to its high performance and the attractive mathematical characteristics that facilitate TTV studies.

3.3.3 **Hartigan Dip test for examining the bimodality**

Table 3.3.1 shows some signs of bimodality on two services before and after the morning peak period. Testing the bimodality is best conducted with the Hartigan Dip test. Dip statistics express the largest difference between the empirical distribution function and a unimodal distribution function that minimizes that maximum gap (Hartigan and Hartigan, 1985). If the *p-value* of the test is more than the significance value (chosen as 0.05), the data is concluded as having unimodal distribution.

Although the bimodality is significant in only two services, the distributions of travel time in many services before and after the morning peak period are also nearly bimodal (*p-value* slightly larger than 0.05). The bimodality of travel time is mainly caused by a mixture of congested and uncongested population of traffic. Earliness or excessive congestion on some days, or generally the spread of congestions could be the main reason. These services are within the congestion build-up and dissipation periods, where speed could be free flow or congested depends on a day-to-day basis. The study was conducted on inbound traffic only, which means the pattern is not repeated for the afternoon.

3.4 **Probabilistic indicator of Public Transport Travel time Variability**

3.4.1 **Probabilistic indicator development**

Lognormal has been recommended as the descriptor of day-to-day public transport travel time in this study. This section investigates the use of *Lognormal distribution* to empirically indicate *day-to-day PTTV on service level* using a probabilistic approach.

TTV or travel time reliability is often indicated by one of the four measures (van Lint et al., 2008): statistical range, buffer time, tardy-trips or probabilistic approach. The probabilistic approach is one of the direct measures to evaluate travel time reliability. Bell and Cassir (2000) defined reliability as "the probability that [a] system can perform its desired function to an acceptable level of performance for some given period of time". The probabilistic approach measures the probability that travel time would be higher than a predetermined threshold under normal traffic conditions subject to day-to-day traffic flow fluctuations. The predetermined threshold is often defined as the median of travel time plus a certain amount of time, or a certain percentage of the median of travel time (van Lint et al., 2008). This section aims to use the p.d.f. of the Lognormal distribution to calculate the probabilistic indicator of PTTV. The probability that bus travel time is larger than a certain value from the median travel time is expressed by Formula (11).

$$\Pr\left(TT_{d,r,s} \geq A\right) \qquad (12)$$

Where,

A = predetermined travel time threshold to be studied, e.g. A = $\alpha \times T50_{r,s}$ or A = $\beta + T50_{r,s}$

α = threshold multiplied with the median (e.g. 1.2)

β = threshold added to the median (e.g. 10 minutes)

$TT_{d,r,s}$ = travel time of the bus of route *r* which is scheduled to start at service *s* of day *d*

$T50_{r,s}$ = median value of the set of travel time samples of route *r* and service *s*

The p.d.f. of Lognormal distribution has the form as in Equation (13)

$$f_X\left(x\right) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\left[\frac{\ln(x)-\mu}{\sqrt{2}\sigma}\right]^2}, \quad x > 0 \qquad (13)$$

Where μ and σ are the two parameters of the Lognormal distribution. Mathematically, the probability $\Pr\left(TT_{d,r,s} \geq \alpha \times T50_{r,s}\right)$ or $\Pr\left(TT_{d,r,s} \geq \beta + T50_{r,s}\right)$ is the integral of the p.d.f. $f_X\left(x\right)$ between threshold value $A = \alpha \times T50_{r,s}$ or $A = \beta + T50_{r,s}$ and the infinity.

$$P = \int_{A}^{\infty} \frac{1}{x\sigma\sqrt{2\pi}} e^{-\left[\frac{\ln(x)-\mu}{\sqrt{2}\sigma}\right]^2} dx \tag{14}$$

Substitute $y = \ln(x)$, which means $x = e^y, dy = \frac{dx}{x}$. Equation (14) becomes.

$$P = \frac{1}{\sigma\sqrt{2\pi}} \int_{lnA}^{\infty} e^{-\left[\frac{y-\mu}{\sqrt{2}\sigma}\right]^2} dy \tag{15}$$

The problem in Equation (15) can be re-written into an equation of the complementary error function.

$$P = \frac{1}{\sigma\sqrt{2\pi}} \int_{lnA}^{\infty} e^{-\left[\frac{y-\mu}{\sqrt{2}\sigma}\right]^2} dy = \frac{1}{2}\left[erfc\left(\frac{lnA-\mu}{\sigma\sqrt{2}}\right)\right] \tag{16}$$

Where *erfc*(x) is the complementary error function

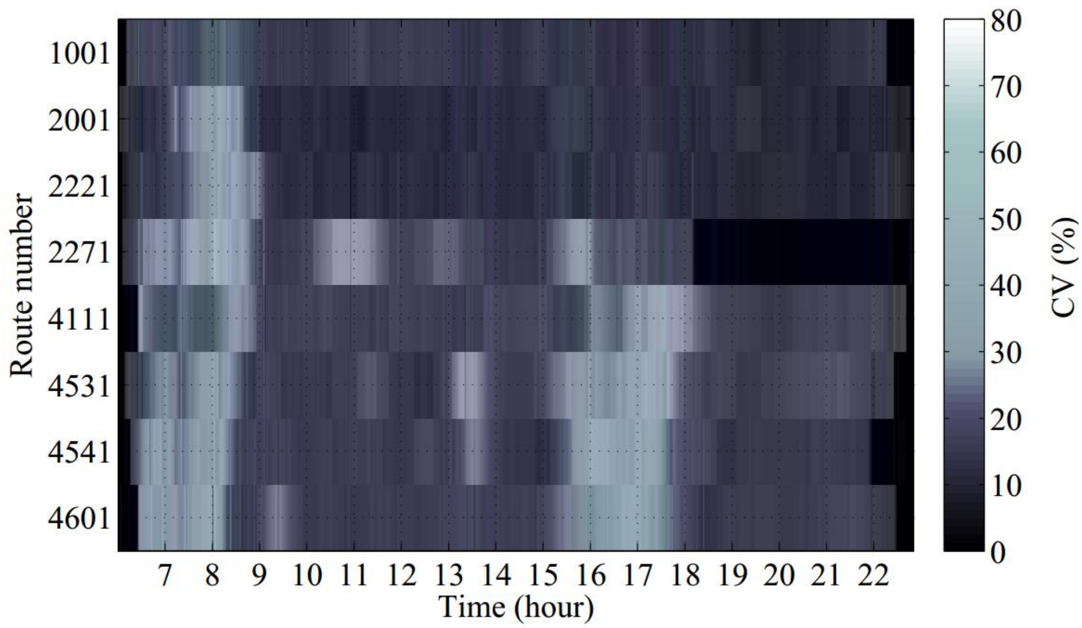
$$erfc(x) = \frac{2}{\sqrt{\pi}} \int_{x}^{\infty} e^{-t^2} dt \tag{17}$$

The value of erfc(x) can be rationally approximated (Cody, 1969) to get the desired quantity. Equation (13)-(17) show that using the p.d.f. of the Lognormal distribution, the probability that the bus travel time exceeds a certain threshold from the median is found.

3.4.2 Public transport travel time variability map of some main routes in Brisbane, SEQ

This sub-section uses the probability indicator in Section 3.4.1 to show the PTTV at the 4 studied sites. The objective is to validate the applicability of the study in monitoring PTTV of multiple routes and corridors. Lognormal distribution is fitted to each set of data using MLE method to find the parameters σ and μ.

Figure 3.4-1(a) and Figure 3.4-1(b) show the PTTV maps of 8 bus routes along the 4 study sites. While Figure 3.4-1(a) demonstrates PTTV in terms of CV of travel time, Figure 3.4-1(b) demonstrates PTTV in terms of the probability that the travel time is higher than 20% of the median: $\Pr\left(TT_{d,r,s} \geq 1.2 \times T50_{r,s}\right)$. The 20% is chosen to be consistent with the threshold used by Van Lint *et al.* (2008), but any threshold can be used to calculate the probabilistic indicator. The two figures confirm that the proposed probabilistic approach captures the variability patterns on each site and indicates PTTV, and show very similar results to the popular approach using CV of travel time. Corronation Drive's routes travel times are highly varied during both morning and afternoon peaks as the corridor is directly connected with the Brisbane CBD. The routes from other corridors are only unreliable during morning peak periods. This section validates that the study can be applied to multiple routes over multiple sites to indicate PTTV.



(a)

(b)

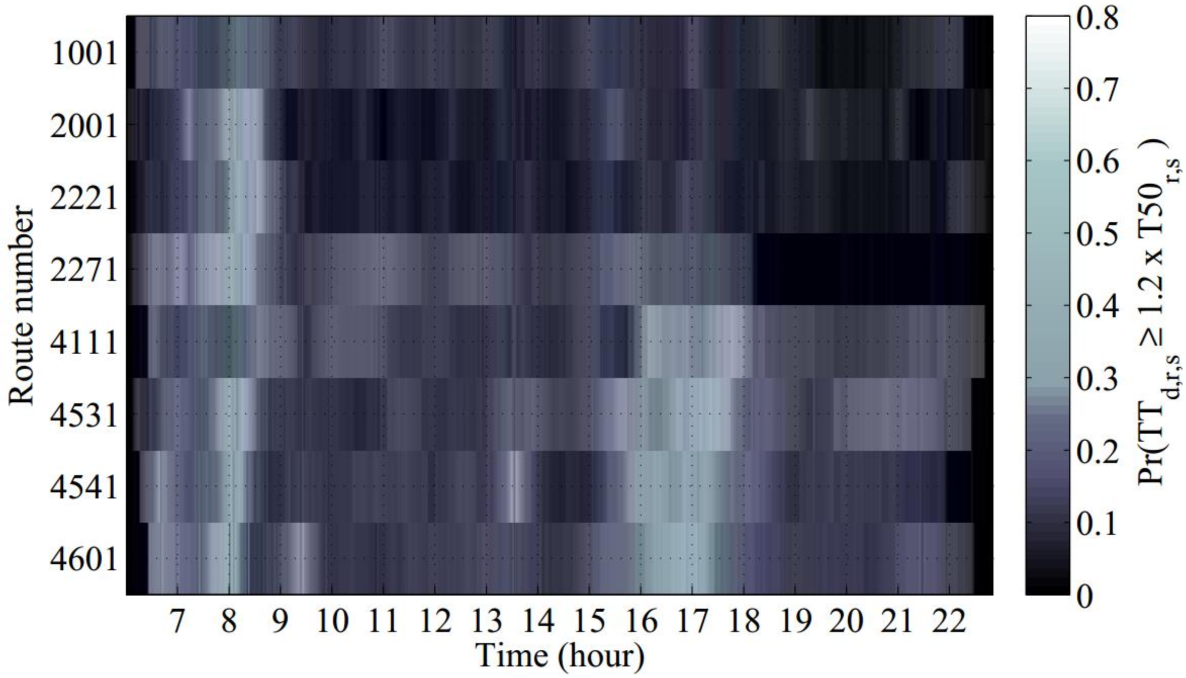


Figure 3.4-1 PTTV map using: (a) CV of travel time and (b) $\mathbf{Pr}\left(\boldsymbol{TT}_{d,r,s} \geq 1.2 \times \boldsymbol{T}50_{r,s}\right)$

3.5 **Summary of Chapter 3**

This chapter established the public transport-oriented definitions of day-to-day TTV and analysed its statistical characteristic. The first, corridor-level PTTV definition is an expansion of commonly used definition of TTV to include all buses that flowing through a corridor to provide the information of variability of buses in general. This is useful to compare between multiple modes of transport. The second, service-level PTTV definition includes only a specific bus route service, which can be used for performance measurement, and optimizing recovery time. The second definition on service level is the most useful as it enables service monitoring and recovery time planning.

The investigation of public transport travel time probability distribution introduced the comprehensive seven-step approach which allows fitting most of continuous probability distributions to all services. Each type of distribution is tested by both KS test with parametric bootstrapping and BIC method, identifying Lognormal distribution as the descriptor of day-to-day public transport travel time. Using the Lognormal distribution p.d.f. to calculate probabilistic indicators of PTTV is useful in PTTV monitoring and recovery time optimization. In fact, data from 8 bus routes along 4 corridors in Brisbane confirmed the applicability of the proposed probabilistic method for PTTV indicators.

3.5.1 Scientific and practical contributions

This chapter significantly contributes to the state-of-the-art through proposing:

1) Oriented definitions of public transport travel time variability (PTTV).
2) A comprehensive hybrid approach to investigate the distribution of public transport travel time, considering all types of continuous distribution types.
3) Probabilistic indicator of the PTTV, which facilitates the calculation of slack time/recovery time and statistical studies of travel time.

The theoretical contribution of this chapter comes from the 7-step approach to comprehensively find distribution of travel time. The 7-step approach combines a Monte Carlo simulation and Maximum Likelihood Estimation to examine the goodness-of-fit of any distribution with limited sample size.

The Section 3.4 confirms that the proposed probabilistic approach captures the PTTV, similar to the traditional CV approach. While CV is only useful for monitoring the PTTV, the proposed probabilistic approach can evaluate the probability of bus travel time over any predefined threshold.

The proposed method facilitates timetabling, especially in determining the recovery time. Taking the median value $T50_{r,s}$ from all historical travel time between two time points as the expected running time, transit operator would be interested in determining a recovery time value β added to $T50_{r,s}$ to accommodate the variance of travel time. This is equal to minimizing the probability that the observed travel time would be higher than the total scheduled travel time.

Minimize $$\Pr\left(TT_{d,r,s} \geq \beta + T50_{r,s}\right) \quad (18)$$

Where:

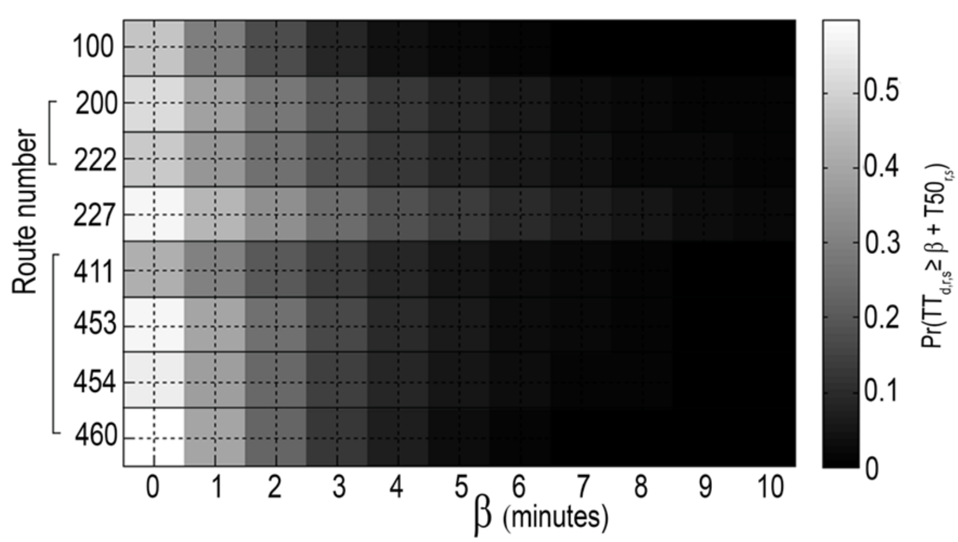
$T50_{r,s}$ = median value of the set of travel time samples of route *r* and service *s*, set as the expected running time

β = recovery time

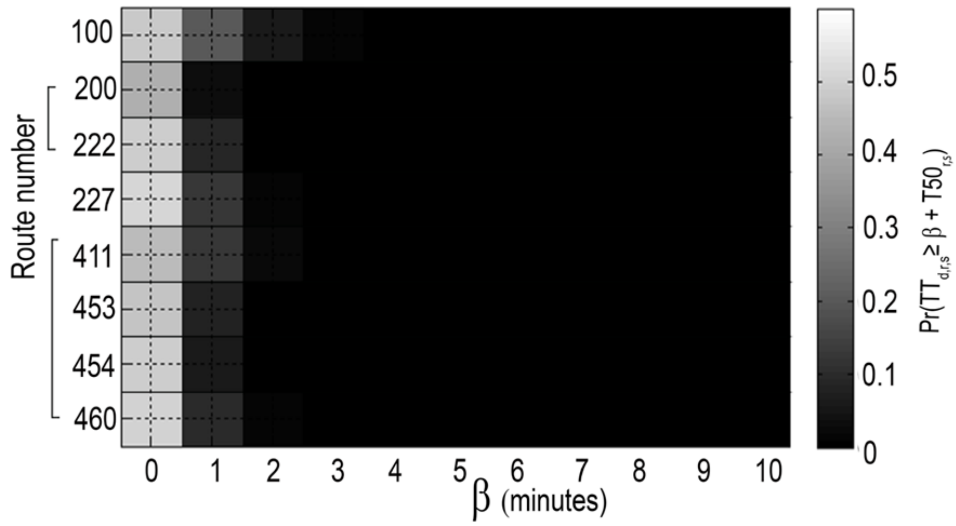
$\beta + T50_{r,s}$ = total scheduled travel time

The optimisation problem above has an obvious minimum at 0 when β is set large enough to accommodate all the perturbation of transit operations. However, various constraints limit the selection of β, for instance larger β means large slack time and lower commercial speed.

Figure 3.5-1 illustrates the value of $\Pr\left(TT_{d,r,s} \geq \beta + T50_{r,s}\right)$ when β varies from 0 to 10 for the different study routes where Figure 3.5-1 (a) is for 8:00 am and Figure 3.5-1 (b) is for 12:00pm. The figure clearly indicates that recovery time is dynamic over both route and time. A static constant recovery time for all the routes may not be optimal. For the study site, if transit operators aims for 90% of buses for on-time, then recovery time for morning period (8:00 am, Figure 3.5-1(a)) should be around 3 to 7 minutes depending on the route. For instance, 7 minutes for route 411 and 3 minutes for route 100. Similarly, for afternoon non-peak period it should be around 1 to 2 minutes. While most transit operators currently set a fixed scheduled travel time for all time-of-the-day, the information in Figure 3.5-1 facilitates a better timetabling to serve all passengers on-time. While adding more recovery time would also reduce commercial speeds, the proposed method enables analytical calculation to balance between high commercial speed and reliable travel time.



(a)



(b)

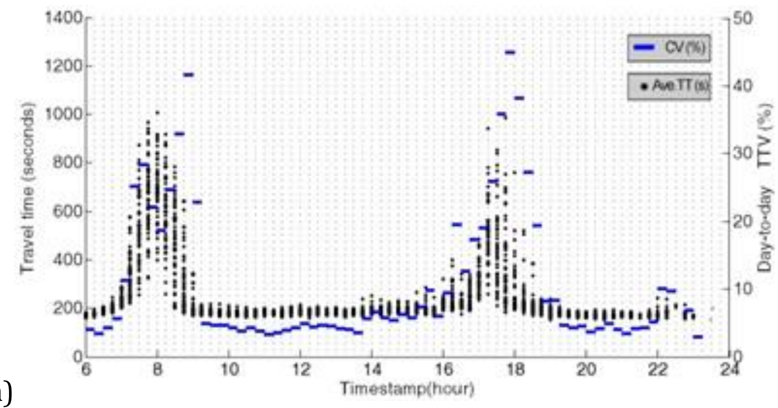
Figure 3.5-1 Value of $\Pr\left(\boldsymbol{TT}_{\boldsymbol{d,r,s}} \geq \boldsymbol{\beta} + \boldsymbol{T}50_{\boldsymbol{r,s}}\right)$ with varied $\boldsymbol{\beta}$ at: (a) 8:00 and (b) 12:00

Travel time statistical studies also require the knowledge of travel time distribution. For instance, dynamic and stochastic traffic assignment usually assumes travel time as random variable and models travel time as a stochastic process follows a probability density function (Mirchandani and Soroush, 1987). The distribution also shows the probability of excessive travel time (incidents), which is importance in route choice modelling (Watling, 2006). The method for exploring travel time probability distribution in this chapter facilitates these studies.

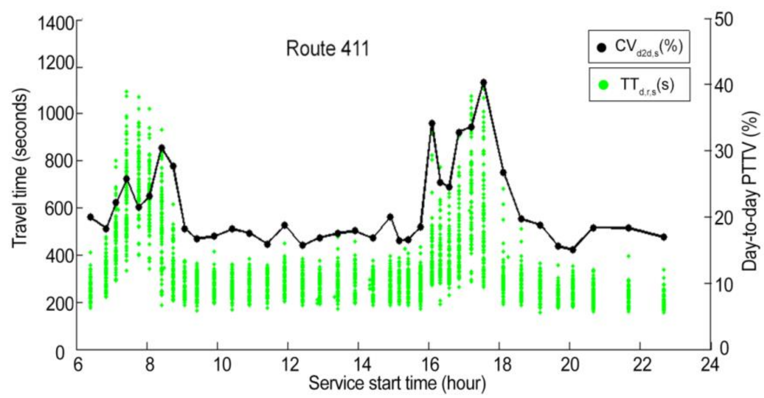
3.5.2 **Knowledge gained**

The following knowledge could be gained from the methodology and the findings of this chapter

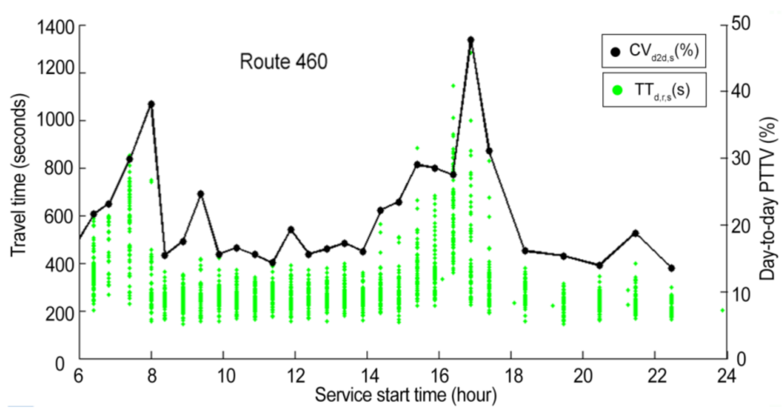
(1) The travel time variability of public transport is significantly different to the TTV of private transport. While TTV is measured for all vehicles, PTTV is best measured by looking at the same service on a multi-day period. Using the same method as in private transport TTV would yield a different result. Figure 3.5-2 illustrates the difference between TTV (estimated from Bluetooth data using the method described in Bhaskar et al. (2012)) and PTTV (obtained from VID data).



(a)



(b)



(c)

Figure 3.5-2 Travel time variability: a) TTV of all vehicles from Bluetooth data, and b) PTTV of Route 411 from VID data and c) PTTV of route 460 from VID data

Figure 3.5-2 demonstrates that PTTV of buses is clearly larger than that of other vehicles. Within the transit mode, different routes also have different PTTV. For instance, route 411 has another smaller peak time perid at 16:00 before the highest peak near 18:00, while route 460 only has a very high peak in PTTV at 17:00.

(2) The travel time of transit vehicle on arterial roads follows a log-normal distribution

(3) PTTV can be indicated by a probabilistic indicator which is more useful than the traditional CV method.

4 Offline transfer coordination

The last chapter established the definitions, model and measure public transport travel time variability (PTTV) by a probabilistic indicator. Based on the knowledge gained, this chapter investigates how passenger transfer can be coordinated in offline schedule planning process.

The contents of this chapter are in preparation to submit in the following publication:

Journal article

J2 Kieu, L. M., Bhaskar, A. & Chung, E. TBA. An evaluation of timed transfer coordination using Event-based Multi Agent Simulation. *Transportation Research Part C. (*Under Review*)*

4.1 Introduction

The literature of offline transfer coordination during planning process could be classified into *timetable synchronisation* (TS) and *timed transfer coordination (*TTC*)*. TS harmonizes multiple transit lines schedules to minimise passenger transfer time. TTC adds a slack time into transit schedule to accommodate the variability of transit vehicle arrival and allows the RV to depart the transfer stop after the FV arrival. TTC focuses on a narrower problem compared to the timetable synchronisation problem. Within the scope of this research, this chapter focuses on the problem of TTC between a single receiving transit line with a single feeding transit line.

The existing studies in literature provide insights into the problem of TTC, which is generally a problem of minimising passenger transfer time in a narrower scope than the TS problem. The existing TTC methods have been relying on the same fundamental assumption that the variability of transit vehicle arrival time, or travel time, is adequately considered in the transfer coordination models. Although the randomness in vehicle travel time and dwell time are better considered compared to TS, the added slack time may not be enough to accumulate the variability in vehicle arrival time. If the transit vehicle arrives at later than the anticipated range, RV may have to wait for a full slack time period without a successful transfer. The travel time variability of transit service therefore is crucial for the successful of offline coordinated transfer models.

Notwithstanding the extensiveness of studies on timed and timetable synchronisation, the impacts of travel time variability on TTC has not been systematically analysed. There is a lack of understanding on PTTV definitions and modelling, which impedes the investigation of arrival variability on passenger transfers. The Chapter 3 of this dissertation has established a comprehensive understanding of the definitions and modelling of PTTV. This chapter aims to use this knowledge to enhance transfer coordination in offline transit planning.

Moreover, due to the unavailability of data, most of the existing studies in TTC assume an arrival rate to model the passenger demand (De Cea and Fernández, 1993; Fu et al., 2003; Liu and Wirasinghe, 2001). Arrival rate is a deterministic variable that usually require manual data collection, which impedes the applicability of the proposed TTC models. This chapter proposes a method to integrate real passenger demand from Smart Card AFC data into a TTC model. The integration of Smart Card AFC data brings more dynamic and better representation of the passenger demand into the offline transfer coordination model.

The chapter consists of 5 sections. After the introduction in Section 4.1, Section 4.2 introduces the case study and the transfer coordinating problem we set out to address. Section 4.3 develops the transfer coordination method. Section 4.4 examines the coordination results with different simulation settings. Finally, the outcomes, knowledge gained and contributions of the chapter are reviewed in Section 4.5.

4.2 **Problem and case study**

4.2.1 **Research problem**

This chapter solves the problem of offline transfer coordination during transit planning process, in order to provide better transfer service to transit customer. A better transfer service is defined as:

- Lower average transfer time
- Lower probability of missing a transfer

These two aspects are also the objectives of this chapter. This chapter focuses on the TTC problem, in particular a transfer between two bus routes at a single stop. Figure 4.2-1 illustrates the research problem. Here, the two bold lines represent the scheduled travel time of the feeding (blue line) and receiving (black line) bus routes. "Planned transfer time" (*PTT)* is the amount of time to allow passenger to transfer from the feeding vehicle (FV) to RV at transfer point. However, due to the variability in vehicle traveling and dispatching time, the real travel time and dispatching time of RV and FV could lies anywhere between their upperbound and lowerbound (dash lines). *PTT* may not be sufficient to accommodate this variability, which leads to a missed connection.

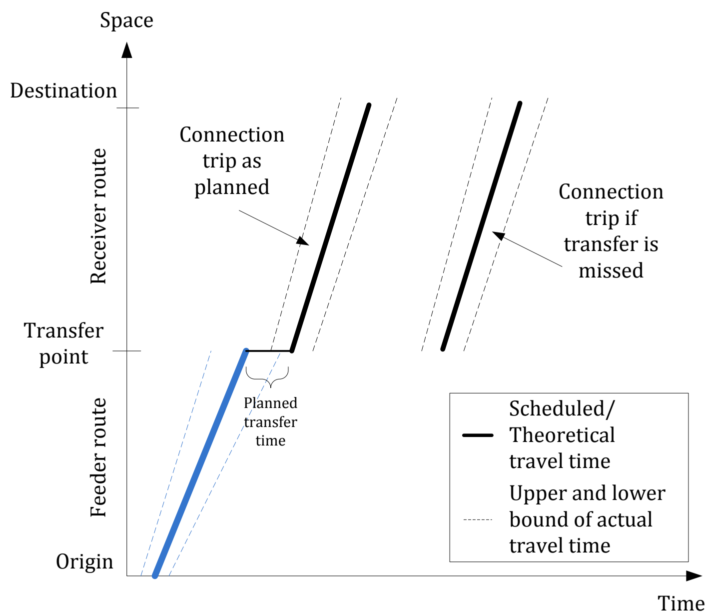


Figure 4.2-1 Transfer coordination problem

The research problem could be broken down into setting of *PTT* to maximise the probability of making a successful transfer and minimise the transfer time. The chapter answers the following research questions:

- How variability is considered in scheduled bus travel time and dispatching time?
- How to consider the passenger demand in TTC?
- How to set the "Planned transfer time" *PTT* so that the transfer probability is maximised and transfer time is minimised?

This chapter aims at reducing transfer time of transferring passengers. Non-transferring passengers arrive according to the schedule and are assumed to be indifferent towards the schedule change.

4.2.2 **Case study**

The last chapter established the definitions and modelled the PTTV using VID data of SEQ, Australia. The VID data is a rich dataset consists of all buses passing an urban corridor over a year period. This dataset facilitates a comprehensive methodology for PTTV definitions and modelling. However, VID data does not provide any information at bus stops. The estimated travel time using VID data is only between arterial intersections.

This chapter uses a more detailed data that provides stop to stop travel time: the AVL data. The AVL data used in this chapter comes from Translink, the transit provider of SEQ, Australia. It is the compilation of arrivals and departure timestamps of several bus routes originated in Logan City, SEQ. The system stores the geographical coordination of every bus stop and calculates a virtual geo-fencing area of 50m around each stop. The arrival and departure timestamp of each AVL record are the times the bus entered and left the geo-fencing area. When the bus does not stop for dwelling, only the arrival time is stored. Table 4.2-1 gives an example of the dataset used for analysis in this chapter.

Table 4.2-1 Examples of AVL data

Day	Trip ID	Route	Stop ID	Arrival	Departure	Direction
7th May	1544261	572	10	14.7025	14.7075	1
7th May	1544261	572	11	14.7178	14.7178	1
7th May	1544261	572	12	14.7272	14.7272	1
7th May	1544261	572	13	14.7336	14.7458	1
7th May	1544261	572	14	14.7514	14.7631	1

The offline transfer coordination in this chapter focuses on the timed transfer coordination from a single feeding transit line to another receiving transit line. The analysis in this chapter focuses on Route 572 and 555, two of the most busy bus lines in Logan City, SEQ as the case study. The reasons why these two routes were chosen for the case study are:

(1) Their high patronage during the study period

(2) For transfer coordination purpose, Route 572 is a local route within the Logan City area, with low frequency (2 buses per hour) whereas Route 555 connects Logan City with Brisbane CBD in high frequency (4 buses per hour). While Route 555 operates partly along the busway and along the Pacific Motorway in SEQ, Route 572 only operates along the arterials in Logan City, SEQ. In the afternoon peak, Route 555 is the feeding bus for the Route 572 in the outbound direction, where passengers travel from Brisbane city to Logan city. A large proportion of Route 572 demand is transferred passengers from Route 555, which means transfer coordination is important for the operation of Route 572.

Route 572 has 60 stops, whereas Route 555 is 27km in length and has 12 stops on each direction. Figure 4.2-2 illustrated the two routes and their descriptive information.

Figure 4.2-2 Route 555 and 572 illustrations and descriptions

The studied transfer stop is the Springwood station. If we name transit stops of each line from Stop 0 to Stop *n* (last stop), Springwood station is the Stop 0 of the Route 572 and the Stop 11 of Route 555. For that reason the Route 555 is divided into 2 sections: Section 1 is from Brisbane CBD to Springwood station, and Section 2 is from Springwood to Loganholme station.

The case study also focuses only on the PM peak period from 14:00 to 18:00, because the demand for outbound direction is highest during this time period. The passenger demand, including each individual passenger boarding, alighting and timestamps is taken from the Smart Card AFC data. This chapter uses AFC and AVL data from July to October 2013, only on the working days (weekdays without public holidays). The Figure 4.2-3 illustrates the demand of Route 555 and 572 throughout different time-of-the-day of the whole study period of 4 months. Each illustrated point represents the number of passengers at a 30 minutes time window over the entire study period from July to October 2013. The data has been obtained from Smart Card AFC data.

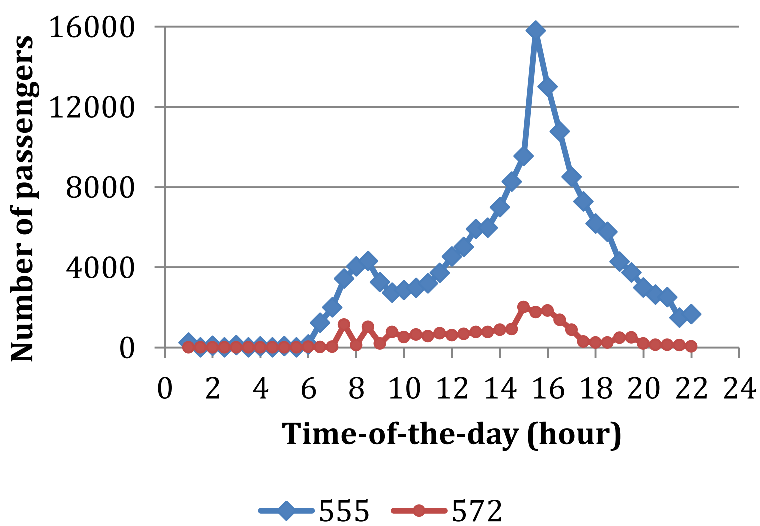


Figure 4.2-3 Number of passengers boarded Route 555 and 572 at different time-of-the-day

Figure 4.2-4 shows a correlation between departure time of RV (Route 572) and arrival time of FV (Route 572).

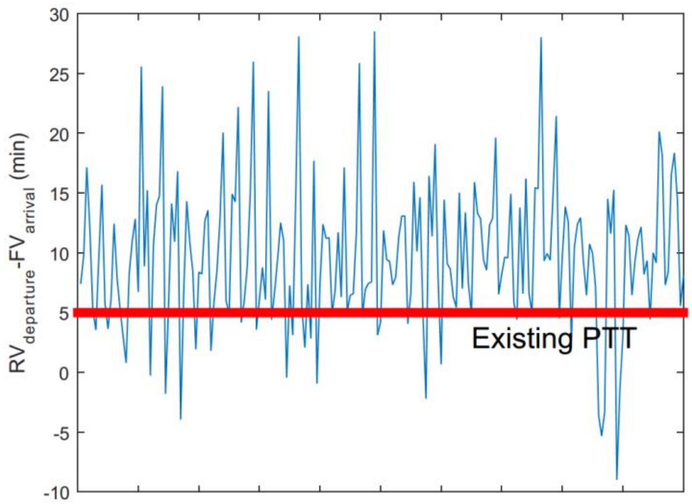


Figure 4.2-4 Correlation between departure time of RV (Route 572) and arrival time of FV (Route 572)

The time gap between departure time of RV (Route 572) and arrival time of FV (Route 572) is fluctuated around a 10 minute average. Generally the existing PTT of 5 minutes seems sufficient to accommodate the transfer from FV to RV. In the next section, this research develops a simulation tool to investigate the value of PTT using observed AVL and AFC data.

4.3 **Methodology**

Transit vehicle operates in a dynamic environment where various factors such as passenger demand, traffic conditions and operation strategies could affect its travel time. Variability is then an inevitable part of transit operations from dispatch to the end stop of a service. Any model to represent the transit system should sufficiently integrate dispatch time variability and travel time variability in the model. Passenger demand also significantly affects bus operations. More passenger means longer dwell time, more stopping at stops for both boarding and alighting.

This section develops a simulation model to integrate both variability and passenger demand in offline TTC modelling. An Event-based Multi Agent Simulation (EMAS) is developed because of the following reasons:

- A simulation approach can adequately **represent the variability** of the bus operation, because all possible operation state could be simulated

- A Multi Agent Simulation can simulate the movements of every passenger in the system. It means the **real passenger demand** could be integrated in the simulation model
- Event-based simulation enables us to **observe the operation state** of the transit system

4.3.1 EMAS agent types and interactions

The EMAS model has two principal types of agent: the vehicle agent (VA) and the passenger agent (PA). Figure 4.3-1 illustrates these two types' characteristics and behaviours in EMAS.

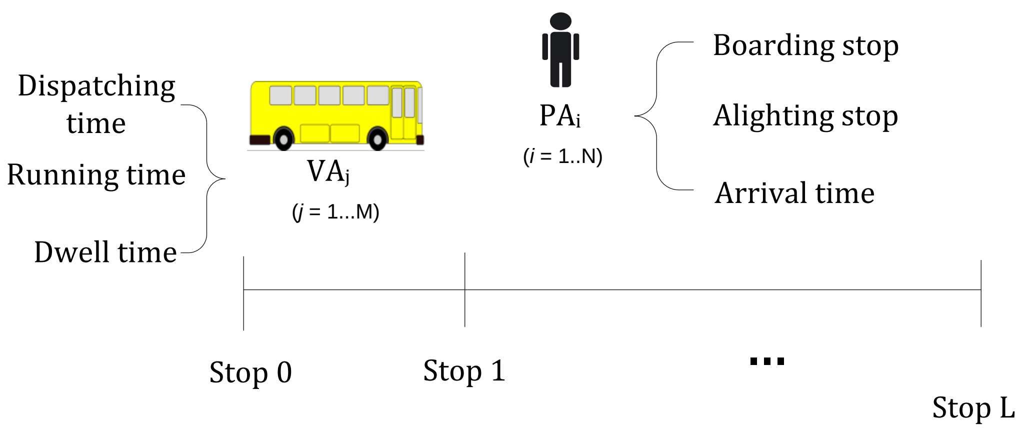


Figure 4.3-1 EMAS agent types

Each run of the EMAS depicts a day in reality, where each VA represents a bus of Route 555 or Route 572. The number of VA equals the number of services M of a day. Each VA is dispatched at "Dispatching time", travels along each link in "Running time" and stop at each stop by "Dwell time". On the other hand, each PA represents a passenger of Route 555 or Route 572. PA plan includes boarding at "Boarding stop", alighting at "Alighting stop" and arrives at the "Boarding stop" at "Arrival time". There is no pre-defined boarding and alighting time for PAs because these depend on the operation of VAs.

Figure 4.3-2 illustrates the interaction of PA and VA in a time-space diagram. While each VA_j is dispatched for a service $Schedule_j$, due to various reasons such as vehicle late arrival or driver behaviour, VA_j could be dispatched earlier or later than this scheduled dispatch time by dispatch time deviation Δ_j. Here, "Dispatching time" is the actual dispatch time AD_j

$$AD_j = \Delta_j + SD_j \qquad (19)$$

Where,

AD_j = Actual dispatching time of vehicle *j*

SD_j = Scheduled dispatching time of vehicle *j*

Δ_j <0 means that VA_j left Stop 0 earlier than scheduled

Δ_j >0 means that VA_j left Stop 0 later than scheduled

VA_j then travels between the first Stop 0 to the last Stop L (L equals 12 for Route 555 and L equals 60 for Route 572) with the "Running time" of $RT_{j0\text{-}1}$, $RT_{j1\text{-}2}$ to $RT_{jL\text{-}1toL.}$ While "Dispatching time" and "Running time" is pre-defined as part of the VA plan, "Dwell time" DT_{j1} to $DT_{jL\text{-}1}$ varies according to the number of boarding and alighting at each stop.

Each PA_i appears at his/her planned "Boarding stop" at "Arrival time" Arr_i where PA_i will board the first arriving vehicle agent VA_j at time B_i. When the boarded agent VA_j reaches PA_i planned alighting stop "Alighting stop", PA_i will alighting at that time A_i.

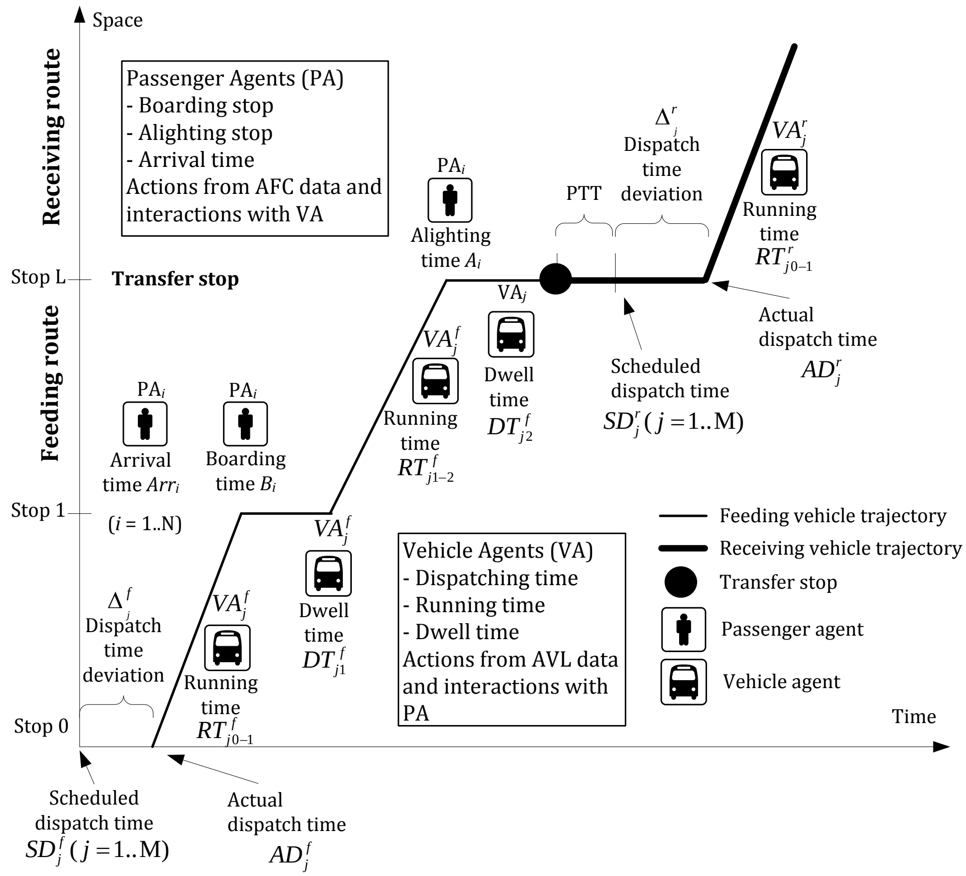


Figure 4.3-2 Time-space diagram of the interactions between EMAS agents

The following sub-sections demonstrate how values of “Dispatching time”, “Running time” and demand-related variables “Dwell time”, “Boarding stop”, “Alighting stop” and “Arrival time” are calculated.

4.3.2 Dispatching time

Dispatch time is the departure time from the first stop of a transit vehicle, or the starting time of a new transit service. Equation (19) calculates the value of “Dispatching time” AD_j from scheduled dispatch time and dispatch time deviation $\Delta_{dispatch}$. Figure 4.3-3 shows the cumulative density function of Δ_j for Route 555 and 572. Δ_j equals zero means on-time dispatching, or dispatching exactly as scheduled.

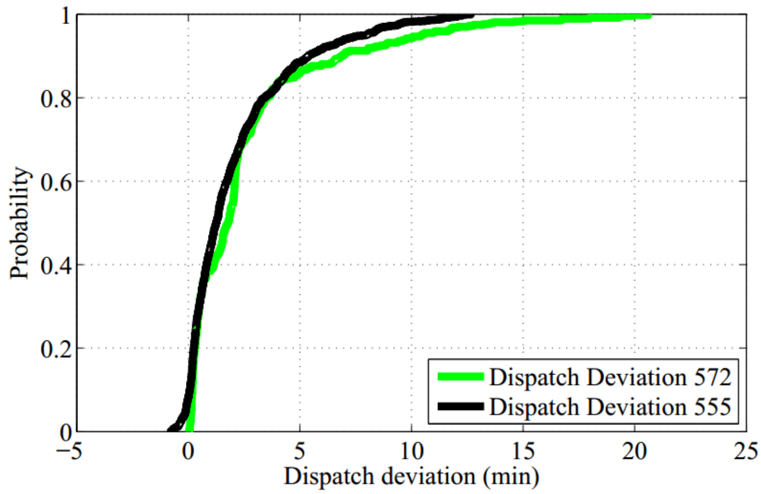


Figure 4.3-3 Dispatch time deviation of Route 555 and 572

The figure shows that nearly 90% of vehicles from both routes dispatched within 5 minutes from the scheduled dispatching time from the first stop. While Route 555 starts from the Brisbane CBD, Route 572 starts from the Springwood station. However, the rest 10% of the vehicles could start up to 20 minutes late compared to the schedule.

4.3.3 **Vehicle running time**

For a transit route of *L* stop, numbering from *0* to *L* we have

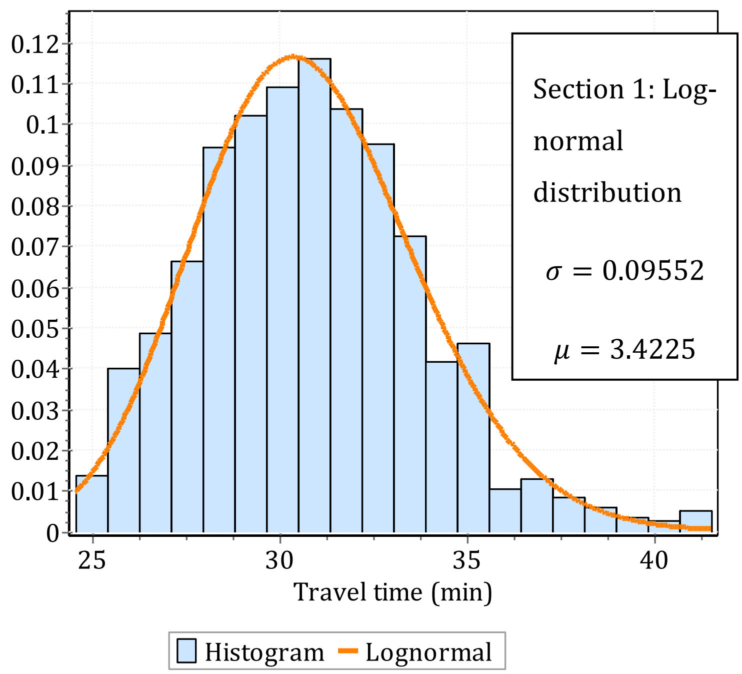
$$TT_j = RT_j + \sum_{s=0}^{L} DT_s^j \qquad (s=0 \ldots L \text{ is the number of stop}) \qquad (20)$$

Where TT_i is the total travel time from Stop 0 to Stop *L* of vehicle *j*. Counted from the departure time from Stop 0 (dispatching time) to the arrival time to Stop *L* (final arrival time).

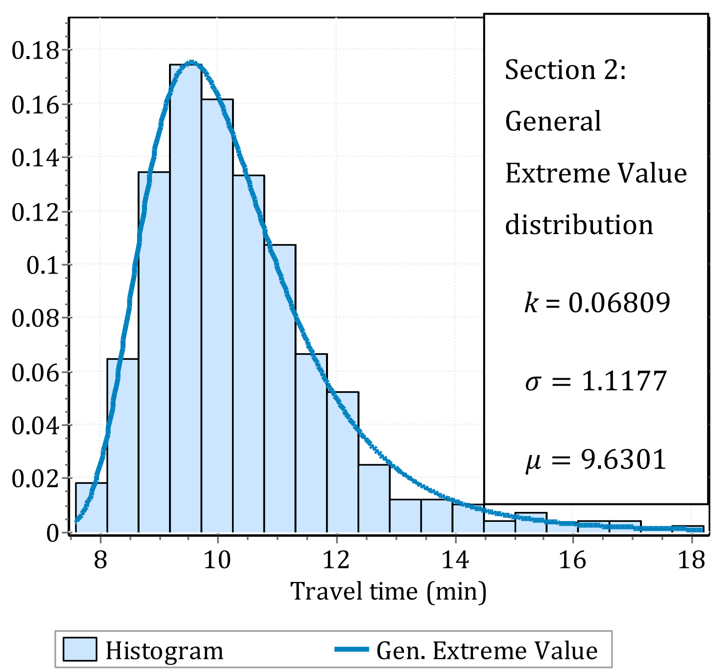
RT_j is the total running time excluding dwell time from dispatching to final arrival time of vehicle *j*.

DT_s^j is the dwell time at stop *s* of vehicle *j.*

The vehicle running time *RT* is separated from the dwell time to represent the variability induced by the traffic condition, regardless of the passenger demand in the system. We assume that *RT* always follows a probability distribution. The Figure 4.3-4 shows the PDF of Route 555 running time without dwell time, obtained from observed AVL data during the study time between 14:00 and 18:00.



(a)



(b)

Figure 4.3-4 Probability density function of Route 555: (a) Section 1; and (b) Section 2

Similar method as described in the Chapter 3 reveals the distribution of running time in Section 1 and 2 of the Route 555. The running time of Section 1 could be best represented by the log-normal distribution, while the running time of Section 2 is modelled by the

General Extreme Value distribution. Both the two running time profiles are right skewed and have a long tail. The PDF of the running time of Route 572 is showed in Figure 4.3-5, where log-normal distribution is again the best descriptor of the running time.

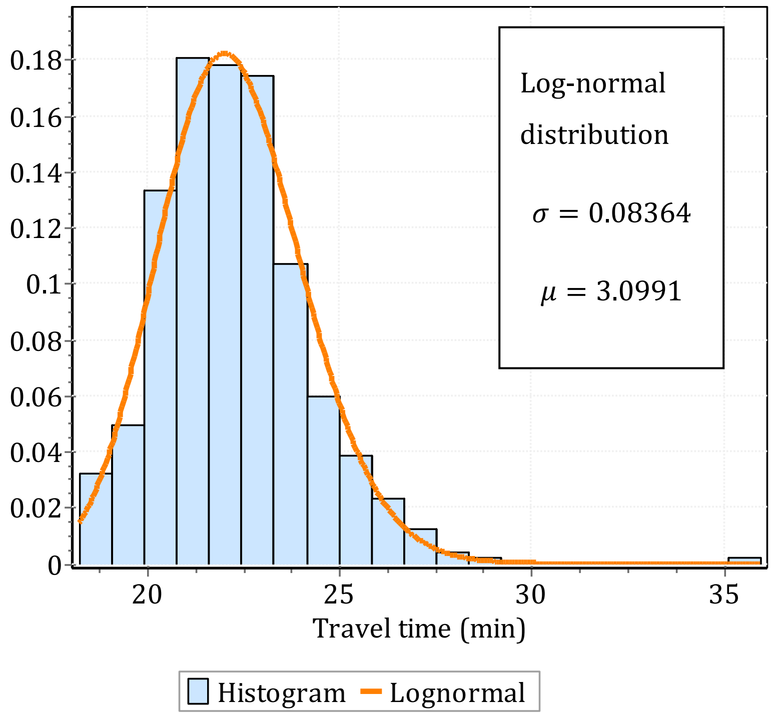


Figure 4.3-5 Probability density function of Route 572

4.3.4 **Passenger related variables**

Passenger demand only affects transit operations at stops, but the impact is significant. Transit vehicle has to stay long enough to allow waiting passengers to board, and alighting passengers to get off the bus. Existing studies in the literature of transit simulation traditionally assume a passenger arrival rate to estimate the number of waiting passenger, and an alighting fraction at each stop to estimate the number of alighting passenger (De Cea and Fernández, 1993; Fu et al., 2003; Liu and Wirasinghe, 2001). While data collection for passenger arrival rate at each bus stop in different time period is time-consuming and expensive, alighting fraction does not sufficiently represent the actual number of alighting passengers.

Therefore, in this section we adopt a different approach to overcome those limitations. The actual passenger demand data from Smart Card AFC data is integrated to the simulation model in the form of passenger agents. Smart Card AFC data includes boarding and alighting time & location of individual passenger at different time period, which represents each agent travel plan. Table 4.3-1 shows an example of the AFC data used in this chapter.

Table 4.3-1 Example of AFC data used in the transit simulation model

Card ID	Boarding stop	Boarding time	Alighting stop	Alighting time
X1	0	8:02:57	11	8:43:12
X2	1	8:05:02	11	8:43:09
X3	5	8:21:42	8	8:36:30

As each EMAS run is a day, each passenger in a day of AFC data is converted into a PA in one EMAS run. Figure 4.3-6 illustrates the PA generation process.

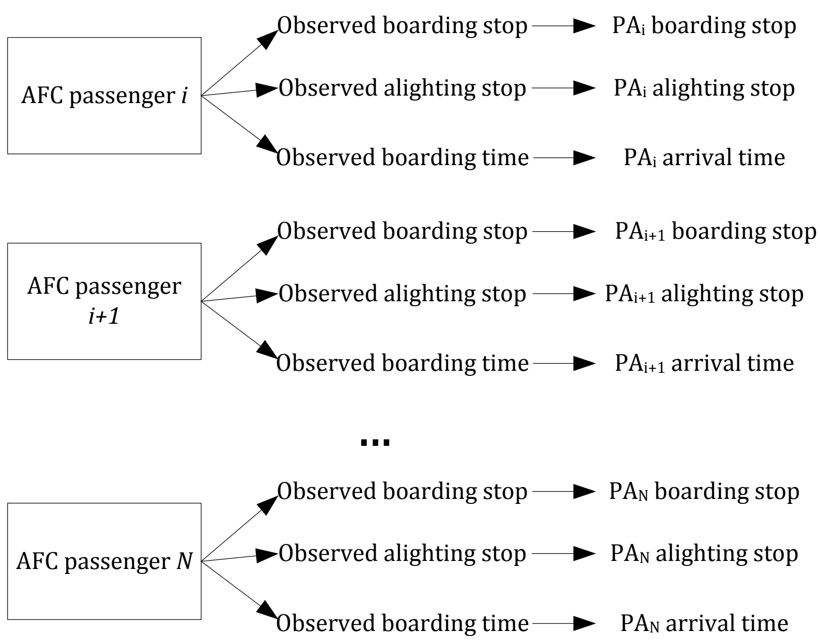


Figure 4.3-6 Generating passenger agents from AFC data

N passengers of day *d* in the AFC dataset is converted to *N* passenger agents, where the "Boarding stop" and "Alighting stop" of agent PA_i are similar to the observed data of passenger *i*. Transferring agents could have 2 sets of "Boarding stop" and "Alighting stop" at Route 555 and Route 572 but only one "Arrival time". A passenger who used Route 555 or Route 572 more than once in a day would be considered as two distinct PAs.

AFC data does not include passenger arrival time (the time passenger arrives at the bus stop to wait for a transit vehicle). We estimate the passenger arrival time from the boarding time by using a proxy. In morning inbound direction, transit vehicle usually arrives to the first stop (Stop 0) of Route 555 earlier than scheduled but would leave the stop as scheduled. As soon as passengers arrive at the stop and see a vehicle, most of them would board the vehicle, even though it is earlier than the scheduled departing time. Therefore, the following assumptions can be made

- Passenger boards a transit vehicle as soon as they see one available, there is no immediate activity before passenger boarding.
- Passenger arrives to all bus stops by a similar distribution as the arrival to the first stop.
- The time between passenger arrivals is frequently assumed as exponentially distributed in literature (Hickman, 2001; Liu and Wirasinghe, 2001). In this thesis, we assume that the passenger waiting time is also exponentially distributed. Figure 4.3-7 illustrates the validity of this assumption.

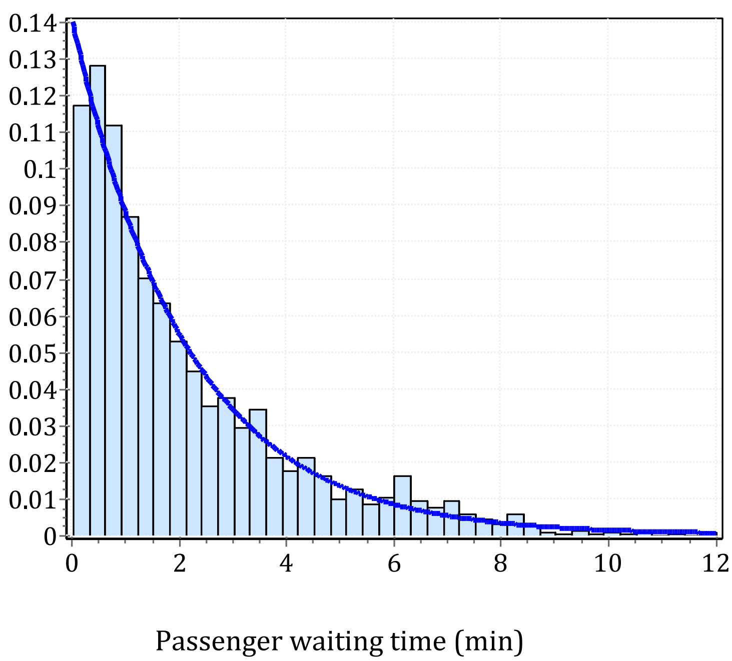


Figure 4.3-7 Distribution of passenger waiting time

Figure 4.3-7 shows that the distribution of passenger waiting time perfectly matches an exponential distribution curve. Arrival time of passenger *i* is estimated from the observed passenger boarding time from AFC data.

$$Arr_i = B_i - W_i \quad (21)$$

Where

Arr_i = Estimated arrival time of individual passenger

B_i = Observed boarding time of individual passenger

W_i = Estimated waiting time of individual passenger

W_i is estimated by an inversion method from Exponential Distribution's parameter

$$W_i = \frac{\log(1-u)}{-\lambda} \quad (22)$$

Where λ = Exponential distribution parameter, in this case λ =0.4716 (Figure 4.3-7)

u is random uniformly distributed parameter in [0,1)

Figure 4.3-8 demonstrates an example of how passenger arrival time is estimated from observed boarding time.

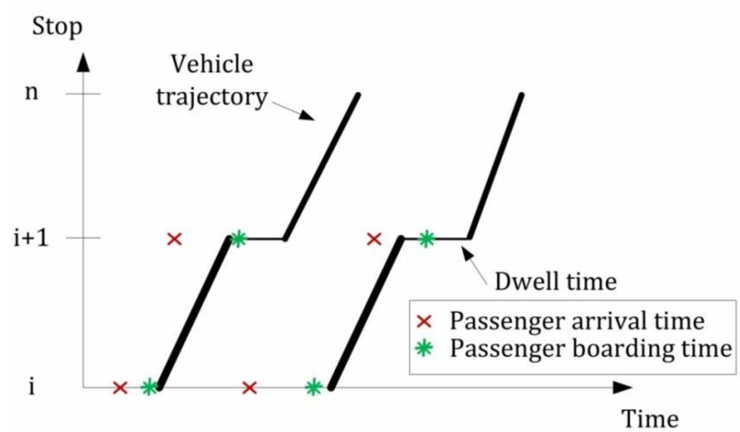


Figure 4.3-8 Estimate passenger arrival time from observed boarding time

The Figure 4.3-8 shows a space-time diagram of lines of vehicle trajectories and asterisk & crosses as passengers boarding and arrival time. The green asterisks show individual passenger boarding time, observed from AFC data. The red crosses are estimated arrival time from observed boarding time.

4.3.5 Event-based Multi Agent Simulation (EMAS) setup

The previous sub-section establishes the principal components of the EMAS model: passenger agents PA, vehicle agent VA along with their dispatch time deviation Δ_j, running time RT_j and passenger arrival time Arr_i. This sub-section develops the EMAS model from these components. Figure 4.3-9 illustrates the flowchart of EMAS model.

The EMAS model has two classes of agents: vehicle agents VA and passenger agents PA. While VA operates by using dispatch time *AD* and running time *RT* generated from probability distributions, PA follows the same plans as transit passengers in the AFC dataset. The simulation starts with randomly choose a day *d* in the AFC dataset to generate the PA set for an EMAS run. Each EMAS run simulates a day in reality.

Vehicle events are arrival and departure timestamps at each transit stop.

1) At the first stop (Stop 0), arrival and departure time of vehicle *i* are equal to the Actual dispatching time AD_j, which could be calculated using Equation (19).

2) At downstream stops (Stop 1 to last stop), arrival and departure time of vehicle *i* is calculated as follows

$$Arr_s^j = Dep_{s-1}^j + \frac{Length_{s-1}}{\sum_{k=0}^{L-1} Length_k} \times RT_j \qquad (23)$$

Where Arr_s^j = Arrival time of vehicle *v* at stop *s* (*s*=1..L)

Dep_{s-1}^j =Departure time of vehicle *v* from the previous stop, stop *s-1*

$Length_k$ = Link length of the section between stop *k* to stop *k+1*

RT_j = Total running time from stop *0* to stop *L*

$\frac{Length_{s-1}}{\sum_{k=0}^{L-1} Length_k} \times RT_j$ is therefore the running time of each section between stop s-1 to stop s

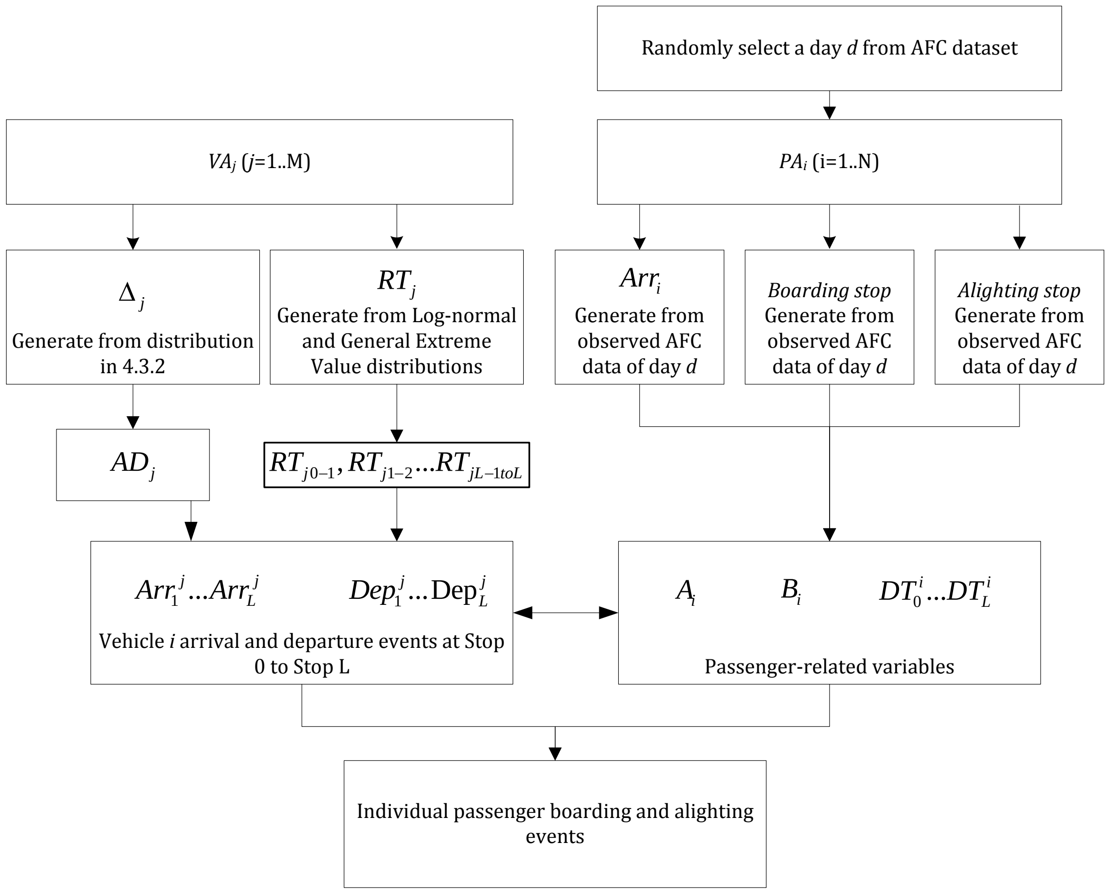


Figure 4.3-9 EMAS model flowchart

The departure time of transit vehicle from stop *s* is calculated as follows

$$Dep_s^j = Arr_s^j + DT_s^j \qquad (24)$$

Where the dwell time DT_s^j is calculated as a function of the number of boarding and alighting passenger. This research adopted the equation proposed by Jaiswal et al. (2010), Bertini et al. (2004) and TCQSM (TRB, 2013) to estimate the time spent for passengers boarding and alighting

$$DT_s^j = 5.8 + 3.6 \times N_B + 0.85 \times N_A \qquad (25)$$

Where DT_s^j = dwell time at stop *i* (seconds)

N_B=number of boarding passengers at stop s

N_A=number of alighting passengers at stop s

The dwell time DT_s^j (seconds) is generally the time spent for passenger boarding or alighting; and added a fixed value of 5.8 seconds for vehicle stopping, accelerating and door opening time. The parameters are adopted from Bertini et al. (2004).

3) Passenger events are the arrival time at bus stops, boarding time to a transit vehicle and alighting time from a transit vehicle. The arrival time of each passenger Arr_i is calculated from Section 4.3.4. Each passenger acts as an agent of predefined travel plan: Arrival time to a predefined transit stop, and a predefined destination stop. Passengers aboard a transit vehicle as soon as the vehicle arrives at transit stop. Passengers leave a transit vehicle at their desired transit stop. Passengers are assumed to board and alight at the same time.

The transferring passenger is the special type of agent. Instead of having only a planned boarding and an alighting stop, these passengers have one more set of boarding and alighting. Transferring passenger plan has a boarding stop of Route 555, a first alighting at stop 11 of Route 555, a boarding at stop 0 of Route 572 (which is exactly the same stop as stop 11 of Route 555 – the Springwood station) and finally an alighting stop of route 572.

4.3.6 **Simulation results verification**

The simulation model has been built using a number of assumptions:

- Passengers board a transit vehicle as soon as they see one available, there is no immediate activity before boarding
- Passenger waiting time follows an Exponential distribution
- Passengers board and alight at the same time as vehicles arrive/depart a transit stop
- The value of dwell time only depends on the number of boarding and alighting passengers
- Transfer occurs at the same bus stop, so the transfer walking time is insignificant and transfer can be made immediately
- The capacity of transit vehicle is assumed large enough to accommodate all waiting passengers

- The total vehicle running time follows a Log-normal distribution or General Extreme Value distribution
- Vehicle travels with constant speed along the route, so travel time of each link only depends on the length of the section. Link travel time is considered as independent variable

This section verifies the simulation result by comparing the observed total travel time and transfer time to the simulated travel/transfer time of individual passengers. The total travel time of passenger *i* is calculated as follows

$$TTT_i = k_{555}(TT_{555} + W_{555}) + k_{572}(TT_{572} + W_{572}) + k_{tf}\ \mathrm{TF}_i \qquad (26)$$

Where TTT_i (min)= total travel time in minutes of the passenger *i* from origin boarding stop to destination alighting stop

k_{555} = 1 if passenger *i* took Route 555, 0 otherwise

k_{572} = 1 if passenger *i* took Route 572, 0 otherwise

k_{tf} = 1 if passenger *i* transferred from Route 572 to Route 555, 0 otherwise. If k_{tf} =1 we also have $k_{555} = k_{572} = 1$

TT_{555} and TT_{572} (min) are the travel time of the segments of the routes 555 and 572 service that passenger *i* took, respectively

W_{555} and W_{572} (min) are waiting time for the Route 555 and Route 572 service that passenger *i* took, respectively

TF_i (min) is the transfer time from Route 555 to Route 572, counted from the time the passenger *i* leaves a Route 555 vehicle at the transfer stop to the time he/she boards a Route 572 vehicle. The transfer stop Springwood station is the Stop 11 in Route 555 and Stop 0 in Route 572.

$$\mathrm{TF}_i = B_i^{572} - A_i^{555} \qquad (27)$$

Figure 4.3-10 and Figure 4.3-11 show the CDFs of total travel time of individual simulated agents and observed passengers at Route 572 and Route 555.

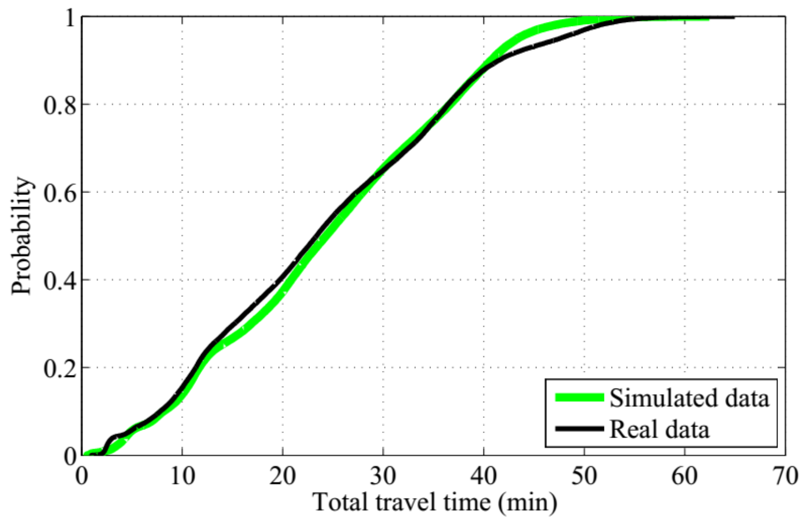


Figure 4.3-10 CDF of individual total travel time from Route 555 passengers: Green lines for simulated agents and Black lines for observed passengers

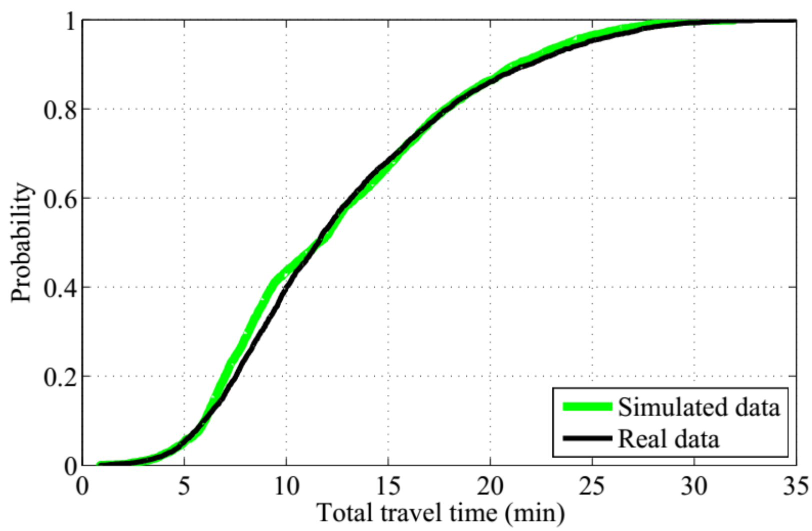


Figure 4.3-11 CDF of individual total travel time from Route 572 passengers: Green lines for simulated agents and Black lines for observed passengers

Figure 4.3-10 and Figure 4.3-11 verify that the total travel time of simulated agents are very similar to the observed passengers in both routes. Figure 4.3-12 illustrates the CDFs of transfer time only for passengers and simulated agents that transferring from Route 555 to Route 572. While transferring passengers are proportioned for only 2.76% of Route 555 (FV), they are proportioned for 26.79% of Route 572 (RV).

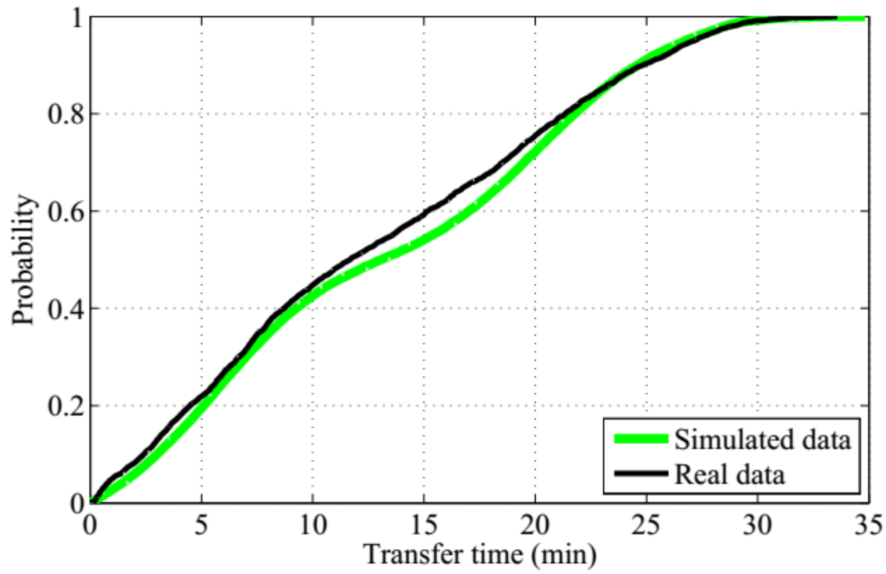


Figure 4.3-12 CDF of individual transfer time from transferring passengers: Green lines for simulated agents and Black lines for observed passengers

While the CDF of simulated agents transfer shows a wave curve pattern, the CDF of observed passengers has similar pattern, but not as clear as the other CDF. This is because for every two Route 555 services, there is only one with *PTT* = 5 minutes to the Route 572 service, whereas the other Route 555 service has *PTT*= 20 minutes to the next Route 572 service. We define the service with *PTT*=5mins as the direct-transfer service and the other one as the non-direct-transfer service. Figure 4.3-13 illustrates the space and time interactions between these two types of Route 555 service to the Route 572.

In reality, passengers who plan to transfer would take the direct-transfer Route 555 service. If they arrive near the non-direct-transfer service arrival, they may take another route or other modes to travel. The information on those passengers who take other alternatives is missing in the observed data, because we have only information on Route 555 and Route 572. However, in EMAS model the simulated passenger agents will follow the original plan even if they have to wait for long time, which creates slightly more drop in CDF slop at 10-15 minutes when passengers missed the first transfer, where their probability of making a successful transfer at that time period is not much increased.

We compromise this slight difference between the EMAS simulation and the observed data for the chance to investigate the transferring time, especially the probability of missing a transfer (PMT) in this chapter. Passengers are assumed to always wait for the transferring service once they already planned to transfer.

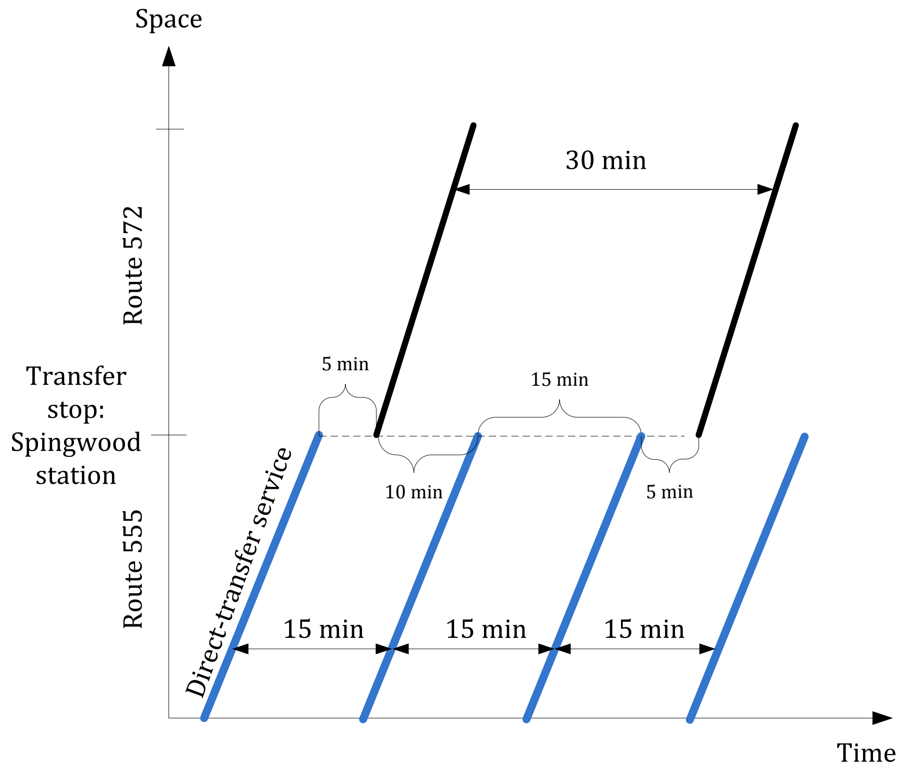


Figure 4.3-13 Direct-transfer and non-direct-transfer Route 555 services

4.4 **Analysis of simulation results**

TTC adjusts the *PTT* and dispatch time of both the transit routes, so that the average transfer time and possibility of missing a transfer are minimised. This sub-section analyses the offline transfer coordination simulation results.

The current *PTT* between a Route 555 arrival at the transfer stop to a Route 572 departure time from the same stop is 5 minutes. However, for every two Route 555 vehicle, only one of them has direct connection of 5 minutes, the other has the time gap of 20 minutes to the next Route 572 arrivals. Therefore, in this section we focus the analysis to transferring passengers of the direct-transferring service (5 minutes of *PTT*) only. This section investigates the mean transfer time and the PMT of 4 main cases:

- Case-1: Different *PTT* adjustment (section 4.4.1)

- Case-2: Different *PTT* adjustment, with on-time dispatching (section 4.4.2)
- Case-3: Different *PTT* adjustment, with longer vehicle running time (section 4.4.3)
- Case-4: Different variability of vehicle running time (section 4.4.4)

4.4.1 Case-1: Passengers transfer time and probability of missing a transfer at different Planned Transfer Time (*PTT)*

Figure 4.4-1 shows the cumulative probability function of passenger transfer time from Route 555 to Route 572 during afternoon peak period.

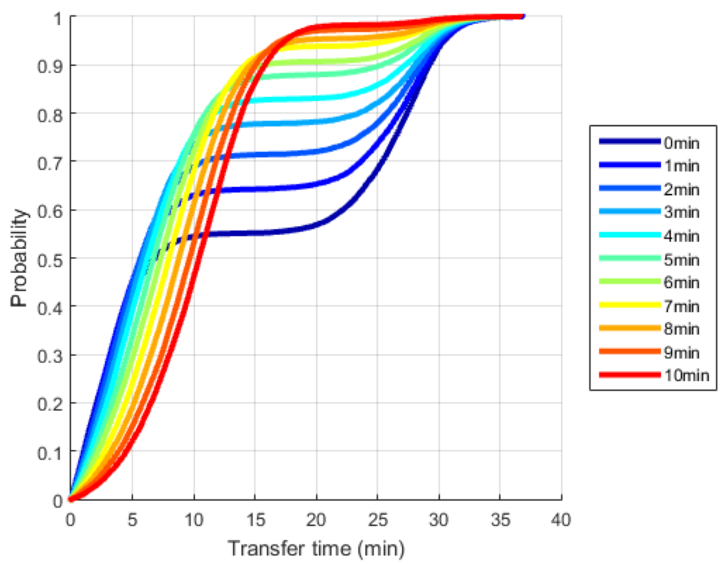


Figure 4.4-1 Transfer time of passengers at different *PTT*

Each line shows the cumulative probability of passenger transfer time being less than a certain value. The value inside the single bracket shows the difference between the simulated *PTT* to the existing *PTT* (5 minutes). As we change the *PTT* from 0 to 10 minutes, the CDF of transfer time is also changing. Figure 4.4-1 shows that the maximum transfer time could be up to 37 minutes because RV can depart later than its departing schedule, while FV also can arrive later than its schedule arrival time at the transfer stop.

Each of the CDF plots could be divided into 3 sections, illustrated in Figure 4.4-2.

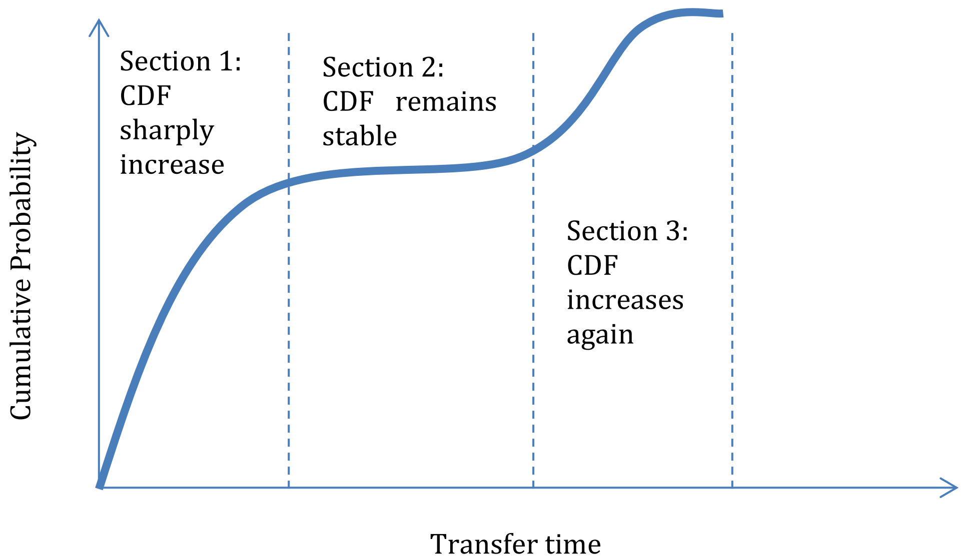


Figure 4.4-2 Three sections of a CDF of transfer time

The CDF plot in section 2 stays relatively the same as the transfer time increases. The slope of CDF also suddenly reduces just before this section, and sharply increases again just after it. This section represents the passengers who missed the first Route 572 service and have to wait for the next one. Because there is no possibility for them to transfer until the next service arrives, the CDF of transfer time stays the same as the transfer time increases. This probability only increases again when the second service arrives. Therefore, the probability of missing a transfer is larger when section 2 is large. Figure 4.4-1 demonstrates that as we increase the *PTT* from 0 to 10, PMT is reduced.

On the other hand, section 1 represents the passengers who could successfully transfer within the defined *PTT* period. As *PTT* increases from 0 to 10, section 1 is larger, representing more passengers that could successfully make the transfer. When *PTT* is set as small, fewer passengers would be able to transfer, but if they could make it, their transfer time will be as small as 0-5 minutes.

Section 3 represents the passengers who missed the first Route 572 service and aboard the second service. This section exists in all *PTT* settings, but for a large *PTT* it is very unlikely that passengers would fail into this section. This fact again demonstrates that if we increase *PTT*, the PMT is decreased.

The existence of these sections suggests a trade-off between the probability that some passengers will experience low transfer time to the probability that some passengers will miss the first transfer. Figure 4.4-3 shows the mean transfer time and PMT at different values of *PTT*.

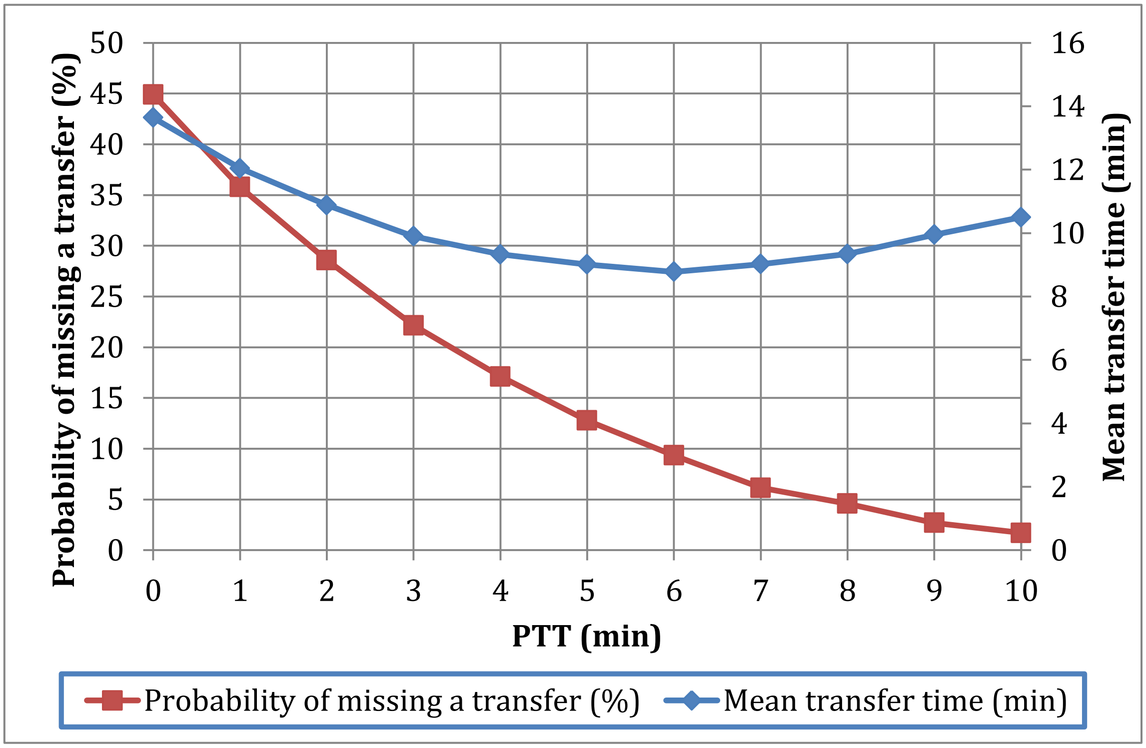


Figure 4.4-3 Mean transfer time and probability of missing a transfer at different values of *PTT*.

The mean transfer time is lowest when *PTT* equals 6 min, where 9.34% of passengers will miss the transfer. Figure 4.4-3 provides a benchmark to choose *PTT* in transit planning. If transit operators are after lowest mean transfer time, and less than 10% of missed transfer is considered acceptable, then *PTT* equals 6 min is the optimal value for *PTT*. Conversely, if minimising the PMT is the first priority, then *PTT* equals 10 will lead to insignificant missed transfer chance.

Transit operators can also calculate the sum of the total travel time from all transferring passengers to determine the optimal PTT. The objective is to choose the value of PTT that minimises the sum of the total travel time, where the total travel time can be slightly revised from the Section 4.3.6 to accommodate a special weight for transfer time namely *TransferWeight*

Minimises $SumTT = \sum_{i=1}^{P} (TT_i + WaitingWeight \times W_i + TransferWeight \times \mathrm{TF}_i)$ (28)

Where $SumTT$ (min) = the sum of individual total travel time of all P transferring passengers in the system.

TT_i, W_i and TF_i (min) are the travel time, waiting time and transfer time of passenger *i*, respectively.

$TransferWeight$ = the weight of transfer time compared to travel time, if *TransferWeight* is defined twice as much as travel time, then $TransferWeight$ =2

$WaitingWeight$ = similar as above, this is the weight for waiting time compared to travel time, for simplicity we assume $WaitingWeight$ =1

Transit operators can determine the values of *WaitingWeight* and *TransferWeight* by surveying transit passengers. Figure 4.4-4 illustrates the values of $SumTT$ at different *PTT* and *TransferWeight*.

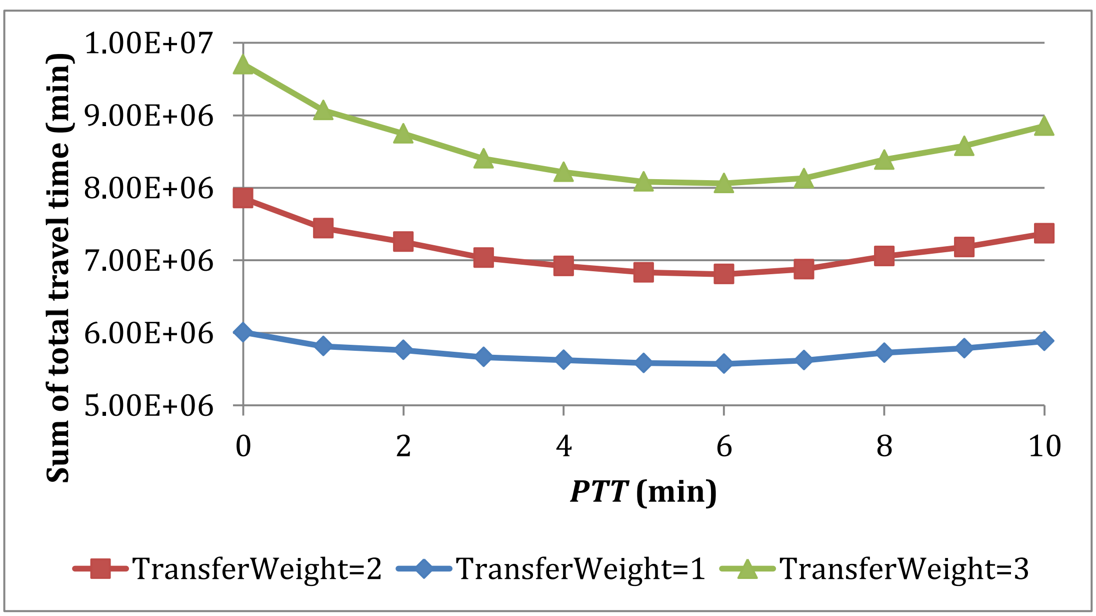


Figure 4.4-4 Sum of individual total travel time when *TransferWeight* equals 1, 2 and 3.

Two major patterns could be observed from Figure 4.4-4:

- While *PTT* =6 min yields the smallest *SumTT* , the differences to its neighbour (*PTT* =4 and *PTT* =6) are insignificant
- If *TransferWeight* is larger, the difference of *SumTT* becomes more significant. It is then more important to choose the optimal *PTT* to minimise the *SumTT*

4.4.2 Case-2: Passengers transfer time and probability of missing a transfer when vehicles are always dispatching on-time

On-time dispatching is an operational strategy in which transit vehicle is always departed from the first stop as scheduled. This sub-section investigates the mean transfer time and PMT when all vehicles are dispatched on-time. Figure 4.4-5 illustrates the CDF of passenger transfer time at different PTT, given on-time dispatching. The figure conveys two important patterns

Each CDF plot still consists of 3 identifiable sections as in Figure 4.4-2. However, Section 1 is much longer and Section 3 is shorter in all CDFs, which suggests fewer passengers missed a transfer. The maximum transfer time exactly equals to Route 572 frequency (30 minutes), less than the previous Case, because Route 572 vehicles are always dispatched on-time.

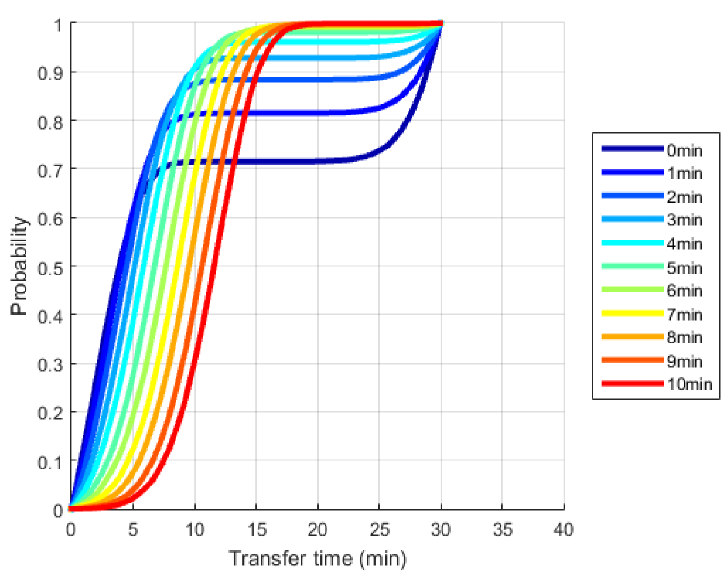


Figure 4.4-5 Transfer time of passengers at different *PTT,* given on-time dispatching

In this particular problem the RV has 30 minutes headway. That is why if RV departs on-time, the maximum transfer time is exactly 30 minutes if FV arrives just after a RV leaves and has to wait for the next RV.

Figure 4.4-6 further investigates the mean transfer time and probability of missing a transfer. The mean transfer time is now lowest at *PTT* equals 3 mins and there is hardly any missed transfer when PTT is higher than 6 mins. Figure 4.4-3 and Figure 4.4-6 show that mean transfer time can be reduced by around 20%, while PMT can be reduced by 80% compared to the real-dispatching case. Transit operator can significantly improve the transfer experience for passengers by simply making all vehicle dispatches on-time.

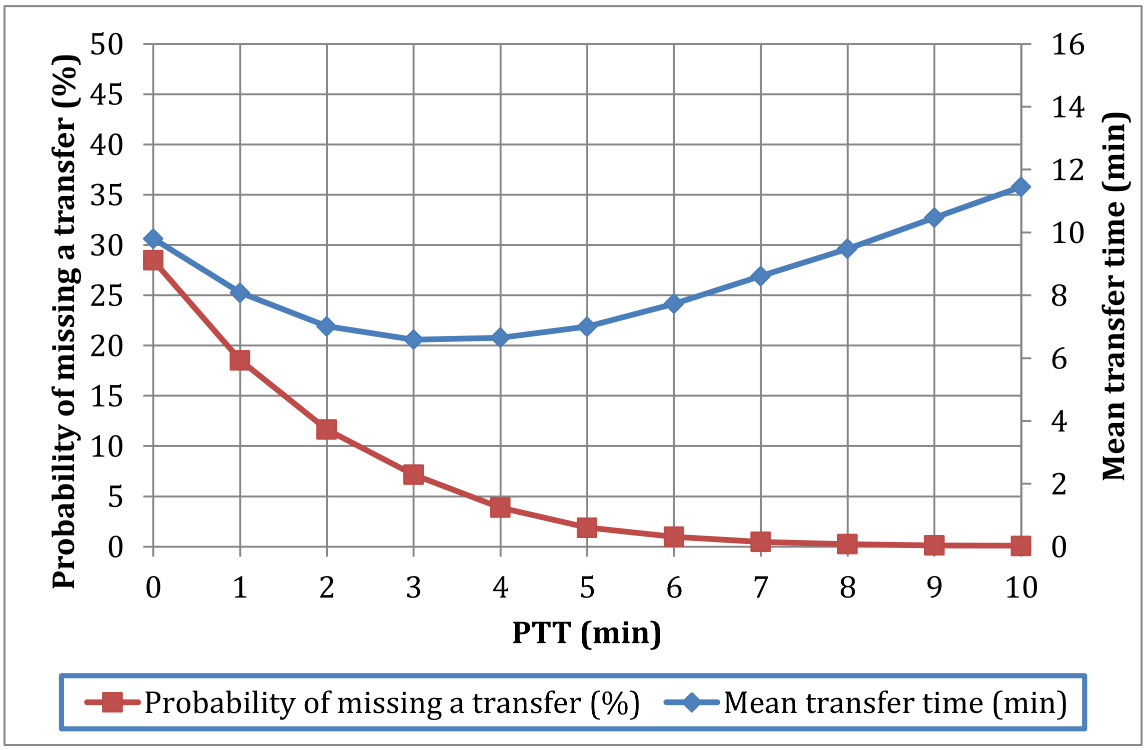


Figure 4.4-6 Mean transfer time and probability of missing a transfer at different values of *PTT*, given on-time dispatching

4.4.3 Case-3: Passengers transfer time and probability of missing a transfer when vehicle running time increases

Running time is an inevitable part of a transit journey. The increase in traffic congestion leads to the increase in travel time of all vehicles, including buses. This section investigates the mean transfer time and PMT when the running time of Route 555 along the Section 1 (Brisbane CBD to Springwood Station) has increases by 10% to 150% from the original observed travel time. The Section 1 of Route 555 is being tested because this section directly affects the transfer time and PMT. For each simulation run, we take the base running time from Log Normal or General Extreme Value distribution and then add an extra running time of 10% to 150% of the base running time. Figure 4.4-7 demonstrates the PMT (primary x-axis) and mean transfer time (secondary x-axis) when the running time (y-axis) increases and *PTT* is set as 0, 5 and 10 minutes.

The PMT significantly increases when the running time increases by 10% to 70% on all PTT settings. At 70%, almost all passengers would miss the first planned transfer service, given that PTT has not been revised to accommodate the new travel time. The PMT is also higher when *PTT* is lower. The mean transfer time varies in a sinusoid curve from 10 to 20 minutes as the vehicle running time increases. This is because when the travel time of Route 555 has increased to a certain value, passengers would likely to catch the next Route 572 service instead of the original planned one. For that reason the mean transfer time has a sinusoid pattern as the running time increases.

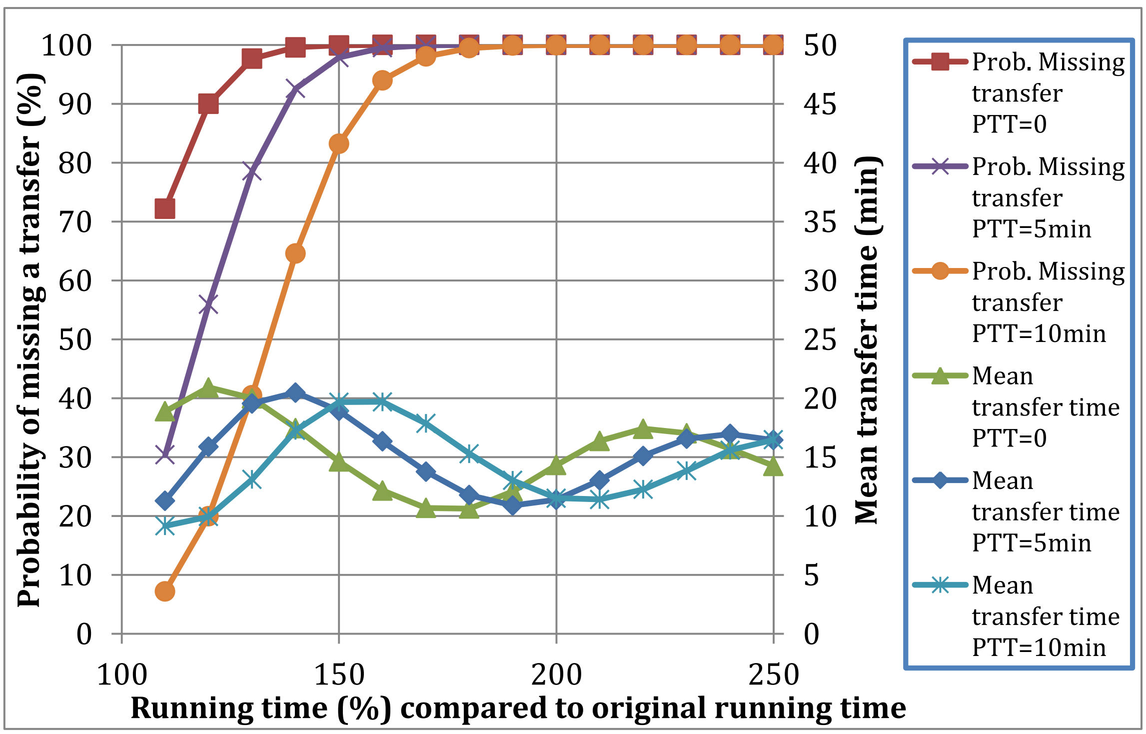


Figure 4.4-7 Mean transfer time and probability of missing a transfer at different vehicle running time

Figure 4.4-7 shows that transit operator should revise Route 555 and 572 schedules as soon as vehicle running time has been changed.

4.4.4 Case-4: Passengers transfer time and probability of missing a transfer at different running time variability.

The previous sub-section investigates the passenger transfer quality when the base running time increases. This sub-section aims to observe the mean transfer time and PMT when the variability of running time increases. Given the probability distribution of this running time is log-normal distribution (see Section 4.3.3), we test different median and Coefficient of Variation (CV) to find the elasticity of PTTV when the PTT is set as the current value (5 minutes).

Given the running time of Section 1, Route 555 as a log-normally distributed variable, the following equation could be obtained

The mean (expectation) of the running time is

$$E(RT_{555}) = e^{\mu+\frac{\delta^2}{2}} \qquad (29)$$

the variance,

$$Var(RT_{555}) = (e^{\delta^2-1})e^{2\mu+\delta^2} \qquad (30)$$

Therefore, the CV (%) is

$$CV_{RT555} = \sqrt{e^{\delta^2}-1} \qquad (31)$$

And the median (minutes),

$$med(RT_{555}) = \mathrm{e}^{\mu} \qquad (32)$$

Where μ and δ are the parameters of the log-normal distribution of Section 1 running time, Route 555.

Given the values of CV_{RT555} and $med(RT_{555})$, the values of μ and δ could be calculated

$$\mu = \log(med) \qquad (33)$$

$$\delta = \sqrt{\log(1+(CV/100)^2)} \qquad (34)$$

These parameters are then used to generate the running time at Section 1, Route 555 for EMAS simulation. Figure 4.4-8 and Figure 4.4-9 illustrates the changes of mean transfer time and PMT at different values of running time median and CV.

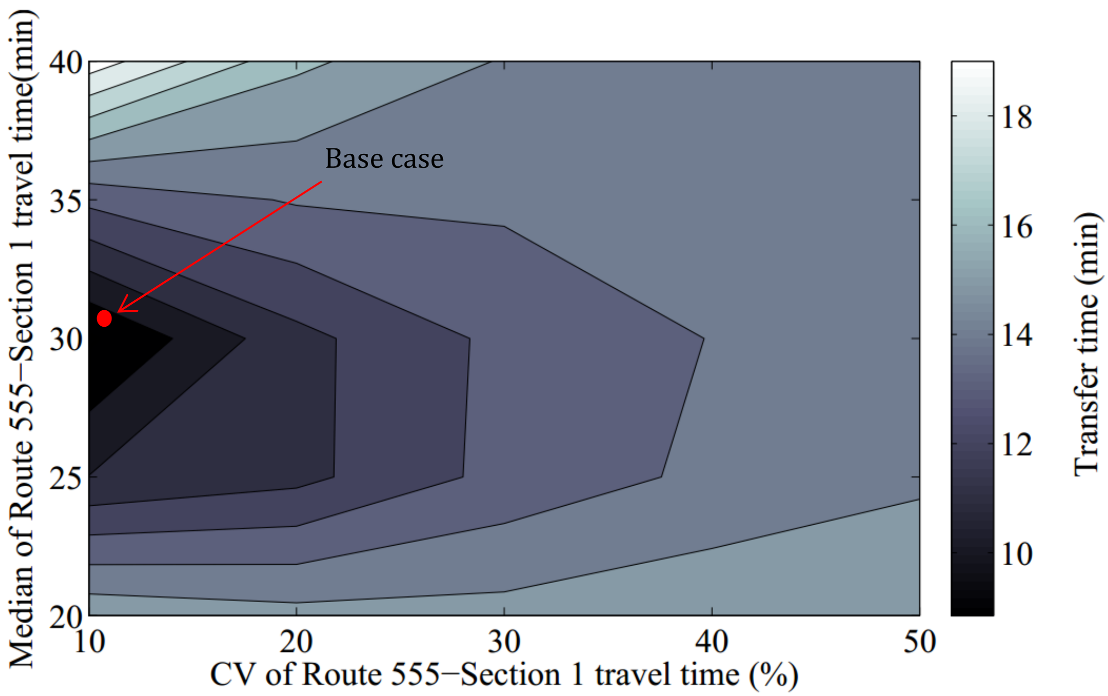


Figure 4.4-8 Mean transfer time at different values of running time median and CV

Figure 4.4-8 shows that the transfer time is lowest when the median of running time is approximately 30 minutes. As the running time is closer to 20 or 40 minutes, the mean transfer time of all transferring passenger increases to about 18 minutes. On the other hand, the mean transfer time increases as the CV is increasing from 10 to 50%.

Figure 4.4-9 shows the PMT at different values of running time median and CV. The figure clearly demonstrates that PMT increases as median and CV of running time increases. Only a low median combined with a low CV of running time would guarantee a low PMT. Figure 4.4-8 and Figure 4.4-9 confirms that the median and CV of running time need to be considered at timetable planning to minimise the mean transfer time and PMT.

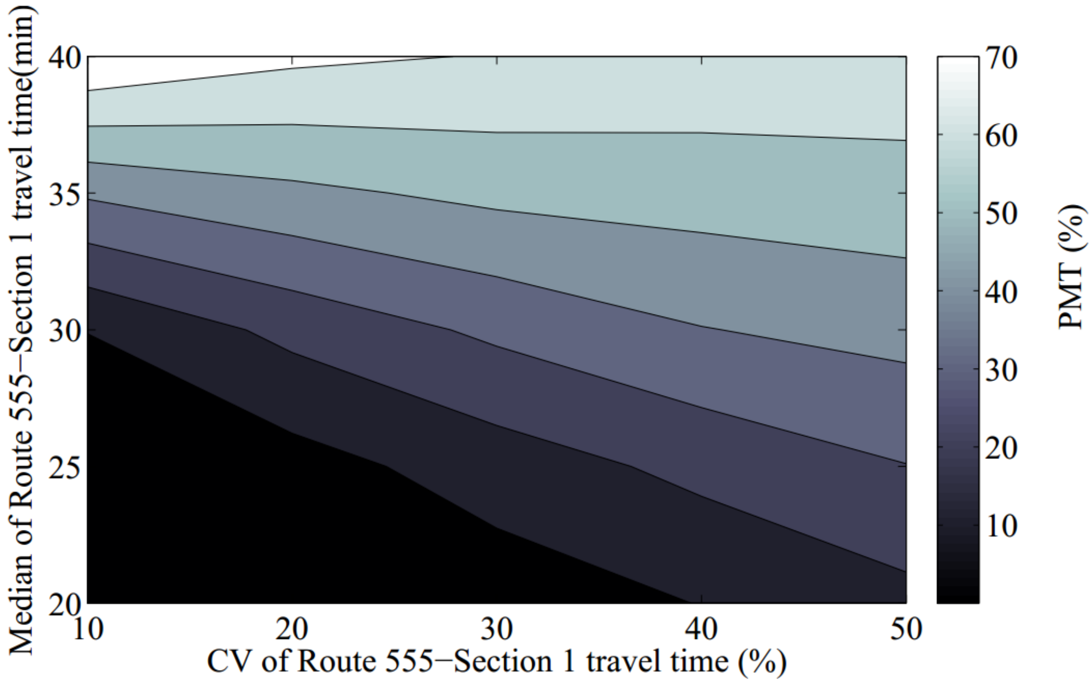


Figure 4.4-9 PMT at different values of running time median and CV

4.5 **Summary of Chapter 4**

This chapter develops an Event-based Multi Agent Simulation (EMAS) model to systematically investigate the mean transfer time and PMT at different dispatching time, *PTT* and travel time values. The EMAS model consists of two principal types of agents: transit vehicles and passengers. The model is primarily based on the variability modelling framework proposed in Chapter 3. Agent events such as passenger & vehicle arrival to stops, vehicle departure and passenger boarding/alighting are generated from the distribution of dispatching time, travel time and passenger arrival. Mean transfer time and PMT are then calculated for each simulated passenger agent. While the EMAS model is still based on several assumptions, its root has been constructed from the distributions of observed travel time and demand. The verification process confirms that the EMAS model represents the observed transit passengers.

4.5.1 **Scientific and practical contributions**

This chapter provides a framework to investigate the most appropriate *PTT* settings to provide better transferring service for transit passengers. Transit operators could use the

EMAS model and observed AFC and AVL data to balance the trade-off between mean transfer time and probability of missing a transfer.

The scientific contribution of this chapter is the integration of travel time variability and real passenger demand into the EMAS model. This chapter transforms observed AVL and AFC data into a simulation model that presents the existing transit system and enables us to test the impact of different strategies to transit operations and passengers.

4.5.2 **Knowledge gained**

The following knowledge could be gained from the development and implementation of the EMAS model in this chapter

1) There is no best value of *PTT* that minimises both mean transfer time and probability of missing a transfer, but the EMAS model could be used to find an acceptable balance between these two values. If the weight of travel, waiting and transfer time cost are known, transit operators can calculate the sum of total passenger cost to choose the value of *PTT* that minimises this sum.
2) Transit operators could reduce both mean transfer time and PMT by 20% by making all transit vehicles to dispatch on-time.
3) As vehicle running time increases, the PMT forms an incremental hike, where most of passengers would miss the original planned transfer if the demand has increased by 70% and the schedule has not been revised to accommodate this change. In fact, PMT is only small when both the median and CV of running time is small. However, the transfer time does not keep increasing, but forms a sinusoid that varies from 10 to 20 minutes.

STAGE 2
Online Transfer Coordination by Exploiting Individual Travel Pattern and Passenger Segmentation

5 Travel pattern analysis

This chapter describes how travel pattern is analysed. It augments the understanding of transit passengers by revealing their temporal and spatial travel behaviours.

The findings of this chapter have been published in the following publications:

Journal article

J3 Kieu, L. M., Bhaskar, A. & Chung, E. 2015. A Modified Density-Based Scanning Algorithm with Noise for spatial travel pattern analysis. *Transportation Research Part C* (In Press). DOI: 10.1016/j.trc.2015.03.033

Conference proceeding papers

C3 Kieu, L. M., Bhaskar, A. & Chung, E. 2013. Mining temporal and spatial travel regularities for transit planning. Australasian Transport Research Forum. 2-4 October, Brisbane, Australia.

5.1 Introduction

Transit providers have limited knowledge about their customers despite the fact that better understanding of passengers is essential to their needs and preferences. Individual passenger behaviours are stochastic and passenger identity is also anonymous to most of transit authorities. The dominant factor for this lack of passenger knowledge is the availability of data. Traditional studies aim to understand passenger behaviour by travel surveys. Although surveys are highly personal and reveal travel purposes, they are generally expensive, limited in sample size and only valid within the study period.

The recent proliferation of data technology provides a new approach to study the passenger behaviour. Smart Card (SC) AFC system has been increasingly popular in public transport, providing a massive quantity of continuous and dynamic data on passenger boarding and alighting locations. Instead of directly asking passengers, it is now possible to track the same passengers for multiple days to observe s/he travel pattern. Travel pattern is the regular time and places that passengers usually travel by public transport. Travel pattern consists of temporal travel pattern, i.e. when the passenger usually use a transit service, and spatial travel pattern, i.e. where the passenger travel to and from. In other words, travel pattern is defined as the repeated performance of travel behaviour sequences. It demonstrates how a passenger regularly travel, i.e. combinations of origin and destination stop, time and mode of travel and other activities such as transfers (Gärling and Axhausen, 2003).

In online transfer coordination, travel pattern reveals the regular route choice of individual passengers. Assuming that passengers follow their usual travel pattern, it is possible to infer passenger transfer decision. The SC data therefore provides a tremendous new opportunity to overcome the major issue of public transit transfer coordination: the lack of passenger transfer plan. This chapter lays the first foundation to that objective by systematically mine passenger travel pattern from SC data.

An emerging number of studies have extensively explored multiday travel pattern (Chu and Chapleau, 2010; Kieu et al., 2014b; Ma et al., 2013) to understand individual travel behaviors (Ma et al., 2013), passenger segmentation (Kieu et al., 2014b), trip purpose (Lee and Hickman, 2014) and explore their potential in transit planning (Utsunomiya et al., 2006). A detailed review of existing advances in SC analysis could be found in the Chapter 2 of this dissertation. Chapter 2 describes the two major trends in the literature of travel pattern analysis:

(1) The literature is more concerned with disaggregated passenger travel pattern, i.e. earlier researches focused on generic transit passengers, while more recent ones focused on group of similar passengers or individual passenger. Disaggregated transit riders analysis, especially individual travel pattern, captures the individuality and stochasticity of human behaviours. It facilitates the inference of passenger behaviours in transfer activities.
(2) The literature evolves from no discretisation of spatial and temporal travel pattern to more systematic and flexible analyse the individuality and stochasticity of passenger travel pattern. Spatial travel pattern analysis was traditionally broken down to stop-to-stop repeated journeys. Recent studies have considered transit stops of immediate vicinity in the same travel pattern, as passengers may have several route or mode choices to travel to the same destination from the same origin. Temporal travel pattern analysis has been broken down to the number of journeys within a time period.

This chapter contributes to the emerging literature of travel pattern analysis by proposing a systematic and comprehensive approach to mine spatial and temporal travel pattern from SC data. The next Section (Section 5.2) describes the methodology of travel pattern mining developed in this study. Section 5.3 proposes Weighted-Stop DBSCAN (WS-DBSCAN), a Density Based Scanning Algorithm with Noise to improve the computation time of the classical DBSCAN algorithm. A numerical experiment will be conducted to validate the performance improvements associated with WS-DBSCAN. Section 5.4 summaries the findings, scientific and practical contributions and knowledge gained from the chapter. Figure 5.1-1 illustrates the framework for travel pattern analysis in this chapter.

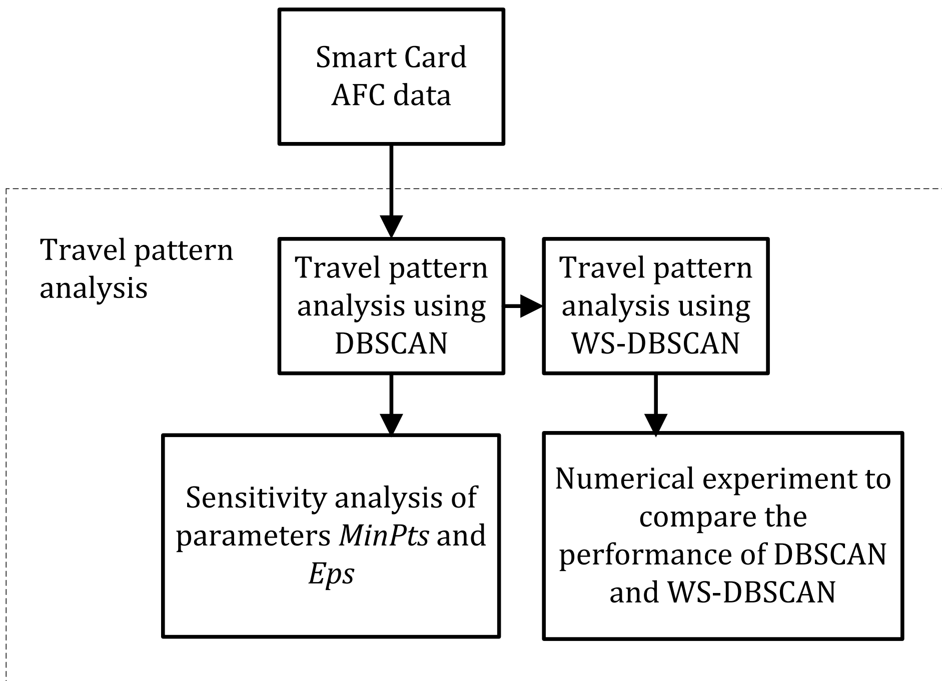


Figure 5.1-1 Study framework of Chapter 5

A transit trip is defined in this research as the travel between two transit stops by the same transit vehicle. Conversely, a transit journey is the travel from the origin stop to the destination stop, which might include several trips and transfer(s) between individual trips. The definitions are illustrated in Figure 5.1-2.

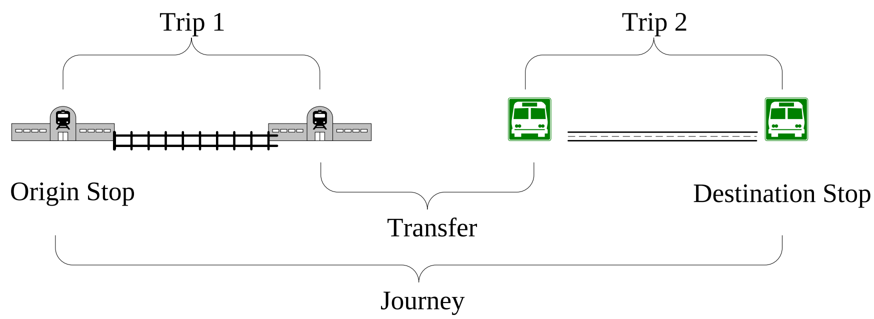


Figure 5.1-2 Trip, transfer and journey definitions

5.2 A comprehensive method for travel pattern analysis

This section proposes a systematic approach to mine travel pattern and segment transit passengers using solely SC data. The section first reconstructs completed "journey" of SC users from individual SC "transactions" (Section 5.2.2). Each "transaction" includes both boarding and alighting time and stop IDs of a transit journey between a touch-on and a touch-off to the ticketing device. Each "journey" is defined as the public transport travel from origin to destination, including the transfers, which might include one or several transactions. Density-Based Scanning Algorithm with Noise (DBSCAN) algorithm is then adopted to mine travel pattern from each SC user's historical itineraries, identify the spatial Origins and Destinations (OD) that the cardholder usually travels as "Regular OD", and the time of regular travels as "Habitual time" (Section 5.2.3). Finally, the section ends with a sensitivity analysis for parameters of the DBSCAN algorithm (Section 5.2.4).

5.2.1 Dataset

The SC data used in this study come from Translink, the transit authority of SEQ, Australia. The dataset is a compilation of around 34.8 million transactions made by a million SCs over 15 thousands transit stops of the bus, city train and ferry networks in SEQ from 1st March to 30th June 2012. Each transaction contains the following fields:

(1) *CardID*: Unique Smart Card ID, which has been hashed into a unique number for maintaining the privacy of the cardholder.
(2) *T_on:* Timestamp for touch on
(3) *T_off:* Time stamp for touch off
(4) *S_on:* Station ID at touch on

(5) *S_off:* Station ID at touch off

(6) *ValidIndicator:* A binary indicator for differentiating a valid (1) or invalid transaction (0). It has been used by the operator for ticketing purpose. Valid transaction is the combination of a touch on and a touch off from the same transit line, within a 2 hours limit (Translink, 2007). Any cases other than that, e.g. no touch off, or touch off at a different line, etc. are indicated as invalid transactions. Only around 3% of the transactions are invalid.

(7) *RouteUsed:* The transit line that the passenger has used.

(8) *Direction:* Direction of travel (Inbound/Outbound)

(9) *Fare:* fare paid for the transaction in AUD.

For the current analysis, the study is performed only on working days (weekdays excluding public holidays and school holidays) because travel behavior on working weekdays can be significantly different than that of weekends and holidays. Table 5.2-1 shows an example of transaction records for a SC holder on June 2012.

Table 5.2-1 Sample transactions of a cardholder on June 2012

Day	Route	Direc-tion	Boar - ding Time	Aligh- ting Time	Boarding stop	Alighting stop	Valid Indic- ator
20-Jun	385	OB	10:38	10:45	Roma St Bus Station Platform 1	'Paddington Central' Latrobe Terrace - 10	1
5-Jun	333	OB	17:48	17:55	King George Square Station 1D	Royal Brisbane & Women's Hospital PL 2	1
5-Jun	330	IB	19:55	20:01	Royal Brisbane & Women's Hospital PL 1	Roma St Bus Station Platform 2	1
5-Jun	385	OB	20:17	20:39	Roma St Bus Station Platform 1	'Hilder Road' Waterworks Road	1
8-Jun	385	OB	18:20	18:42	King George Square Station 1C	'Hilder Road' Waterworks Road	1

5.2.2 **Reconstruction of travel itineraries**

The first step in travel pattern analysis is to reconstruct the full travel itinerary from individual transactions. The flowchart on Figure 5.2-1 illustrates the algorithm to connect individual transactions from each SC user on each working day into completed journeys from first origin stop to the last alighting stop. The algorithm is built on a binary "*ReconstructingIndicator*" to identify on-going/new journey status; and a "*JourneyID*" to distinguish the completed journeys.

A fixed threshold of 60 minutes is then used to decide if the two transactions are connected. This threshold has been chosen differently in the literature (Seaborn et al., 2009). The 60 minutes is chosen in accordance with Brisbane's public transport threshold for continuation journeys (Translink, 2007). Here, the first origin stop and the last alighting stop of a completed journey are defined as the *"origin stop"* and the *"destination stop"*, respectively. The following 4 steps describe the journey reconstruction process.

1) STEP 1: A binary *ReconstructingIndicator* is defined and assigned as zero.
2) STEP 2: The *ValidIndicator* is checked. If the indicator is equal to 0 (which denotes an invalid transaction) the corresponding journey will be discarded.
3) STEP 3: If *ReconstructingIndicator* is zero, a variable *OriginLocation* is defined and set as equal to the current *T_on*. We also assign a new unique *JourneyID*, change *ReconstructingIndicator* to one, save the current transaction and move to the next transaction.

   If *ReconstructingIndicator* is one and the time gap between the current *T_on* and the last *T_off* is less than 60 minutes, we move to Step 4.

   If the time gap is more than 60 minutes, transactions with previous *JourneyID* is connected into a completed journey. New *JourneyID* and *OriginLocation* are assigned, in which the current transaction is identified as the first leg from the origin stop. The *ReconstructingIndicator* is set as 1.
4) STEP 4: If the current *S_off* is different to *OriginLocation*, the transaction is connected to the journey as a continuation journey and we move to the next transaction. If it is the last transaction of the day, or *S_off* is equal to *OriginLocation*, the journey reconstruction process is completed and we move back to Step 1.

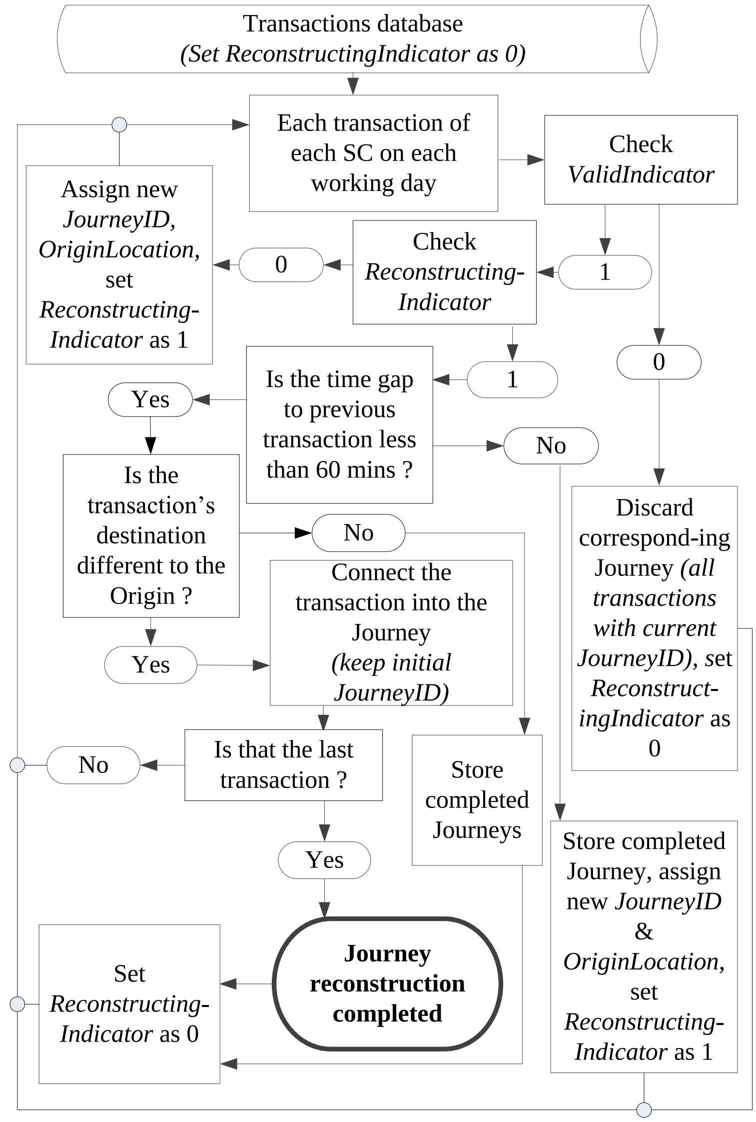


Figure 5.2-1 Journey reconstruction flowchart

The four-step process reconstructs full itineraries from AFC data, enables us to observe the origin-destination locations and journey chains of each individual passenger. Table 5.2-2 shows an example of trips from Card ID X1 and X2 with Origin, Destination time, Stop and Route sequence as well as the time spent for traveling and transferring.

Table 5.2-2. Example of completed journeys

SC ID	Day	Trip ID	Origin Time (min from 0h)	Destination Time (min from 0h)	Stop ID Sequence	Total travel time (min)	Total transfer time (min)	Total time (min)	Route ID Sequence
X1	1/4	1697	680.2	686.54	5→4	6.34	0	6.34	999
X1	1/4	1083	557	566.9	54371→24653	9.9	0	9.9	726
X2	1/4	1415	898.08	905.24	12861→2452 →15212	7.16	41.42	48.58	550→562
X2	1/4	1412	887.45	944.63	10730→499 →88	57.18	32.7	89.88	690→999

5.2.3 Mining spatial and temporal pattern from travel itineraries

This section presents the method of mining spatial and temporal travel pattern from the historical journey database. The spatial origin and destination stops are represented as geographical coordinates (geographical position), whereas temporal boarding and alighting times are represented as timestamps.

We adopt a density-based clustering algorithm because of the following reasons:

1) Density-based algorithms identify clusters of high density and noise of low density. In travel pattern analysis, noise is anomaly travel pattern which does not follow any regular travel pattern or in other words, trips which are randomly made. Our goal is to find the clusters (regular pattern) and differentiate it with the noise (anomaly pattern).
2) Density-based algorithms can identify cluster of any shape and size. Travel pattern could also form any shape and size due to its nature of human behaviour pattern.
3) Density-based algorithms do not require predetermination of initial cores or number of clusters. This feature is also essential for travel pattern analysis because the number of patterns from an individual passenger is unknown.
4) Discretization of place and time is a major concern in travel pattern analysis. The existing literature has showed that there is a need for a systematic and flexible solution to spatial temporal pattern analysis without limiting to stop-to-stop repeated trips and time-window discretization. Density-based scanning algorithms

systematically produce a flexible range of high density for each passenger spatial and temporal travel pattern.

A decent number of density-based clustering algorithms can be found in literature such as DBSCAN (Ester et al., 1996) and more complex methods such as OPTICS (Ankerst et al., 1999), and DENCLUE (Hinneburg and Keim, 1998). DBSCAN is then chosen as the algorithm over other density-based scanning algorithm because: (1) DBSCAN has a simpler, more robust but amendable structure that we can tweak for travel pattern mining purpose, (2) DBSCAN has all of the four aforementioned features of a density-based clustering algorithm.

DBSCAN algorithm

The Density-Based Spatial Clustering of Application with Noise (DBSCAN) algorithm defines clusters as dense regions, separated by regions of lower point density. The algorithm has two global parameters: the maximum density reach distance ε and the minimum number of points *MinPts*. A point can be considered as a “core point” i_c if it has at least *MinPts* points (density) within a radius ε, as expressed in formula (35).

$$\left|N_{\varepsilon(i_c)}\right| \geq MinPts \qquad (35)$$

Where:

$$N_{\varepsilon(i_c)} : \{i \text{ points in the dataset} \mid d\left(i_c, i\right) \leq \varepsilon\}$$

$N_{\varepsilon(i_c)}$ is the number of points *i* in the dataset that has distance to i_c that is $d\left(i_c, i\right)$ less than ε. The most common distance metric used is Euclidean distance.

We define the ε*-neighbourhood* $N_{\varepsilon(i_c)}$ for a point *p* as the number of points in the dataset that has distance to *p* less than ε, including the point *p* itself. The most common distance metric used is the Euclidean distance. Each point in the data set is classified as:

1) *Core point*: A point is considered as a *core point* if its ε*-neighbourhood* is greater than or equal to *MinPts*.
2) *Border point*: A point is considered as a *border point* if its ε*-neighbourhood* is less than *MinPts* but the point in itself lies within ε*-neighbourhood* of a *core point*.

3) *Noise*: A point is considered as a *noise* if it is neither a *core* nor a *border* point.

A cluster is defined by combining the *core* points which are connected by their associated *border points*. Interested reader can refer to Ester et al. (1996) for more detailed description of DBSCAN. Figure 5.2-2 provides an example of *core, border point* and *noise* in DBSCAN definitions. The illustrated circles are centred at a point and have a radius of ε .Considering *MinPts* as 4:

a) Point p_1 is a core point because its ε -*neighbourhood* is four (q_1,q_3,p_2 and p_1 itself). It's a core point because this ε -*neighbourhood* is equal to MinPts. Similarly point p_2 is also a core point.

b) Point q_1 is a *border point* because its ε -*neighbourhood* is 3 (p_1,n_1 and q_1 itself) and point q_1 lies within the ε -*neighbourhood* of the core point p_1. Similarly point q_2 and q_3 are *border points*.

c) Point n_1 is the noise because its ε -*neighbourhood* is only 2 and it is not within the ε -*neighbourhood* of any core point.

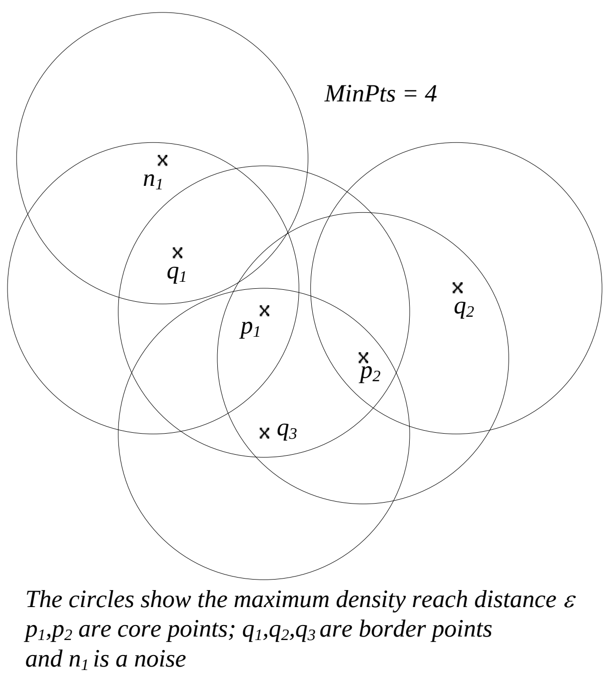


Figure 5.2-2. An example to illustrate *core point, border point and noise point* definitions for DBSCAN

Mining spatial travel pattern (Regular OD)

This section describes the mining process for Regular ODs. A two-step procedure is applied to separately mine regular last alighting and first boarding stops of each SC user. Figure 5.2-3 illustrates the process of mining travel pattern of a SC user on morning trips as an example for explaining the clustering method. Here, the A points represent the first boarding stops, C points represent the last alighting stops, and B points represent the transfer stops in the SC user historical itineraries. The two levels of DBSCAN application are described in the following steps.

1) *Level 1:* The first level of DBSCAN groups only the last alighting stops (C points). It is important to notice that for underlying the recurring patterns, each trip's last alighting stop is considered as a point in the database. In Figure 5.2-3 the 42 trips made at the same stop C1 form 42 records at the same coordinates. The DBSCAN algorithm goes through each alighting stop record to detect whether the studied record is a regular or anomaly travel pattern. The DBSCAN algorithm with $\varepsilon = 1000\text{m}$, and *MinPts* = 8 is applied to define Cluster 1 at stop C1, and the other two points as anomaly pattern.
2) *Level 2*: Now if we locate the origin stops (Stop A) and transfer stops (Stop B), the travel pattern can be identified. The second level of DBSCAN algorithm groups only the origin stops (A points). Similar to Level 1, here the DBSCAN algorithm also goes through each boarding stop record. The same DBSCAN algorithm with $\varepsilon = 1000\text{m}$, and *MinPts* = 8 is applied, identifying two clusters of boarding stops at stop A1 and A2.
3) If both origin stop and destination stop are not noise, the corresponding OD is identified as a Regular OD. In our example, the OD pairs A1-C1 and A2-C1 are Regular ODs. Figure 5.2-4 illustrates the boarding and alighting pattern of mined Regular OD pattern at morning peak (7:00), midday (12:00) and afternoon peak (17:00) time-of-day.

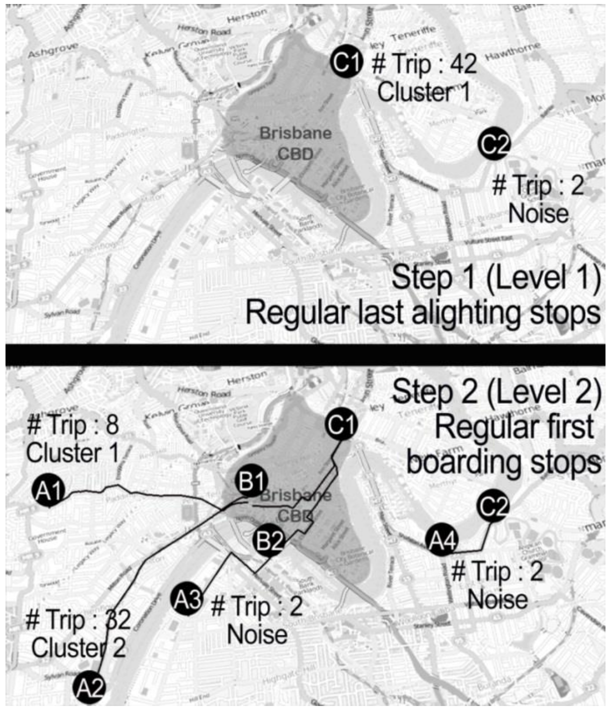


Figure 5.2-3. Two-step DBSCAN application for Regular OD mining

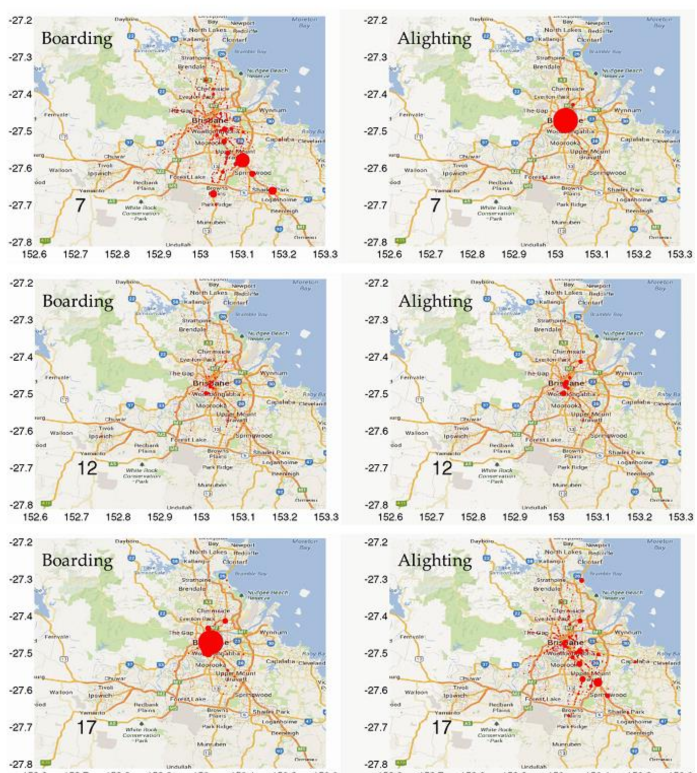


Figure 5.2-4 Boarding and Alighting Regular OD pattern at different time-of-day (Boarding pattern on the left and Alighting pattern on the right)

Mining temporal travel pattern (Habitual time)

This section presents the application of DBSCAN to mine Habitual time, i.e. the time SC user habitually board a transit vehicle. Given that the reliability of travel time during peak periods can have impact on the alighting time, boarding time is chosen instead of alighting time for DBSCAN application because SC users can actively choose the boarding time but cannot choose the time when they arrive at the destination. A 1-dimension DBSCAN is applied with ε equals to 5 minutes and the value *MinPts* equals to 6. Table 5.2-3 presents an example of three SC users' travel regularity, in which passenger X2 was chosen as the example in Figure 5.2-3.

Table 5.2-3. Example of travel pattern: (a) Regular OD, and (b) Habitual time

(a)

SC ID	Regular OD ID	% Regular Trip	Origin Stop ID	Destination Stop ID	Number of Trips	Route ID sequence
X1	1	43.02	5198	5210	37	420
	2	31.40	5873	5198	27	458
X2	1	13.56	4364	1882	8	999 → 370
	2	54.24	8	1882	32	999 → 370
	3			8	12	370 → 999
X3	1	21.28	1878	2890	10	543 → 141 → 139
	2	17.02	1878	2888	8	542 → 141 → 169

(b)

SC ID	Habitual time ID	% Habitual Trip	Habitual time pattern (min from 0)	Number of Trips
1	1	48.84	486.42	42
	2	45.35	1062.32	39
X2	1	37.29	398.13	22
	2	30.51	519.06	18
	3	18.64	956.6	11
X3	1	36.17	551.85	17

5.2.4 Sensitivity analysis of *MinPts* and *Epsilon*

The application of DBSCAN requires two important parameters: the minimum number of boarding *MinPts* and the density reach distance ε .

For spatial travel pattern analysis, the maximum density reach distance ε denotes the walking distance of the passenger from one to another stop of the same boarding pattern. ε can be found by travel survey and is vary from case to case. Burke and Brown (2007) found that people in Brisbane and Perth, Australia walk significantly longer than people in US cities, where a rule-of-thumb of 500m has usually been used to measure the preferable walking distance to transit stops (TRB, 2013). If ε increases, the algorithm would define more stops as regular. ε should not be too large since both origin and destination of the transit trip might be clustered into the same boarding pattern if ε is larger than the travel distance.

The examination of *MinPts* can be broken down into how transit operators define travel pattern. Given the number of boarding over a study period, *MinPts* is equal to the minimum boarding made to be considered as "regular". For instance, a value of *MinPts* equal to 2 means that any repeated boarding will be considered as regular. Figure 5.2-5 illustrates the *MinPts* and ε sensitivity analysis results.

The percentage of regular journeys noticeably increases when ε increases from 400 to 600m because most passengers would prefer walking within these distances. Another significant increase could be seen when ε exceeds 1200m, where the origin and destination are grouped into the same pattern. The value ε chosen for this study is 1000m.

We choose the value of *MinPts* to maximize the proportion of regular travel pattern, but conversely, the algorithm should minimize the proportion of passenger who rarely travels but still being assigned with regular pattern because these behaviors could be unreliable. Figure 5.2-6 demonstrates the number of passengers with Regular OD but traveled less than 10 times during the 4 months study period. Given that ε has been chosen as 1000m, *MinPts* has been chosen as 8 for the case study.

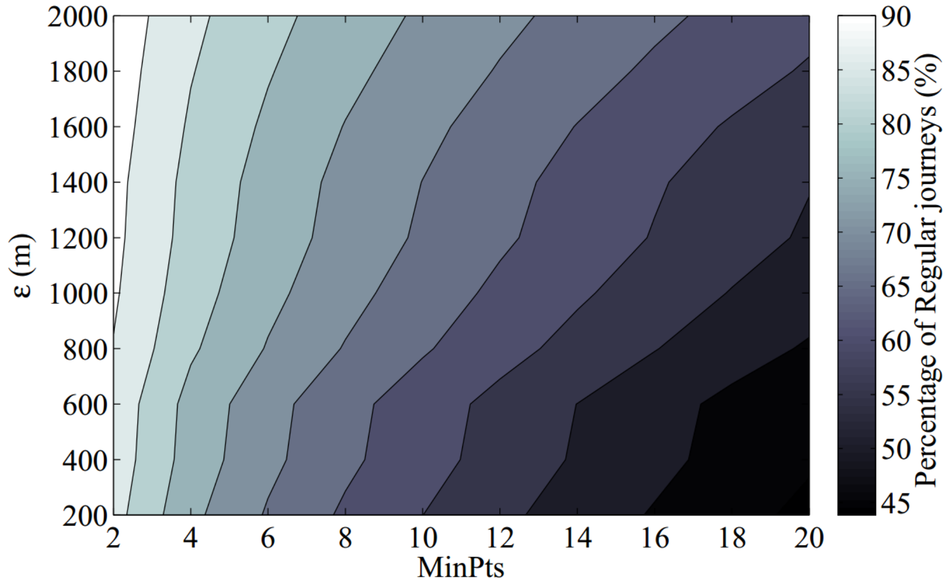


Figure 5.2-5. *MinPts* and ε sensitivity analysis for Regular OD mining

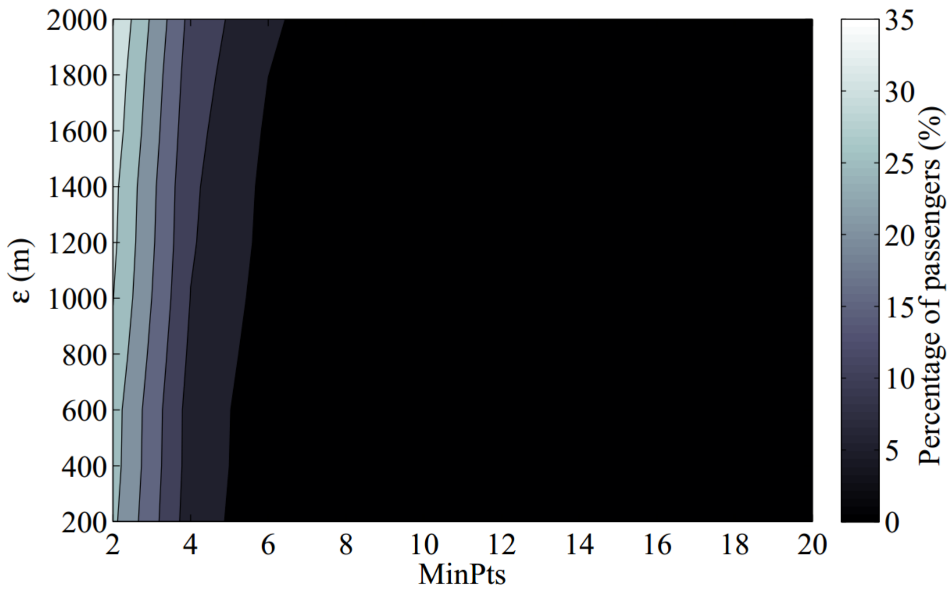


Figure 5.2-6. Percentage of passenger with Regular OD but traveled less than 10 times

The parameters for temporal travel pattern analysis have been chosen by a similar approach. Figure 5.2-7 shows the percentage of Habitual journeys for different values of *MinPts* and ε .

For temporal travel pattern analysis, the maximum density reach distance ε denotes the variability of boarding times within the same travel pattern. ε has been chosen as 5 minutes to allow some variability in vehicle arriving times. *MinPts* has been chosen similar by the same logic as the spatial pattern analysis. Figure 5.2-8 demonstrates the number of passengers with Habitual time but travelled less than 10 times during the 4 months study period.

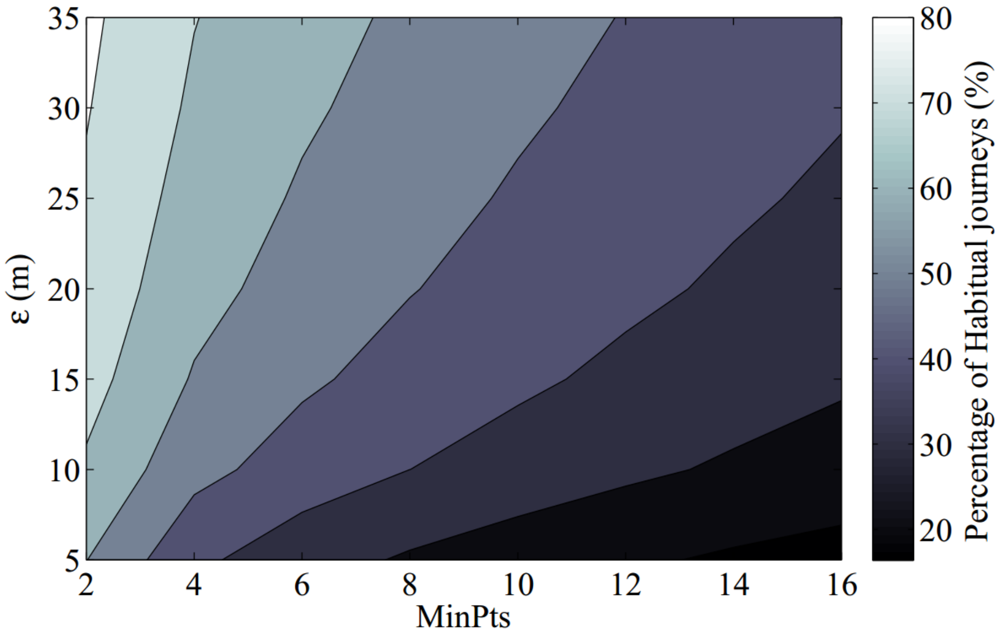


Figure 5.2-7. *MinPts* and ε sensitivity analysis for Habitual time mining

MinPts should also be chosen considering the observation period of historical itineraries data. When the number of the total journeys increases, the observation period becomes longer. The value of *MinPts* is then only valid for a specific period. Figure 5.2-9 demonstrates the percentage of regular journeys at different period when *MinPts* varied from 2 to 16, and is equal to 1000 m.

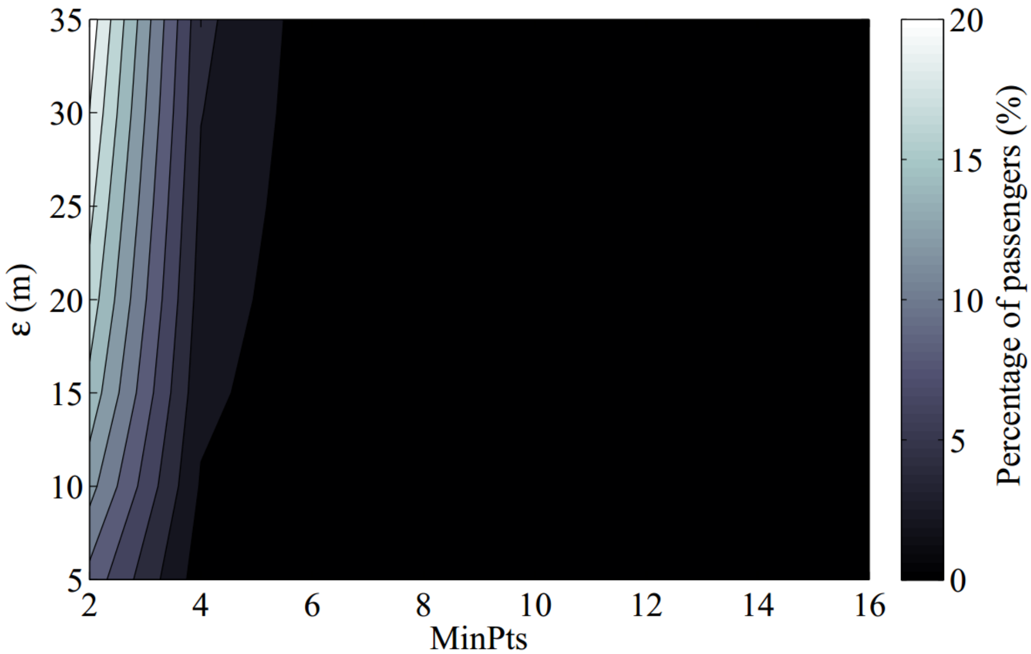


Figure 5.2-8. Percentage of passenger with Habitual time but traveled less than 10 times

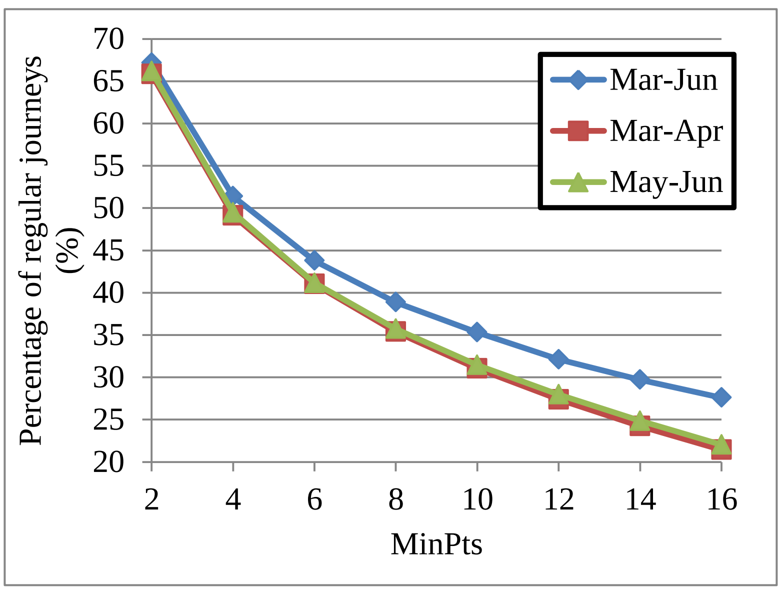


Figure 5.2-9 Sensitivity analysis of MinPts at different observation period

Different values of *MinPts* have been used on the whole dataset (Mar to Jun 2012) and two shorter periods (Mar to Apr 2012 and May to Jun 2012). Shorter observations show lower share of regular journeys, especially when *MinPts* becomes larger. It is because there are less spatial travel patterns that are repeated for more than *MinPts* times within a shorter period. In practice the observation period should be fixed and should not be too long, because passenger travel pattern can change significantly during a long time period. The historical itineraries data can be stored for a period of several months in a rolling horizon process, i.e. detecting and updating the passenger individual travel pattern data in each period. Figure 5.2-9 also shows that the regular journeys shares are similar at different *MinPts* when the observation periods are equal.

The correlation relationship between MinPts and ε also decides the mining results from DBSCAN. For instance in Regular OD mining, small values of ε and high values of *MinPts* require a high density of journeys on a single OD pair. This results in very little flexibility in defining a Regular OD because only highly repeated journeys within small immediate vicinity will be considered as a Regular OD pattern. Conversely, large values of ε and low values of *MinPts* may result in greater error in the number of journeys related to a single OD, since the geographic spread of O's and D's can be very large and the chance for incorrectly aggregating ODs becomes much larger. A short survey could solve the problem of choosing the best parameters or validate the mining results. In the meantime, the sensitivity analysis of *MinPts* and ε as discussed in this paper provides insights into the sensitivity of these parameters.

5.3 Weighted-Stop DBSCAN (WS-DBSCAN) algorithm for computation time improvements

DBSCAN provides a systematic method to mine individual passenger travel pattern from travel itineraries. The density-based nature of the algorithm means that Regular OD and Habitual time pattern of transit journeys are distinguished from the anomaly patterns. However, the major disadvantage of the DBSCAN algorithm is its quadratic computing complexity, which leads to (Kieu et al., 2015b):

(1) Extremely slow computation time, a full dataset of SEQ takes 55-60 hours for a Core i5, 8GB Ram personal computer. This is a critical restriction to apply the algorithm in practice. Transit passengers make transit journeys on a daily basis. To make the best use of the individual travel pattern for instance in transfer coordination, the travel pattern has to be updated daily to observe the changes in passenger behaviours. At the end of a day (e.g. midnight), transit authorities collect all SC transactions of the day and update the travel pattern of each individual

passenger before the first service of the next day. For that reason, there is a need for an algorithm which is significantly more time-effective to observe the evolution of travel pattern on a daily basis and finish the job in a short time. This issue has not been addressed in existing literature. The existing approaches in travel pattern analysis have been developed with high computing complexity, which makes daily analysis an absurd task.

(2) Due to the quadratic complexity of the existing methods in the literature, the computation time would be multiplied by the number of transit journeys in the dataset. At some point it would exceed the computation power of a commercial computer, if no time-effective method is introduced. Running DBSCAN incrementally will be more computationally efficient because the required RAM and computational power will be less. However, the DBSCAN algorithm itself still has quadratic computing complexity.

This section proposes a novel density-based algorithm to transform the quadratic complex classical DBSCAN to a problem of sub-quadratic complexity, in particular a combination of linear and quadratic complexity with fewer elements. The algorithm is named *Weighted-Stop DBSCAN* (WS-DBSCAN).

5.3.1 **Introduction to the WS-DBSCAN algorithm**

DBSCAN provides a good solution to identify spatial travel pattern from passenger historical itineraries. However, the major disadvantage of the DBSCAN algorithm is its quadratic computing complexity, which restricts transit operators to update individual travel pattern daily. DBSCAN takes 60-65 hours for a Core i5, 8GB Ram personal computer to analyze the travel patterns of the whole Smart Card database of SEQ, Australia. Although transit authorities could employ a faster computer, running DBSCAN for daily update of individual travel pattern is an absurd task.

This section develops the theoretical foundation of the *Weighted-Stop DBSCAN* (WS-DBSCAN) algorithm to transform the quadratic complex classical DBSCAN to a problem of sub-quadratic complexity, in particular a combination of linear and quadratic complexity with fewer elements to detect and update the changes in travel pattern of individual transit passengers. The objective of WS-DBSCAN is similar to the classical DBSCAN in travel pattern analysis, i.e. to detect each studied transit journey (transit OD) as a spatial travel pattern or not, and update the corresponding travel pattern. This section only describes the process of detecting and updating regular origin pattern – the Level 1 of the two-level travel pattern analysis described in Figure 5.2-3. The Level 2 could be analyzed by WS-DBSCAN using similar method.

The following three principal features distinct WS-DBSCAN to the classical DBSCAN.

- WS-DBSCAN follows the same two-level analysis process as described in Figure 5.2-3 but instead of finding regular pattern as the first-time analysis, WS-DBSCAN utilizes the existing travel pattern knowledge of each passenger. Although WS-DBSCAN can also be used for first-time travel pattern analysis, it is best used for detecting and updating the changes in individual travel pattern
- DBSCAN performs neighbourhood search from each and every point to decide if the point is a core, border or noise point. Conversely, WS-DBSCAN only performs neighbourhood search when it is compulsory
- Most of transit passengers repeatedly board or alight a transit vehicle from a stop. The classical DBSCAN treats each boarding/alighting as a unique point, which means there are overlapping points in the dataset. WS-DBSCAN significantly reduces the computation time by specially treating those overlapping points and their related points in a faster linear algorithm. WS-DBSCAN clusters the stops rather than the boarding/alighting itself, and gives each stop a weight i.e. the number of times the passenger boarded/alighted from that particular stop. Figure 5.3-1 illustrates an example of historical boarding from an individual passenger to emphasize the difference between DBSCAN and WS-DBSCAN

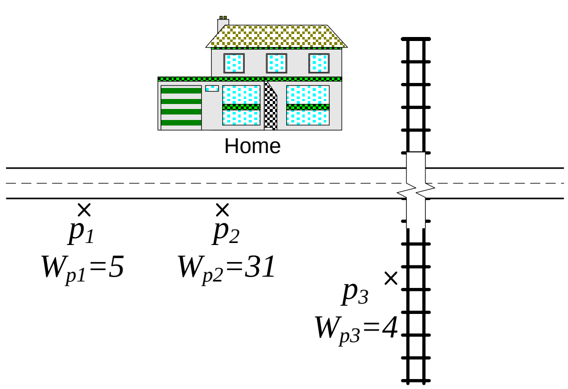


Figure 5.3-1 An example of individual historical boarding

The passenger in the Figure 5.3-1 regularly boarded a transit vehicle from one of three stops p_1, p_2 and p_3, where he/she made 40 boarding within the study period. The weights W_{p1}, W_{p2} and W_{p3} are the number of times the passenger boarded from each stop. The classical DBSCAN treats the dataset in Figure 5.3-1 as 40 unique points and repeatedly calculate the distance between each and every point. WS-DBSCAN, by contrast, only examines 3 points as stops p_1, p_2 and p_3.

Following the definitions from the classical DBSCAN paper (Ester et al., 1996), we propose the basic terminologies for WS-DBSCAN.

Definition 1: The **weighted ε -neighbourhood** of a transit stop *p*, denoted by $N_\varepsilon(p)$, is defined by

$$N_\varepsilon(p) = \sum_{q=1}^{n} W_q + W_p \mid q \in D, dist(p,q) \le \varepsilon$$

Where:

W_q is the weight of each stop *q* i.e. number of times the passenger boarded a transit vehicle from stop *q*

W_p is the weight of stop *p* itself,

$dist(p,q)$ is the Euclidean distance between stop *p* and *q* and

D is the stop dataset.

Definition 2: A stop *p* is a **core stop** if and only if $N_\varepsilon(p) \ge MinPts$

If *p* is a transit stop and the passenger has made more than *MinPts* number of boarding in a *weighted ε -neighbourhood* around *p*, then *p* is called a core stop.

Definition 3: A stop *q* is **directly reachable** from a stop *p* wrt ε and *MinPts*, if

1) $q \in N_\varepsilon(p)$, and
2) $N_\varepsilon(p) \ge MinPts$ (i.e., *p* is a core stop)

Definition 4: A stop *q* is a **border stop** when it is not a *core* stop, but directly reachable from a core stop *p*.

Figure 5.3-2 demonstrates an example of core and border stop in WS-DBSCAN. Here for *MinPts* equals to 4, stop p_1 and p_2 are core stops, whereas q_1 is a border stop for p_1. The arrow illustrates that q_1 is *directly reachable* from p_1, but p_1 is not *directly reachable* from

q_1. In contrariety, p_1 and p_2 have two-way *directly reachability* between them, because both p_1 and p_2 are core stops and lie within the ε distance of each other. A border point is *directly reachable* only from a *core* point and not from another *border* point. However, a *border* point can be *directly reachable* from multiple *core points*.

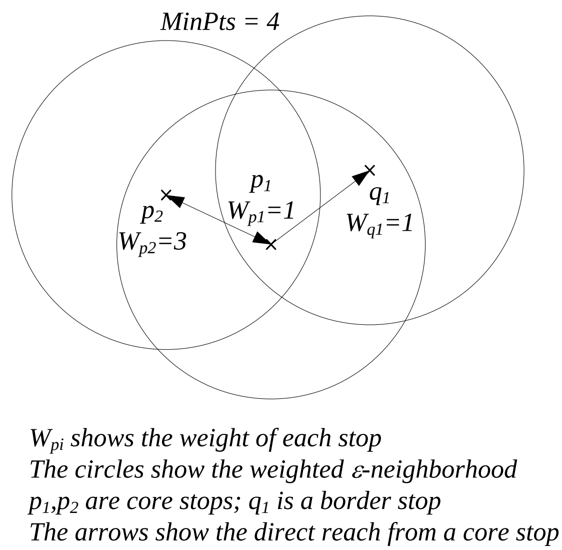
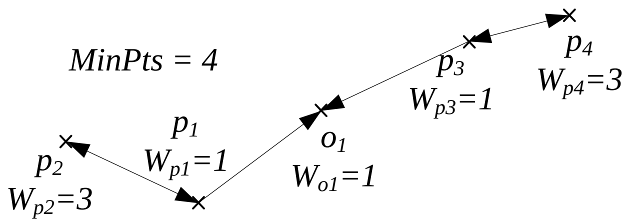


Figure 5.3-2 An example of core stop, border stop and direct reach in WS-DBSCAN

Definition 5: A stop *q* is **reachable** from a stop *p* wrt ε and *MinPts* if there is a chain of stop $p_1,\ldots,p_n$, $p_1=p$, $p_n=q$ such that p_{i+1} is directly reachable from p_i.

Definition 6: A stop *p* is **connected** to a stop *q* wrt ε and *MinPts* if there is a stop *o* such that *o* is reachable from both *p* and *q* and *vice versa*.

Figure 5.3-3 shows an example of reachable and connected stops in WS-DBSCAN. Here, p1, p2, p3 and p_4 are core points. Pont o_1 is a *border* point to both p_1 and p_3 and reachable from both p_1 and p_3. As indicated in the figure, p_1 and p_2 are *reachable*, and p_3 and p_4 are *reachable*. Therefore, p_2 and p_4 are connected through o_1.



p_1,p_2,p_3,p_4 are core stops; o_1 is a border stop
o_1 is reachable from p_2 and p_4, but p_2 and p_4 are not reachable from o_1
p_2 and p_4 are connected by o_1

Figure 5.3-3 An example of reachable and connected stops in WS-DBSCAN

Definition 7: A **cluster** C wrt ε and *MinPts* is a set of stops acting as a regular pattern. A cluster would have at least one *core* stop, and satisfy the following conditions:

1) $\forall p,q$: if $p \in C$ and q is directly reachable from p wrt ε and *MinPts,* then $q \in C$ (Maximality)
   This condition is to guarantee that all stops within a reachable area are considered in the same origin pattern. It also denotes that a regular pattern would have at least *MinPts* number of journeys, because cluster C would have at least a *core* stop p and its corresponding border stops q.
2) $\forall p,q \in C$: p is *connected* to q wrt ε and *MinPts* (Connectivity & Uniqueness)
   All stops in a cluster are at least *connected*, if not *directly reachable* or *reachable*. This condition is also to guarantee that two clusters would be distinct and stops from cluster C would not be connected from another cluster because if any stop is connected from two clusters, then the two clusters would be clustered as one. Thus any *core* or *border* stop would belong to one and only one cluster.

Definition 8: **Anomaly** stops wrt ε and *MinPts* are the stops that do not belong to any travel pattern. They are not *directly reachable* to any stop. Thus they are not core or border stops, and *vice versa*.

5.3.2 The WS-DBSCAN algorithm

This section describes the WS-DBSCAN implementation to detect a pattern for an origin stop S_t from a newly made journey and update the existing knowledge of passenger P travel pattern. The detection and pattern update of the destination stop from the same journey is done using similar method.

The existing travel pattern knowledge has the form of a historical stop database [S_H] for passenger *P* that stores historical origin stops with their corresponding *Weight* and *ClusterID*. Here, the *Weight* W_i of each stop S_i is the number of times the passenger has boarded a transit vehicle from that specific stop. *Cluster number* C_i of each stop *i* indicates if stop S_i is a regular $(C_i > 0, C_i \in \mathbb{Z}^+)$ or anomaly stops (C_i =-1). Different positive C_i means different regular travel pattern. Table 5.3-1 shows an example of historical stop dataset [S_H] and studied stop S_t.

Table 5.3-1 Examples of: a) Historical stop dataset [S_H] and b) Studied stop S_t

a)

Historical origin stops [S_H]		
Stop S_i	*Weight* W_i	*ClusterID* C_i
O1	8	1
O2	2	1
O3	14	2
O4	1	-1
O5	2	-1

b)

Studied new stop [S_t]		
Stop S_i	Weight W_i	ClusterID C_i
S_t	1	Unknown

WS-DBSCAN detects a travel pattern by assigning a *ClusterID* for S_t

- WS-DBSCAN assigns an existing positive *ClusterID* if S_t belongs to an existing pattern
- WS-DBSCAN assigns a new positive *ClusterID* if S_t together with some other stops in [S_H] form a new pattern
- WS-DBSCAN assigns *ClusterID* equals -1 if S_t is an anomaly pattern

After each implementation, WS-DBSCAN increments the corresponding *Weights* by one and updates *ClusterID* according to the assignment of S_t's *ClusterID*. Figure 5.3-4 and the following steps describe the algorithm.

1) STEP 1: The first step is to check the sum of weights of all stops in [S_H]

$$W_{[S_H]} = \sum_{i=1}^{m} W_i \mid i \in [S_H]$$

If $W_{[S_H]} \geq MinPts - 1$ then we proceed to STEP 2. Else S_t is stored into [S_H] as an anomaly stop because there is then no possibly for passenger *P* to have any travel pattern formed. Here, *MinPts-1* is used because the current journey contributes to a weight for the current stop.

2) STEP 2: If S_t already belongs to [S_H] and has a positive *ClusterID* C_t. Its *Weight* W_t in [S_H] is then incremented by one. Else the algorithm proceeds to STEP 3.
3) STEP 3: The following calculations are performed to checks if S_t could form a cluster with any stops in [S_H]
   - Calculate the *weighted* ε *-neighborhood* of S_t when the dataset is [S_H]

   $$N_\varepsilon(S_t) = \sum_{q=1}^{n} W_q + 1 \mid q \in [S_{RN}], dist(q, S_t) \le \varepsilon$$

   If $N_\varepsilon(S_t) \ge MinPts$, S_t is a *core* stop. Three are there possibilities: a) it belongs to one existing cluster; b) to multiple existing clusters; and c) does not belongs to existing cluster so should be assigned a new cluster number.

   a) $\exists q \in N_\varepsilon(S_t), \mathrm{C}_q \in \mathbb{Z}^+$

   If within $N_\varepsilon(S_t)$ there is only one regular stop q, then S_t belongs to the existing cluster of q and is assigned the corresponding cluster number. All stops within its *weighted* ε *-neighborhood* are also assigned the same cluster number.

   b) $\exists q_1, q_2..q_n \in N_\varepsilon(S_t); \mathrm{C}_1, \mathrm{C}_2..\mathrm{C}_\mathrm{n} \in \mathbb{Z}^+$
   $\exists \mathrm{C}_{qj} \ne \mathrm{C}_{qk} (j, k \in \{1, 2..n\})$

   If within $N_\varepsilon(S_t)$ there are multiple regular stops $q_1, q_2..q_n$ (n>1), where at least there are regular stops j and k belongs to two different clusters $\mathrm{C}_{qj} \ne \mathrm{C}_{qk} (j, k \in \{1, 2..n\})$, we merge their clusters and S_t to a combined cluster C_q because by adding S_t all these stops will be *connected* (See Definition 7). All these corresponding stops are then assigned a new combined cluster number C_q.

   c) $\nexists q \in N_\varepsilon(S_t), \mathrm{C}_q \in \mathbb{Z}^+$

   If within $N_\varepsilon(S_t)$ there is no regular stop, S_t forms a new cluster with the stops in its *weighted* ε *-neighborhood*. All these corresponding stops are then assigned a new cluster number.

   The corresponding *Weight* of S_t is incremented by one in each of these possibilities.

- If $N_\varepsilon(S_t) < MinPts$, S_t is not a *core* stop but it could be a *border* stop if any stop *q* within its *weighted* ε *-neighborhood* is a *core* stop.

  $$N_\varepsilon(q) = \sum_{r=1}^{k} W_r + W_q \mid r \in [S_t, S_H]$$
  $$\text{Where}: q = 1 \ldots n, dist(S_t, q) \le \varepsilon$$

  If any $N_\varepsilon(q) \ge MinPts$, S_t is then a border stop. Similar to the previous case, S_t and its corresponding stops are assigned with an existing or new cluster number.

- If $\forall N_\varepsilon(q) < MinPts$, we can conclude that S_t is anomaly stop and store it in [S_H] with *ClusterID* equals -1. The corresponding *Weight* of S_t is incremented by one.

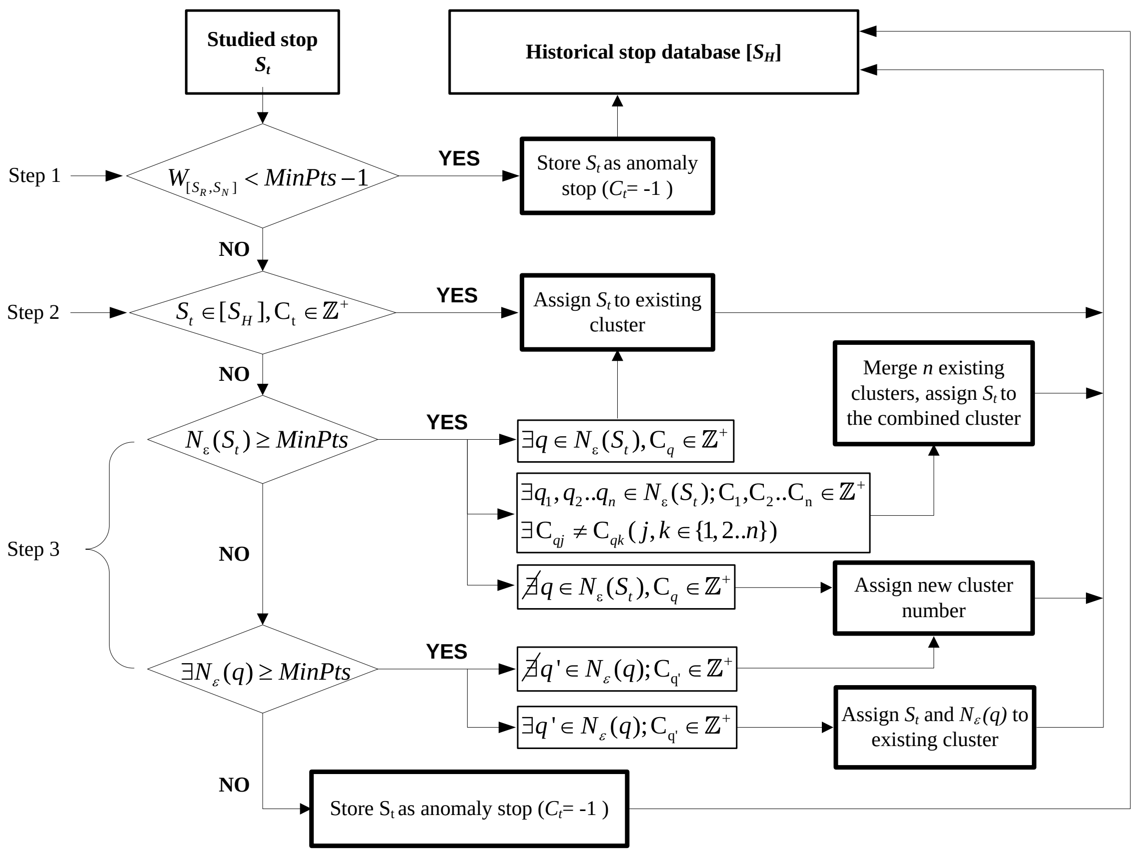


Figure 5.3-4 WS-DBSCAN algorithm

5.3.3 An example of WS-DBSCAN implementation on full OD pattern detection and update

This section describes the WS-DBSCAN implementation on detecting and updating a full travel itinerary by an example. Figure 5.3-5 shows WS-DBSCAN implementations on the journeys the passenger *P* made within the day *d*.

Input 1: Historical itineraries database

Origin stops

	Weight	Cluster ID
O1	8	1
O2	2	1
O3	14	2
O4	1	-1
O5	2	-1

Destination stops

	Weight	Cluster ID
D1	10	1
D2	1	-1
D3	14	2
D4	2	-1

Spatially OD pattern

	OD pattern	Weight	Spatially Regular
O1-D1	[1;1]	8	Yes
O3-D3	[2;2]	14	Yes
O4-D1	[-1;1]	1	No
O2-D1	[1;1]	2	Yes
O5-D4	[-1;-1]	2	No

Input 2: Day *d* itineraries (S_t)

St Journeys		
O1-D1	O1-D3	O4-D1

WS-DBSCAN

Output 1: WS-DBSCAN clustering results

St Origin stops

	Cluster ID
O1	1
O1	1
O4	-1

St Destination stops

	Cluster ID
D1	1
D3	1
D1	1

Output 2: Updated historical itineraries database

Updated Origin stops

	Weight	Cluster ID
O1	10	1
O2	2	1
O3	14	2
O4	2	-1
O5	2	-1

Updated Destination stops

	Weight	Cluster ID
D1	12	1
D2	1	-1
D3	15	2
D4	2	-1

Updated Spatially Regular OD

	OD pattern	Weight	Spatially Regular
O1-D1	[1;1]	9	Yes
O3-D3	[2;2]	14	Yes
O4-D1	[-1;1]	2	No
O2-D1	[1;1]	2	No
O1-D3	[1;2]	1	No
O5-D4	[-1;-1]	2	No

Figure 5.3-5 An example of WS-DBSCAN implementation

WS-DBSCAN requires two types of input:

- Input 1 is the historical itinaries databases that stores the historical origin stops, destination stops; and a spatially regular OD database that stores the full OD itineraries. Each historical origin and destination stop is associated with a *Weight* and a *ClusterID*. Cluster number differentiates the regular origin/destination patterns and anomaly pattern. Each OD itinerary in the Spatially OD pattern database is also associated with a *Weight*, a variable *OD pattern* and a binary variable indicating regular/anomaly OD pattern. The *OD*

pattern stores the *Cluster numbers* of both origin and destination stop in the format [$O_{Clusternumber}$;$D_{Clusternumber}$].
Here O1 and O2 both belong to origin cluster 1, so both O1-D1 and O2-D1 have [1;1] for their *OD pattern*. We define an OD pattern *i* as a regular OD pattern if the total *Weight* of its *OD Pattern* is larger than *MinPts.*

- Input 2 is the journeys that passenger *P* made during the studied day, where *P* made three journeys within the day *d* in this particular example. Each OD itinerary in Input 2 is fed into the WS-DBSCAN algorithm. Here, passenger P made 3 journeys O1-D1, O1-D3 and O4-D1 during the study day *d*.

WS-DBSCAN provides two sets of output. While Output 1 represents the pattern detection, Output 2 represents the pattern update feature of WS-DBSCAN.

- Output 1 is the assigned cluster number of each itinerary in Input 2. Here O1, D1 and D3 are identified as regular stops and O3 as anomaly stop.
- Output 2 takes Output 1 results and shows the updated spatial travel pattern in terms of origin/destination and OD pattern. Here among the three journeys passenger *P* made within the day *d*, O1-D1 is clearly a spatial regular OD pattern and O4-D1 and O5-D4 are clearly an anomaly patterns. Although both O1 and D3 are regular stops, the pair O1-D3 is an anomaly pattern because its *OD Pattern* does not have a *Weight* higher than *MinPts*.

5.3.4 **Numerical experiment**

This section validates the applicability of WS-DBSCAN to the real data, in comparison with the classical DBSCAN algorithm.

Experiment setup

The numerical experiment is set to emulate a working environment to compare the performance of classical DBSCAN and WS-DBSCAN. The last working week (Monday to Friday) of June, 2012 has been used as the testing dataset, whereas the other weeks acted as the historical itineraries data. The experiment emulates a working environment by the following three steps

1) At the end of each day in the testing dataset (last working week of June 2012), we collect all Smart Card transactions of the day
2) The algorithm illustrated in Section 5.2.2 reconstructs individual transactions into passenger itineraries
3) The classical DBSCAN and WS-DBSCAN analyzes the studied day itineraries and relates with the historical itineraries data to detect and update the travel pattern. The implementation of DBSCAN and WS-DBSCAN has been described in Figure 5.2-3 and Figure 5.3-5, respectively.

We adopt the same example of detecting and updating passenger *P* travel pattern after day *d* in Figure 5.3-5 to compare the two algorithms. While Input 1 and Input 2 in Figure 5.3-5, are fed into WS-DBSCAN, historical OD journeys similar to Figure 5.2-3 and Input 2 are fed into DBSCAN.

Experiment results

Table 5.3-2 shows the comparison between the time efficiency of DBSCAN and WS-DBSCAN. We compare the two performances by calculating the ratio between WS-DBSCAN computation time and DBSCAN computation time.

$$Q_t = \frac{t_{WSDBSCAN}}{t_{DBSCAN}} \times 100\%$$

Where t_{DBSCAN} and $t_{WSDBSCAN}$ are the computation time of the DBSCAN and WS-DBSCAN implementation, respectively.

Table 5.3-2 Computation time comparison of DBSCAN and WS-DBSCAN to detect and update each studied journey.

Algorithms	Mean(s)	Median(s)	Mean Regular Detection(s)	Mean Anomaly Detection(s)
DBSCAN	23.34×10^{-2}	23.23×10^{-2}	23.52×10^{-2}	22.72×10^{-2}
WS-DBSCAN	10.78×10^{-4}	10.47×10^{-4}	10.23×10^{-4}	11.17×10^{-4}
Q_t	0.46%	0.45%	0.43%	0.49%

Mean and Median of computation time are for a two-level analysis detection & update for a studied journey in the testing dataset in seconds. The time is counted from an itinerary is presented, until the update process is completed.

WS-DBSCAN costs only around 0.46% in computation time compared to the classical DBSCAN, while provides the same mined travel pattern results as DBSCAN by sharing the same clustering method and parameters. Table 5.3-3 shows the observed computation time for detecting and updating the travel pattern of all passengers travelled on each day from 18th to 22nd June 2012.

Table 5.3-3 Travel pattern detecting and updating time (hour) for each testing day

Day	18th Jun	19th Jun	20th Jun	21st Jun	22nd Jun
DBSCAN	23.59	24.79	25.29	25.72	25.30
WS-DBSCAN	0.11	0.11	0.12	0.12	0.12
Q_t	0.46%	0.44%	0.47%	0.47%	0.47%

Computation time is counted in hours. The analysis has been performed on all travelled passengers on each day

While DBSCAN took approximately a day to detect and update the changes in spatial travel pattern of all passengers travelled on each testing day, WS-DBSCAN takes 6-7 minutes of computation time. Figure 5.3-6 illustrates the computation time of WS-DBSCAN when the passenger has different number of journeys and number of OD pairs in the historical dataset. The computation time varies from 8.5×10^{-4} to 12.5×10^{-4} second per journey. The WS-DBSCAN is exceptionally fast when the number of journeys in the historical dataset is large and the number of OD pairs is small. The algorithm provides a decision in the shortest time when the number of journeys is less than *MinPts*, because the studied journey is definitely an anomaly pattern. The algorithm is only slightly slower for passengers whose the number of journeys is close to the number of OD pairs. These passengers only account for less than 3% of the population.

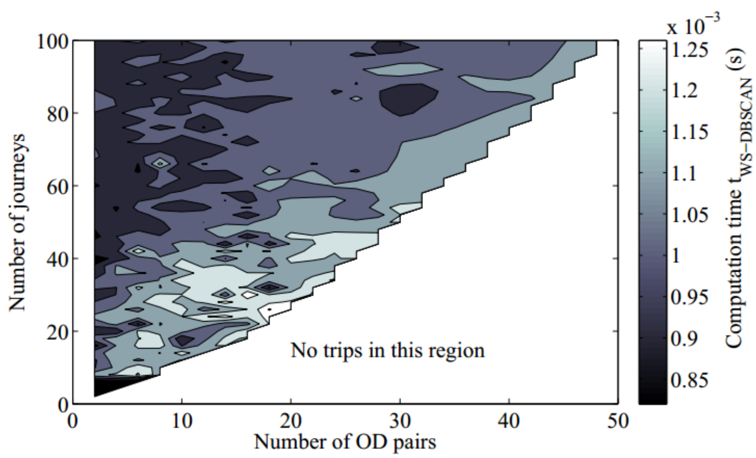


Figure 5.3-6 WS-DBSCAN computation time

WS-DBSCAN time-effectiveness is further illustrated in comparison with the DBSCAN computation time. Figure 5.3-7(a) shows that DBSCAN cost more as the number of journeys increases, reflecting its quadratic computation complexity. The difference between the computation time of DBSCAN and WS-DBSCAN algorithm on the same problem is demonstrated in Figure 5.3-7(b). The figure shows that the time savings by using WS-DBSCAN instead of DBSCAN is greater as the number of journeys is getting larger.

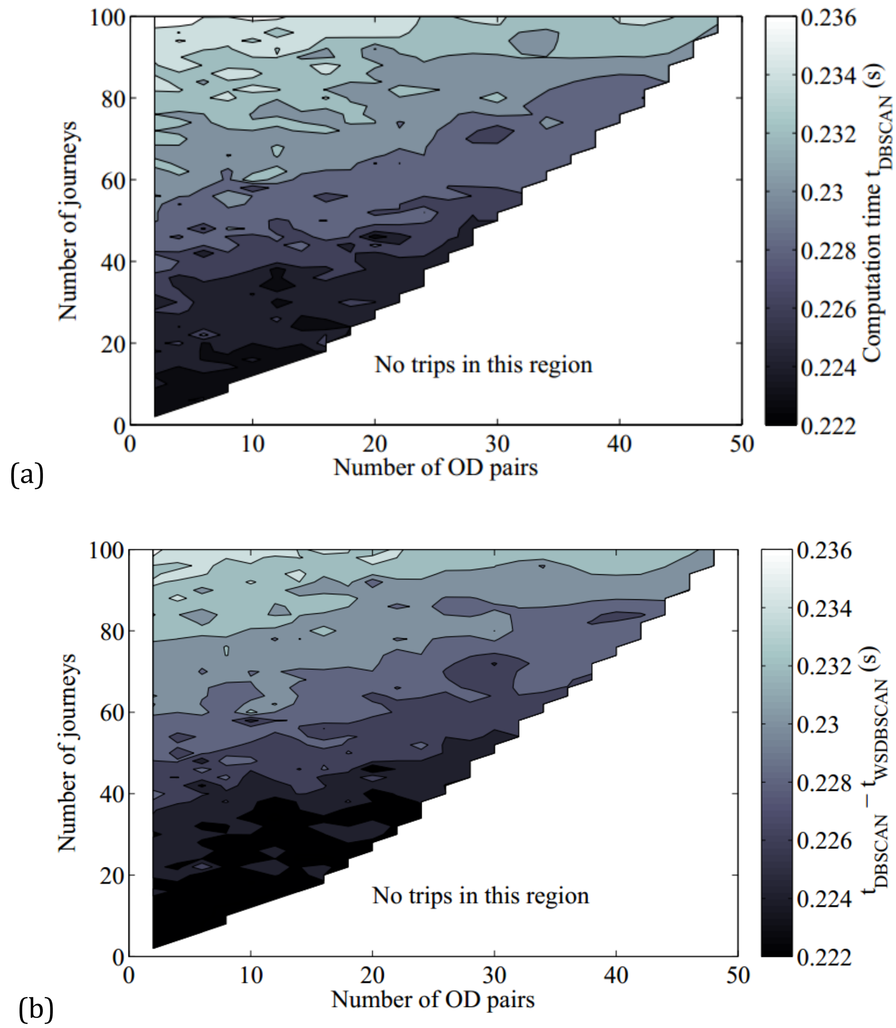


Figure 5.3-7 DBSCAN computation time: a) in seconds, b) in comparison with WS-DBSCAN

The numerical experiment demonstrates that WS-DBSCAN is more than 200 times faster while provides the same travel pattern analysis as DBSCAN.

5.4 **Summary of Chapter 5**

This chapter proposes a systematic and comprehensive approach to mine spatial and temporal travel pattern from SC data. A heuristic logical method firstly merges the SC transactions into completed transit journeys from origin to destination, including transfers. The classical DBSCAN is then applied on the historical travel itineraries, revealing the spatial and temporal travel pattern of individual passengers. A sensitivity analysis then provides a clue on how to choose parameters *MinPts* and ε for DBSCAN application. Finally, a novel algorithm named Weighted-Stop DBSCAN is developed to reduce the computation time of travel pattern analysis, especially for the practice application where transit authorities need to update individual pattern on a daily basis. The main difference between WS-DBSCAN to classical DBSCAN and other algorithms for travel analysis is its logical mechanism. Each stop in the historical dataset is given a weight to reduce the neighbourhood search, and only perform neighbourhood search when it is really necessary. WS-DBSCAN on average detects a regular/irregular boarding pattern in 0.45% of what it costs for classical DBSCAN.

5.4.1 **Scientific and practical contributions**

The findings of this chapter augment the understanding of individual passenger travel behaviours. The algorithms introduced in this chapter: DBSCAN and WS-DBSCAN as well as the data handling and processing method allow transit authorities to observe the spatial and temporal usage pattern of their customers on a daily basis. Various practical applications could be originated from the knowledge of travel pattern. Before and after studies could be performed to see the anticipated changes in travel behaviours, for instance a reduction in ticket fare during off-peak period may encourage passengers to travel more during off-peaks. Transit authorities can also look at the route choice, more choice or frequency of use for passengers of different types or at different geographical area. Interested readers of the potential application of travel pattern could find more detailed information from Utsunomiya *et al.* (2006).

This chapter also conveys two principal scientific contributions:

1) A comprehensive approach to mine individual travel pattern from Smart Card AFC transactions, including itineraries reconstruction and travel pattern analysis
2) A novel algorithm named WS-DBSCAN to enhance the computing time of travel pattern analysis by 200 times.

5.4.2 Knowledge gained

Through the development of algorithms for travel pattern analysis through assessing their outputs, the following knowledge could be gained:

4) ε and *MinPts* are the key parameters to mine the travel pattern of individual passenger.
5) Existing algorithms in travel pattern analysis do not facilitate the daily analysis of individual passenger travel pattern because of their quadratic computing complexity.
6) The computation time can be reduced by more than 200 times compared to the classical DBSCAN by taking advantage of the characteristic of SC data and by a more logical algorithm. It is now possible to observe the changes in travel pattern on a daily basis.

6 Passenger segmentation

The last chapter describes how travel behaviours are observed by mining individual travel pattern from SC data. This chapter further augments the passenger characterisation by segmenting transit customers into identifiable types of similar behaviours and needs.

The contents of this chapter have been published in the following publications:

Journal article

J4 Kieu, L. M., Bhaskar, A. & Chung, E. 2015. Passenger Segmentation using Smart Card data. *IEEE Transactions on Intelligent Transport System*. Vol 16, Issue 3, June 2015.
DOI 10.1109/TITS.2014.2368998.

Conference proceeding papers

C4 Kieu, L. M., Bhaskar, A. & Chung, E. 2014. Transit passenger classification by temporal and spatial travel regularity mined from Smart Card data. 93rd Annual Meeting of the Transportation Research Board. 12-16 January, Washington DC, US.

6.1 Introduction

Better understanding of passengers is essential for transit authorities to satisfy customer needs and preferences. The Transportation Research Board has published a handbook on using market segmentation to increase patronage (Elmore-Yalch, 1998). Most of transit operators have defined classes of customers, but not market segments. For instance, operators in South East Queensland (SEQ), Australia classify passengers into 6 types (Adult, Senior, Child, Pension, Secondary School Student and Student) according to age and occupation. While this classification is still useful for fare collection, whether these types respond differently to alternative services and whether new policies benefit them is unknown.

The aim of this chapter is to develop a passenger segmentation method that goes beyond the classical classification of passengers. Market segmentation of transit passenger offers various benefits to transit authorities to better cater their customers.

(1) Targeted survey could aim for the passengers of low transit usages to understand the disutility that limits the level of ridership.
(2) Before-after studies could observe the changes in passenger market to understand the evolution of passenger demand.
(3) Incentives and personalized service can be given to passengers of regular usages to encourage passenger to use public transport for commuting.
(4) The observation of travel pattern also benefits operational strategies such as transfer coordination and origin-destination demand management by monitoring and inferring passenger movements through their travel habits.

For transfer coordination, passenger market segmentation also brings valuable benefits. Passengers have different needs for transfer, in which some of them usually take direct journey while others take transfers. Market segmentation augments the understanding of individual passenger, revealing their mobility needs. Assuming that passengers would follow their usual behaviours, market segmentation is an important component in a transfer coordination model in forecasting the number of transferring and non-transferring passengers.

However, transit authorities in generally has little knowledge about their customers. Traditional studies on passenger travel pattern and passenger segmentation solely focus on the use of transit user surveys. A decent amount of research has also segmented transit passenger based on travel behaviours, for fare elasticity (Hensher, 1998) or increasing transit patronage (Elmore-Yalch, 1998; Shiftan et al., 2008). According to Elmore-Yalch (Elmore-Yalch, 1998), transit passenger segmentation could follow one of the three major approaches: (1) physical segmentation based on basic information such as demographic, geographic and geodemographics; (2) product usage segmentation based on ridership such as frequency of use; (3) physiological segmentation based on the characteristic of individual passenger and (4) benefit segmentation based on passenger requisite. Henser (Hensher, 1998) segmented the transit customer market into 4 classes of non-concession and concession passengers travelling long or short trips to estimate fare elasticity. Shiftan et al. (Shiftan et al., 2008) proposed a structural equation modelling approach to segment transit passengers according to the sensitivity to time, need for fixed schedule, and willingness to use transit. However, these surveys are generally expensive to perform, limited in sample size and only valid within the study period. For transfer coordination purpose, this type of market segmentation is far from utilisable because only a fraction of the total population is surveyed and their behaviours have been observed for only a short amount of time.

This chapter proposes a new method for passenger market segmentation using solely SC data. The passengers are segmented into types of similar travel behaviours, through the similarities and differences in their spatial and temporal travel pattern. This chapter uses the mined travel pattern of each individual passenger from Chapter 5 to segment her/him into one of the predefined types of passengers. The next Section (Section 6.2) describes the methodology of passenger segmentation. Section 6.3 analyses the segmentation results. Finally, Section 6.4 summaries the findings, scientific and practical contributions and knowledge gained from the chapter. Figure 5.1-1 illustrates the framework for passenger segmentation in this chapter.

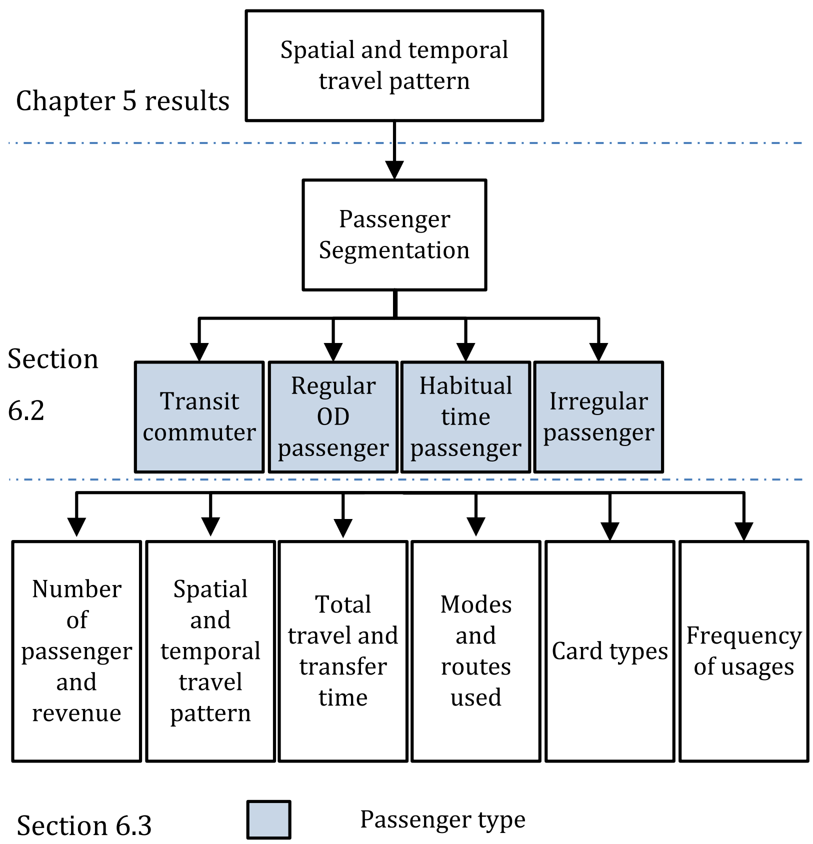


Figure 6.1-1 Study framework of Chapter 6

6.2 **Market segmentation methodology**

The market segmentation analysis follows a priori segmentation where identifiable passenger classes are selected from the SC user population based on the proportion of Regular OD/Habitual time trips in the total transit usage. In a priori market segmentation, the cluster-defining descriptions are selected in advance by the researcher and conducting the study will not influence the definitions of these pre-defined segments (Elmore-Yalch, 1998). A priori segmentation is based on the assumption that there are stereotypes about different classes. According to 4 major approaches of transit passenger segmentation in Elmore-Yalch (1998), our approach could be classified as a physiological segmentation, where passenger travel characteristic, i.e. spatial and temporal travel pattern defines the type of passenger. Four segments of passenger can be identified:

(1) Passengers with more Regular journeys than Habitual journeys are hereafter called *"Regular OD passengers"*. They have regular places to travel, but are flexible in travelling time.

(2) Passengers with more Habitual journeys than Regular journeys are hereafter called "*Habitual time passengers*". These passengers use public transport at fixed times-of-the-day, but travel between multiple ODs.

(3) Passengers with both Regular and Habitual journeys of more than 50% of their total journeys are hereafter called "*Transit commuters*". They are commuters who usually use public transport at Habitual times for trips between Regular ODs.

(4) Passengers without neither Regular nor Habitual journeys are hereafter called "*Irregular passengers*". They may have repeated journeys, but those are not enough to be considered as regular travel pattern. For instance if *MinPts* equals 8, seven repeated trips cannot make a regular travel pattern.

Each SC user itinerary is re-visited during the passenger segmentation process. Figure 6.2-1 illustrated the heuristic rule to segment transit passenger according to the proportion of Regular OD and Habitual time journeys. Passengers during the study period travelled for a certain number of journeys following Regular OD, Habitual time pattern or not following any pattern. Each of them is represented as a point in Figure 6.2-1. The colour of the point represents the number of journeys made within the study period.

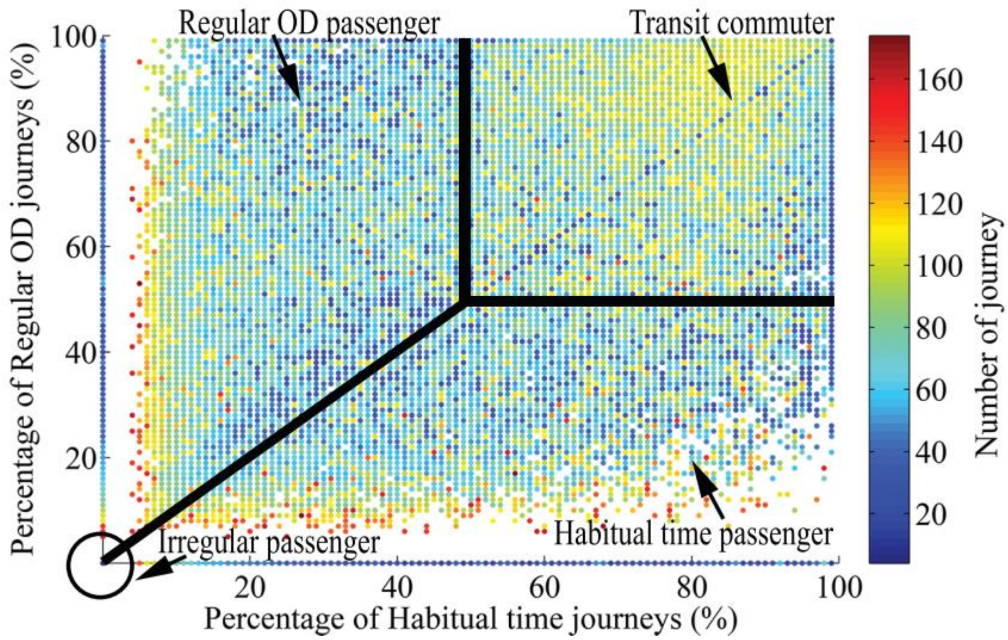


Figure 6.2-1. A priori rule for transit passenger segmentation

Only passengers with no recognizable pattern are segmented into the *Irregular Passenger* type. The other passengers could be grouped into 3 identifiable types. *Transit commuters* followed spatial and temporal patterns in most of their journeys. They also made significant number of journeys. *Regular OD passenger* made more spatially regular than habitual temporal journeys, and vice versa for *Habitual time passenger.* These heuristic rules are translated to *a priori* rules for market segmentation (Kieu et al., 2015c):

(1) *Rule 1:* If no temporal or spatial travel pattern is identified, the passenger is classified as an *Irregular passenger*.

(2) Rule 2: If more than 50% of the journeys were made within Habitual times and between Regular ODs, the SC user is classified as a *Transit commuters*

(3) Rule 3: The remaining passengers are segmented into *Regular OD passengers* if the proportion of Regular OD journeys is more than Habitual time journeys, and vice versa for *Habitual time passengers.*

6.3 **Passenger segmentation analysis**

This section augments the transit passenger characterization by analysing the market segmentation results. This section further disaggregates each passenger type into subsegmentations of different transfer behaviours, modes and routes used, card types and usage frequency. In other words, this section aims to exploit the coarse-grained information of passenger types toward a more fine-grained understanding of market segments, their needs and the capabilities required to serve them.

Figure 6.3-1 illustrates each market segment contributions in the number of passengers and fare revenue. The dominance of *Irregular passengers* (64%) denotes that most of SC users do not have regular travel patterns. *Transit commuters* account for only 14%, while *Regular OD passengers* and *Habitual time passengers* account for 13% and 8%, respectively.

However, *Transit commuters* made the largest contribution (46%) to the ticket revenue. This fact designates that those who use public transport regularly as the main travel mode are still the major income contributor for transit operators. Conversely 64% of their customers (*Irregular passengers*) contributed for only 17% of the revenue.

For further analysis this section analyses these four passenger segments in terms of spatial and temporal daily usage (Section 6.3.1), total travel and transfer time (Section 6.3.2), modes and routes used (Section 6.3.3), card type (Section 6.3.4), and frequency of use (Section 6.3.5).

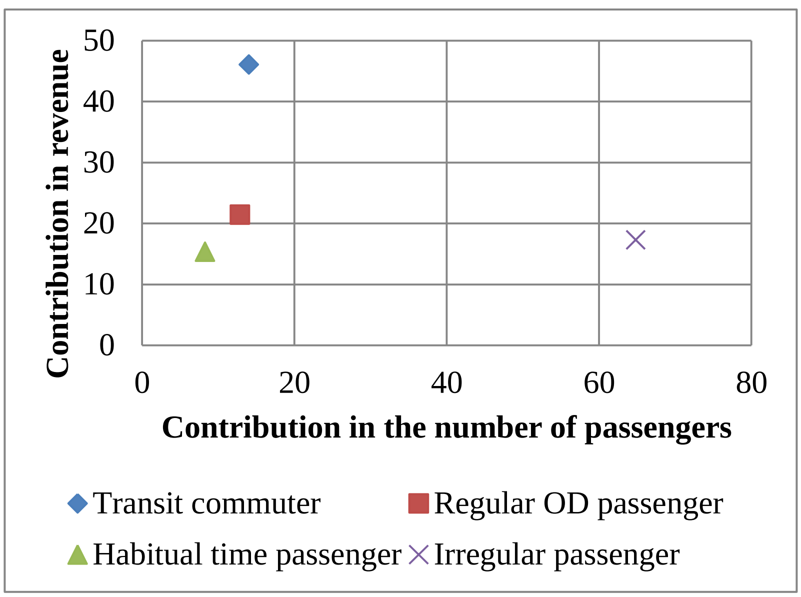


Figure 6.3-1. Passenger segmentation result

6.3.1 Spatial and temporal pattern of daily usage

This section exploits the usage pattern of each passenger type to understand the daily usage of transit network. Figure 6.3-2 illustrates the average number of journeys is made per passenger at different time-of-the-day.

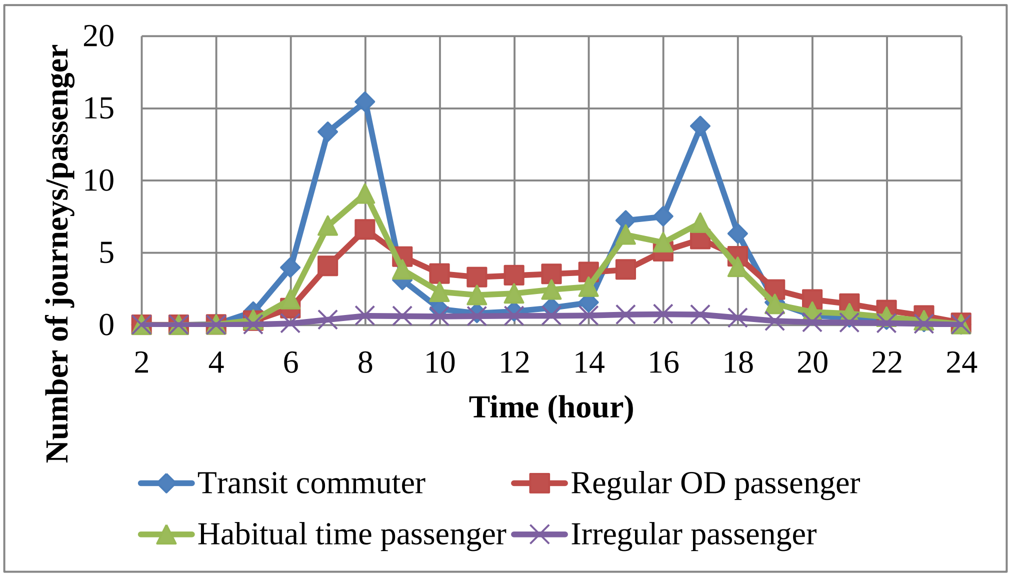


Figure 6.3-2. Average journeys made by each type of passenger over the observation period within the 1-hour study period

Figure 6.3-2 shows that *Transit commuters* travelled mainly during peak periods, while Irregular passengers travelled any time, but generally started later in the morning (from 8AM) and finished earlier (6PM) than any other classes. One trip purpose assumption can be made that *Transit commuters* travel mostly for school and work based trips and *Irregular passengers* travel mostly for less tightly scheduled trips, such as for leisure or shopping activities. *Regular OD passenger* as those who are flexible in time made the most number of journeys during off-peak periods. Conversely, *Habitual time passengers* as those who follow temporal travel pattern travelled mainly during peak periods, similar to the *Transit commuters.*

Figure 6.3-3 demonstrates the number of boarding on the Brisbane bus network at 8:00, 12:00 and 17:00 from each passenger type, where the size of circles represents the number of boarding within the study period. It shows the typical travel to work pattern from *Transit commuters, Regular OD* and *Habitual time passengers* where passengers boarded a bus from outside to travel inside the Brisbane CBD at 8:00, and vice versa for

17:00. The number of boarding from *Irregular passengers* is much less and shows no similar pattern.

At 12:00 and 17:00, the largest source of demand for *Regular OD passengers* was at South West of the CBD, where the University of Queensland is located. This pattern suggests that the majority of *Regular OD passenger* could be tertiary students, who are flexible in time but having regular travel destination.

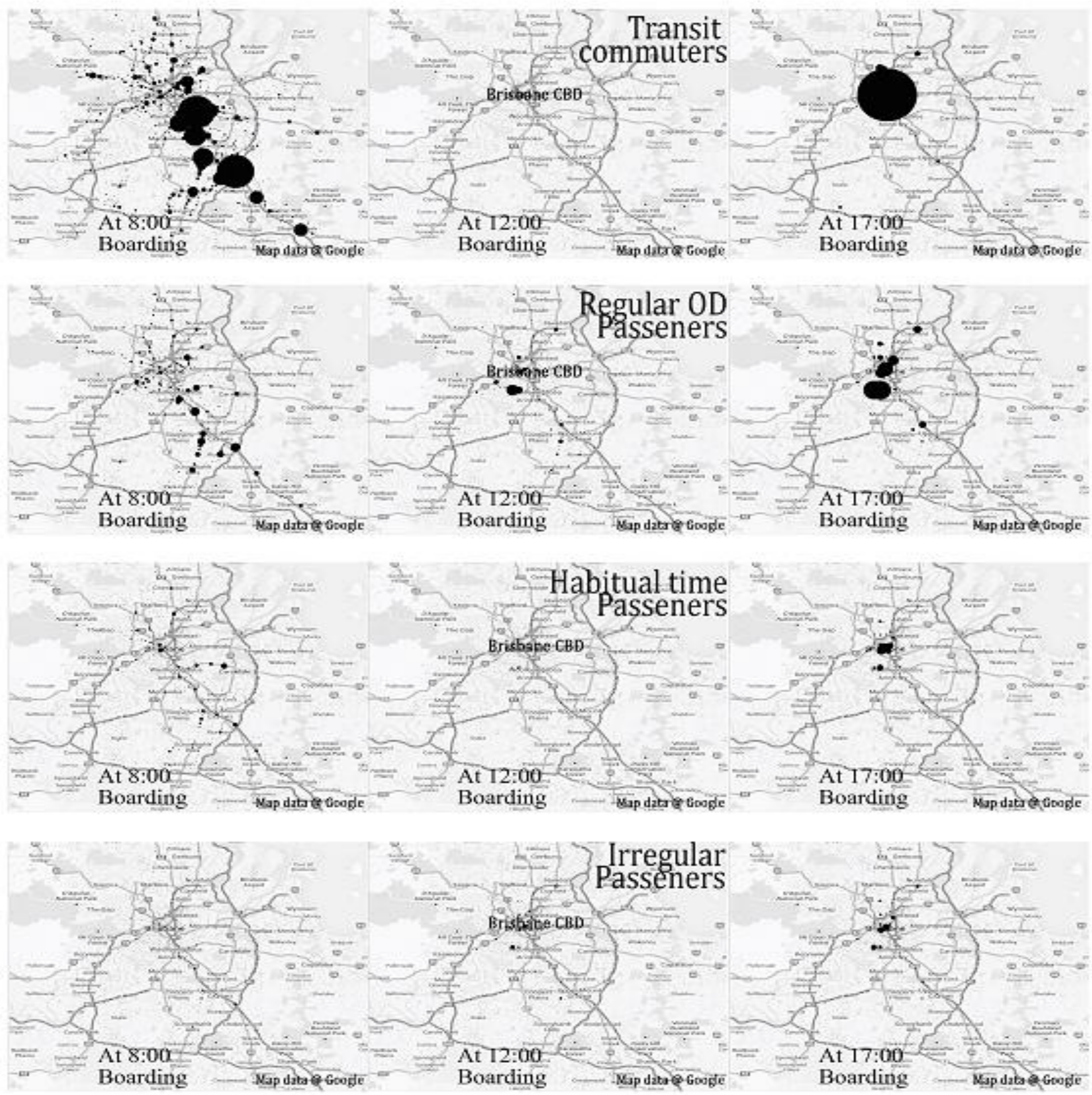


Figure 6.3-3 Number of boarding at 8:00, 12:00 and 17:00

6.3.2 **Total travel and transfer time**

This section exploits the differences between passenger types in terms of the total travel and transfer time to augment the understanding of passenger behaviours. Figure 6.3-4 shows the empirical cumulative density function (CDF) of the total journeys travel time made by different types of passenger.

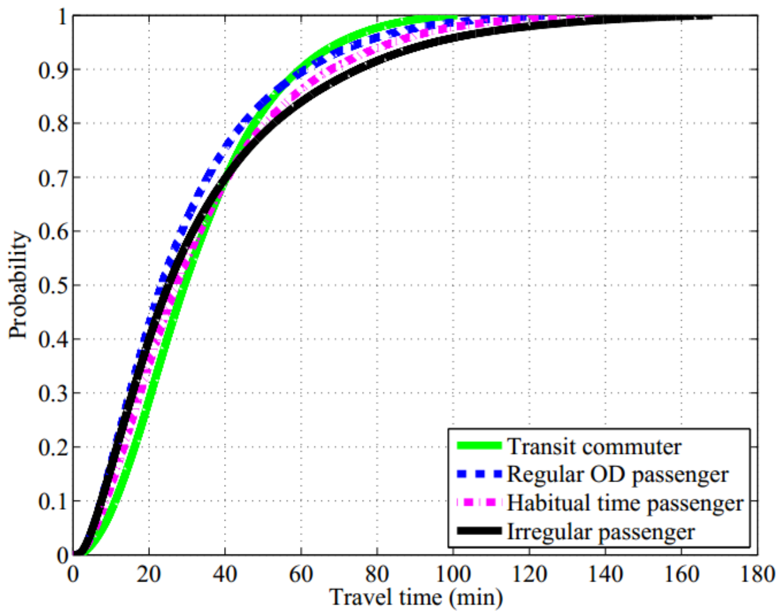
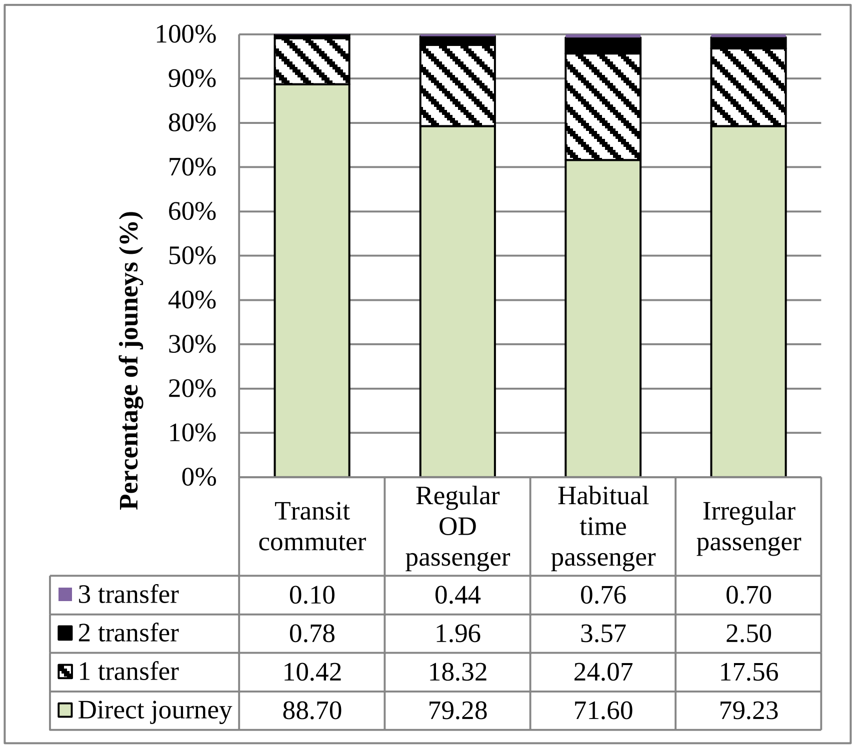


Figure 6.3-4. CDF of total travel time

The total time spent on travelling was relatively similar among different passenger types. *Transit commuters* spent slightly less time for travelling than *Irregular passengers* and other types. This difference might come from the difference in transfer time, which is illustrated in Figure 6.3-5.

Figure 6.3-5 shows that the majority of passengers make journeys with no transfer. *Transit commuters* made significantly less transfer than those of *Irregular* and *Habitual time passengers.* Nearly 90% of *Transit commuters* made no transfer during their journeys, leaving only over 10% of journey having 1 transfer and insignificant number of journeys having 2 and 3 transfer. Conversely over 20% of *Irregular passenger* journey were involved with any a transfer. This fact implies that transfer is one of the most important disutilities of transit system, which may discourage passenger to commute on a daily basis. It is consistent with findings in literature, where existing studies believed that transfer could be the decisive factor to transit quality of service (Mohring et al., 1987). *Habitual* *time passengers* show high mobility needs, with more transfers than any other passenger types. A journey by *Habitual time passenger* on average would consist of 1.33 legs, compared to only 1.12 legs in *Transit commuters'*.



	Transit commuter	Regular OD passenger	Habitual time passenger	Irregular passenger
3 transfer	0.10	0.44	0.76	0.70
2 transfer	0.78	1.96	3.57	2.50
1 transfer	10.42	18.32	24.07	17.56
Direct journey	88.70	79.28	71.60	79.23

Figure 6.3-5. Proportion of journeys with none, 1, 2 and 3 transfers

Figure 6.3-6 further augments the understanding of passenger transfer behaviour by looking at the time spent for each transfer by each type of passenger. Figure 6.3-6 shows that passengers spent up to 55-58 minutes for a transfer, with 60 minutes as the time limit for making a transfer in SEQ, Australia. *Transit commuters* in general spent less time for each transfer than any other passenger types, whereas *Irregular passengers* spent the largest amount of time. Different type of passenger devotes different amount of time for transferring reveals the variation in travel behaviour. While most of *Transit commuters* would take the fastest transfer to reach the destination, *Irregular passengers* may spent time doing other activities during the journey. In fact, 80% of *Transit commuters*' transfer time was less than 15 minutes, whereas 80% of *Irregular passengers* spent less than 30 minutes for transferring. Therefore any transfer coordination improvements would directly benefit the *Transit commuters*.

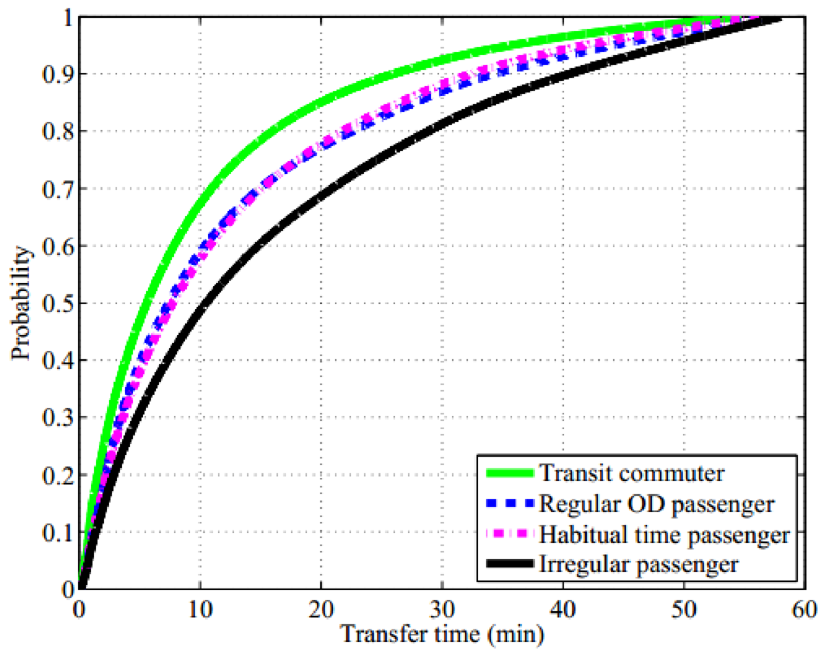


Figure 6.3-6. CDF of the time spent for each transfer

6.3.3 Modes and routes used

This section investigates the passenger mode and route choice over the bus, city train and ferry systems in SEQ, Australia. Table 6.3-1 shows how different passenger type used the transit system. The "Train only", "Bus only" and "Ferry only" modes represent the journeys made by a single transit mode, whereas "Bus-Train", "Bus-Ferry" and "Train-Ferry" represent the corresponding two modes that were used for travelling. There is no journey used all the three modes of transit.

Table 6.3-1 Mode choice decision of different passenger types

	Modes used (%)					
Passenger Type	Train only	Bus only	Ferry only	Bus-Train	Bus-Ferry	Train-Ferry
Transit commuter	42.78	50.02	2.25	4.60	0.29	0.05
Regular OD passenger	24.54	63.94	4.32	6.27	0.71	0.22
Habitual time passenger	17.05	73.33	1.40	7.46	0.64	0.11
Irregular passenger	24.57	64.42	4.04	6.05	0.68	0.25

The number of bus journeys exceeded train journeys in all passenger type, whereas the ridership share for ferry was insignificant compared to the other two modes. Service coverage could be the reason for this figure. While the bus network in SEQ consists of over 24000 stops and the rail system consists of 146 stations, there are only 24 ferry terminals of 11 ferry lines. The ferry system with limited commercial speed and service coverage did not attract passengers with tight schedule. Only 2.25% of *Transit commuters*' and 1.4% of *Habitual time passengers'* were ferry journeys. The insignificant numbers of Bus-Ferry and Train-Ferry journey also suggest poor connectivity of the ferry to rail and bus networks.

Transit commuters travelled noticeably more train itineraries than any other type. The city railway network in SEQ has a clear centripetal structure, which facilitates the going to school/work activities to the Brisbane CBD of the *Transit commuters*. Conversely, the bus network structure is more centrifugal and has a widespread coverage. Passenger with mobility needs to multiple destinations such as *Habitual time* passenger consequently used more buses than any other passenger type.

Figure 6.3-7 illustrates the route choice decisions of bus riders during the study period. The bus routes are classified into high frequency lines (equal or less than 15 minutes per vehicle) and low frequency lines (larger than 15 minutes per vehicle). The SEQ network consists of 38 high frequency lines over the total of 446 bus lines.

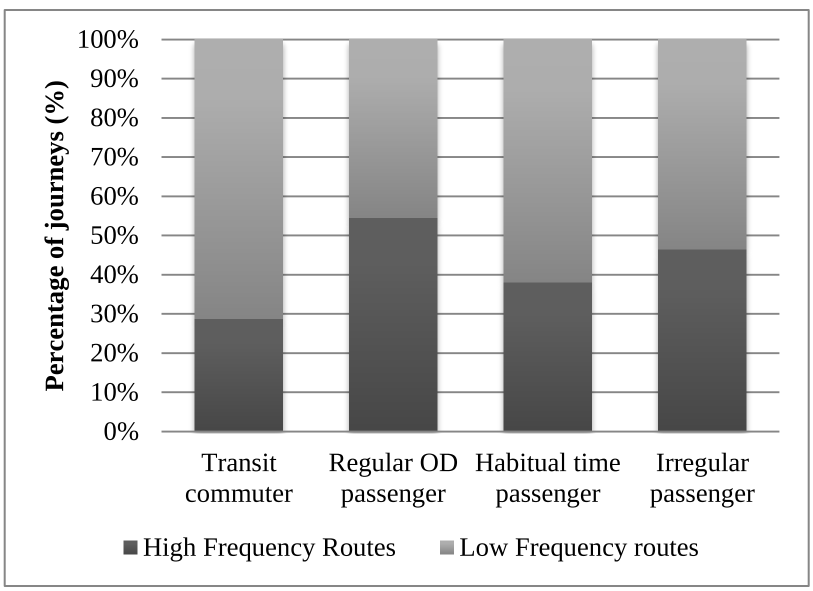


Figure 6.3-7. High frequency and low frequency route choice decisions of different passenger types

Despite the limited number of high frequency bus lines (approximately 8.5% of the total number of lines), Figure 6.3-7 clearly shows that up to 54% of *Regular OD passengers* journeys were from those high frequency lines. The figure was also high in *Irregular passengers, Habitual time passenger* and *Transit commuters* with 46%, 38% and 29% respectively. The results show that high frequency services were desirable for transit passengers of any type. These lines promote the preferable "turn up and go" behaviour, where passengers randomly arrive to transit stops without checking a schedule (Farag and Lyons, 2008).

Passengers of high temporal travel pattern such as *Transit commuters* and *Habitual time passengers* were less dependent on high frequency bus lines than *Regular OD* and *Irregular passengers*. This fact denotes that passengers on a time habit are more willing to check the timetable and take the less frequent bus lines. This finding is consistent with the literature. Farag and Lyons (2008) found that people would only turn up and go if there are no time constraints and the service is frequent.

6.3.4 **Card types**

This section analyses proportion of each passenger type under the 6 classes of SC cards in Queensland, Australia (Adult, Senior, Child, Pensioner, Secondary School Student and Student) to augment the understanding of these types.

Figure 6.3-8 shows that Adult is the largest contributor in all passenger types. Most of the *Transit commuters* are Adults, who are currently charged with highest ticket fare than any other card class. Their ticket fares along with their high number of journeys explain why *Transit commuters* are the main contributors of ticket revenue. However, a large proportion of Adult cards are *Irregular passengers*, which indicates that public transport is not the main mode of transport for those people. Most of Child cards (children 5 to 14 years inclusive) are also Transit commuters due to their tight schedule and lack of travel activities. It is essential that the transit system is safe and reliable so that parents allow their young children to travel by public transport; otherwise there would be more drop-off/pick-up cars on the roads. School students still have a tight daily schedule similar to Child class. However, they have more travel activities and require more mobility than the Child class, which makes *Habitual time passenger* as the biggest contributor for this class. The majority of Tertiary students are *Regular OD passengers.* Their flexible study schedule is probably the reason for this trend. The major contributor in Senior and Pensioner classes is *Irregular passengers* because passenger from these classes are flexible in time and having no mobility need for work or study.

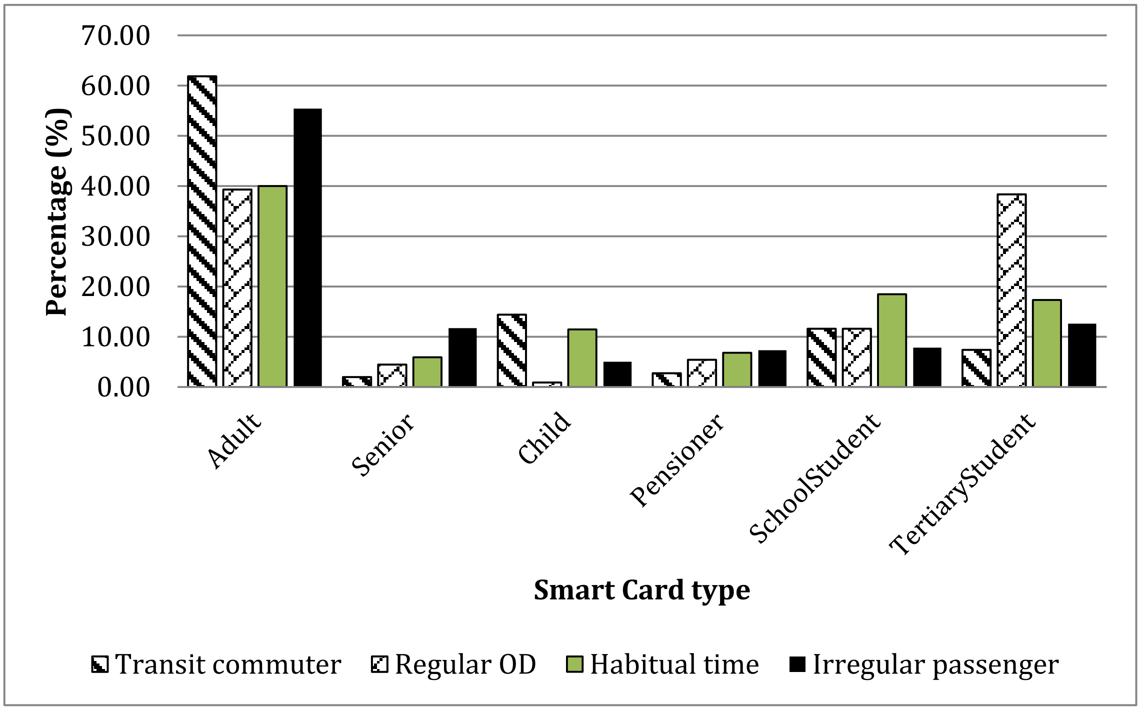


Figure 6.3-8. Proportion of each passenger type over different SC card class

6.3.5 **Frequency of transit usages**

This section investigates the transit usage frequency of different passenger types by data mining techniques. A dataset containing the number of boarding and travel days has been constructed for every passenger. Table 6.3-2 shows an example of the dataset.

Table 6.3-2. Dataset used in frequency of transit usage analysis

SC ID	Number of travelled day(s)	Number of journey(s) made
X1	48	86
X2	36	59
X3	23	47
X4	3	5
X5	1	2

The number of travel days and journeys made represent the frequency of use from each passenger. This section aims to find a threshold to differentiate between frequent and infrequent transit passenger. For that purpose, a *k*-mean algorithm is used to classify transit passenger into 2 clusters. The *k*-mean algorithm seeks to minimize the sum of all points to the centroid of each cluster (Morency et al., 2007). The objective function of the algorithm is expressed in formula (2)

Minimize: $$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (2)$$

Here,

j=1...k, where *k* is the number of predetermined clusters, in this case *k*=2

i=1…n, where *n* is the number of data points, in this case is the passengers, *n*=1,010,158

$\left\| x_i^{(j)} - c_j \right\|^2$ = distance measure between a data point $x_i^{(j)}$ and the cluster center c_j. Points $x_i^{(j)}$ and c_j are located in a 2-dimension space of number of travel days and number of trip made.

The algorithm is composed of the following steps:

a) Place all the points (passengers) into the 2-dimension space

b) Assign each point into the cluster of closest centroid

c) Recalculate the positions of the 2 centroids

d) Repeat step b and c until the centroids being stationed.

Figure 6.3-9 illustrates the classification result, whereas Figure 6.3-10 shows the proportion of frequent and infrequent passengers in each passenger type.

The majority of *Transit commuters* used the transit system frequently during the study period, while almost all *Irregular passengers* did not travel frequently. It means that passengers using public transport on a spatial and temporal travel pattern would also travel more than those having no travel pattern.

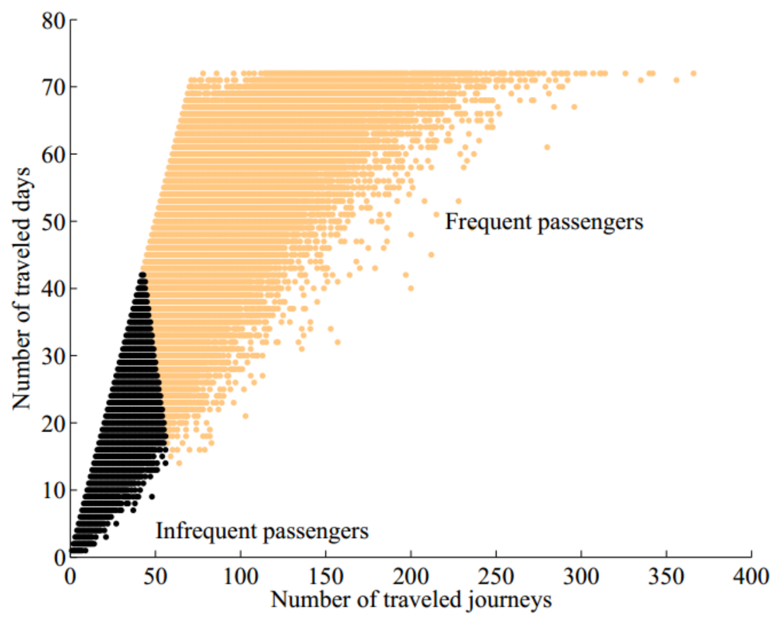


Figure 6.3-9. Classification of frequent and infrequent passenger

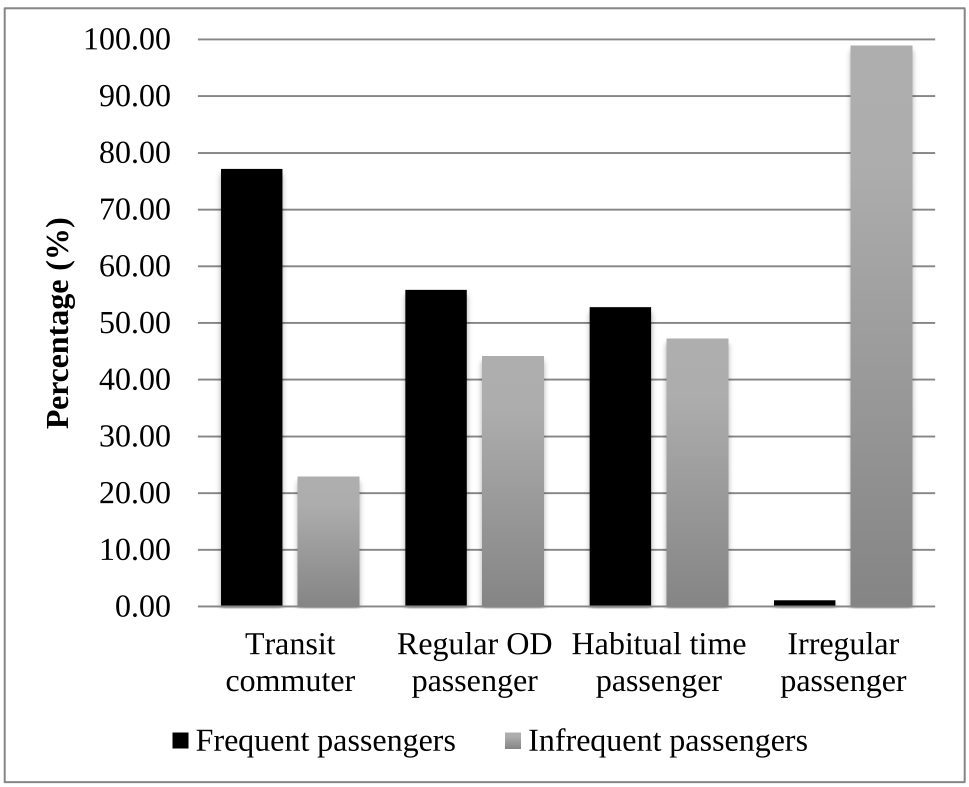


Figure 6.3-10. Frequency of transit usage in each passenger type

6.4 **Summary of chapter 6**

This chapter proposes a new method to segment transit passengers. The passengers were segmented into *Transit commuters, Regular OD passengers, Habitual time passengers,* and *Irregular passengers* by *a priori* passenger market segmentation approach. Mined spatial and temporal travel pattern from Chapter 5 have been used to identify passengers of similar travel behaviours. This section sums up the knowledge gained from analysing the passenger segments, as well as the scientific and practical contributions of this chapter. Table 6.4-1 shows the descriptive statistic of each passenger type.

Table 6.4-1. Descriptive statistic of transit passenger type

	% Card	% Revenue	Average transfer	Time per transfer (min)	Mean legs/journey	% Frequent	% Infrequent
Transit commuter	14.04	46.04	1.29	9.83	1.12	77.14	22.86
Regular OD passenger	12.86	21.38	3.24	12.79	1.24	55.84	44.16
Habitual time passenger	8.28	15.32	4.50	12.59	1.33	52.78	47.22
Irregular passenger	64.82	17.26	4.11	15.96	1.25	1.10	98.90

6.4.1 **Scientific and practical contributions**

The scientific contribution of this chapter is an automatic method to segment transit passengers into identifiable types of similar travel pattern. Unlike the existing transit market segmentation methods in the literature, the proposed approach in this chapter uses solely SC data without the need of a travel survey. The method proposed in this chapter provides a new method to continuously observe the evolution of transit passenger demand in both their travel behaviours and mobility needs. The method is easily replicated in any transit systems with SC system.

To transit authorities, all passengers deserve the utmost attention. The understanding of each passenger types, behaviours and needs facilitate the development of transit system and service provision to better serve each individual passenger. The characterization of passenger demand by the proportion of each type shows the overall service requirements for each region. For instance, an area of mainly *Regular OD passengers* would not require as much timely service as an area of *Transit commuters*, whereas too many *Irregular passengers* suggests a problem in transit service provided. Transit authorities could aim to raise the number of high-value customers such as *Transit commuters* for revenue and transit-oriented developments. Nevertheless, they could also fulfil the needs of other passenger types to maintain the customer equity and overall attractiveness of the system. This section suggests several practical service improvements using the knowledge of passenger segmentation.

1) Targeted survey could aim for the *Irregular passengers* to understand the disutility that limits the level of ridership. The segmentation results indicate that before thinking about attracting new customers, transit authorities should firstly encourage the majority of their customers to choose public transport as the main travel mode. The enormous number of operated SC does not tell much about passenger transit usages because 64% of them rarely travel. Transit authorities could pay special interest to passengers who were not *Irregular passengers* before, but recently became *Irregular passengers*. These are the potential customers whose behaviours have changed due to certain reasons that need to be identified. While mobility needs and lack of access to other mode of transport could be the reasons for using public transport, people who recently became *Irregular passengers* would have different reasons for ceasing their public transport use. Understanding these reasons would benefit transit authorities to prevent the reduction of patronage. Conversely, the reasons for an *Irregular passenger* to transform to another passenger type would be interesting successful stories to learn for further improving the transit system.
2) Transit authorities could also observe the impacts of recent transit policies to their customers. For instance, a policy on reducing transit fare during off-peak period would cause passenger, especially people who have flexible daily schedule such as *Regular OD passengers* to travel more during off-peaks. Transit authorities could foresee the number of affected passengers for this policy by looking at those who usually travel at the end of the peak period and are flexible in time. The number of passengers at each type before and after a policy implementation is an important evaluation of different fares, marketing and servicing strategies. For instance, more *Transit commuters* and less *Irregular passengers* mean that more passengers become daily user of public transport.

3) Finally, incentives and personalized service can be given to *Transit commuters, Regular OD* and *Habitual time passengers* to encourage passenger to use public transport for commuting. The characterization of regular behaviour provides a tremendous opportunity for transit authorities to provide personalized information and incentives to each passenger. Once a passenger enrolled in the system, real-time information on their regular journeys could be given to individual passenger. Special incentives can be given to promote the commuting behaviour, for instance by reducing ticket type on regular journeys. Although many SC systems are not associated with user contact information, travel pattern can be stored for each individual passenger through smart card IDs. Transit passengers can use a provided smartphone application to get customized real-time information from service providers for the service they regularly use. The information is given though the input of smart card ID and a proof-of-card ownership by the barcode behind each SC. By managing the customized information by hashed unique smart card ID, the information and service can remain customized for each individual and at the same time, maintain privacy.

6.4.2 Knowledge gained

The understanding of each passenger type augments passenger characterization. The following knowledge about transit riders could be gained from the passenger segmentation analysis.

1) The majority (64%) of operated SC are *Irregular passengers*, who do not follow any travel pattern. These passengers rarely travel by public transport (99% of them are infrequent user of the transit system) and in total contributes to only 17% of the total ticket revenue. It means that selling more SC would not earn much profit to both transit authority and the environment but they should be encouraged to make more journeys.
2) Most of *Transit commuters* would travel during peak periods and travel from outside to inside the CBD in morning peak, and vice versa for afternoon peak. *Transit commuters* only proportioned for around 14% of the SC population, but contributed to 46% of the revenue because the majority of them are frequent transit users (77%). It means that encouraging passengers to travel more regularly would also increase their frequency of travel. However, these passengers are directly affected by the transfer time, which could be one of the decision factors limiting their patronage.

3) *Regular OD passengers* represent people who are flexible in time but regularly travel between origin-destination pairs such as tertiary students. *Regular OD passengers* travel more in off-peak period than any other types.
4) *Habitual time passengers* represent people who usually travel within a regular time period, but travel to different destinations. Due to the need of traveling to multiple destinations, this type of passenger requires more transit mobility. Consequently, they take more transfers and more bus journeys than any other types. Examples of them are school students.

7 Online transfer coordination

The last two chapters develop a framework to mine individual passenger travel pattern and segment transit passengers into 4 identifiable classes. This chapter uses passenger travel pattern knowledge gained from these chapters to propose an Online Transfer Coordination Framework (ONTF) for better coordinated transfer to transit passengers in real-time.

The contents of this chapter are in preparation to submit in the following publications:

Journal articles

J5 Kieu, L. M., Bhaskar, A. & Chung, E. TBA. Transferring demand prediction for timed transfer coordination in public transport operational control. *Journal of Advanced Transportation*. (Under Review)

7.1 Introduction

The "hub-and-spoke" is a very successful transfer coordination system in air transportation, where incoming and outgoing flights are coordinated. In real-time when the incoming flight has been delayed for a certain amount of time, air controller may delay an outcoming flight to allow passenger transfer. The successful of transfer coordination in air transportation is highly dependent on three principal factors (Dessouky et al., 1999): (1) the delay of the incoming flight, (2) the number of transferring passengers, and (3) the frequency of the outgoing flight. While considerable research has been devoted to offline transfer coordination in transit planning, rather less attention has been paid to ONTF in operational strategies. ONTF in public transit is not as popular and successful as in the hub-and-spoke system air transportation, mainly because of the lack of knowledge on the second factor among the three aforementioned ones. In public transit, the number of transferring passenger is unknown due to the lack of passenger travel plan. It is then not possible to calculate the cost induced by the online transfer decision to transferring and non-transferring passengers.

Despite the lack of this information, the problem of online coordination in public transit has been addressed by several studies in the literature. The problem is often defined as a single transfer problem between one or several feeding (incoming) transit line with a single receiving (outgoing) line at a single transfer stop. Most of these studies relied on forecast of travel time and demand to predict the delay of the Feeder Vehicle (FV) and the number of transferring passengers. Dessouky et al. (1999, 2003) proposed travel time and passenger demand prediction algorithms using analytical simulation models to estimate the vehicle holding time for transfer coordination. The authors revealed that the presence of real-time AVL data and vehicle holding decision has the potential to reduce passenger transfer time. Chowdhury and Chien (2001) dynamically dispatched transit vehicle according to a cost function of holding vehicle cost, delay cost and passenger missed connection cost. Chung and Shalaby (2007) also used similar approach to estimate a cost function of transfer time, in-vehicle passenger waiting time and downstream passenger waiting time. The authors investigated the trade-off between these cost and emphasised that an online control was important to maintain coordinated transfer due to unexpected delays of transit vehicles. Hadas and Ceder (2010a) developed dynamic programming optimisation models of vehicle holding, skipping stop and short-turning to enhance coordinated transfer in real-time. The simulation analysis showed that the proposed model could reduce the total travel time by 10% and increase the chance of direct transfer by 200%.

The existing studies in literature provided insights into the problem of ONTF. Most of these studies showed the potential of ONTF in reducing passenger delay and enhancing the probability of transfers. The importance of travel time and passenger demand prediction have also been emphasized (Chung and Shalaby, 2007; Dessouky et al., 1999; Dessouky et al., 2003). However, due to the lack of passengers' transferring plan data, most of the recent advances in the literature were based on simulation, leaving the question of their practical applicability unanswered. The prediction of passenger transferring demand was performed using assumptions of transferring faction of the demand, rather than by looking passenger's transferring behaviours. These transferring fractions are deterministic and whether they sufficiently represent the real transferring demand is also unknown.

This chapter fills these gaps using the passenger travel pattern and segmentation knowledge gained from the Chapter 5 and 6. Passengers' transferring plan is forecasted using historical passenger travel pattern. The two principal contributions of this chapter includes: (1) the integration of passenger travel pattern to predict the number of transferring passengers; and (2) the development and testing of the ONTF control framework using real world AVL and AFC data. Figure 7.1-1 illustrates the ONTF control framework

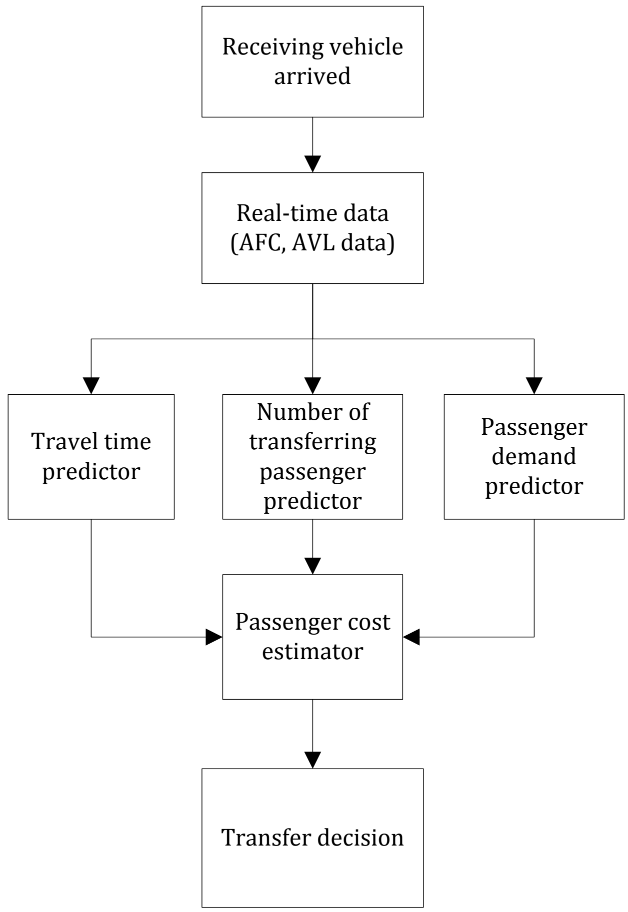


Figure 7.1-1 Study framework

Three main predictions are combined to calculate these costs:

- arrival time of Feeding Vehicle (FV)
- number of transferring passengers from feeding to Receiving Vehicle (RV)
- non-transferring demand of RV

We predict the number of transferring passenger using knowledge of individual travel pattern. A travel time and a demand predictor are also developed to predict the other two unknowns in passengers expected travel time. We adopted different statistical and computational intelligence models to compare and choose the best model in terms of predicting accuracy and computation time to be used in the ONTF framework. While statistical models are descriptive, and represent the statistical properties of data and their dependence on covariates, computational intelligence models such as Artificial Neural Network (ANN) generally would encapsulate the complex relationship between the dependent and independent variables (Meireles et al., 2003). The travel time cost to each individual passenger is estimated and compared to issue a transferring decision that is best for the majority of passengers. A numerical sensitivity analysis using observed and simulation data under different predicting power, arrival time and passenger demand range will investigate the feasibility of the proposed framework in practice.

The chapter is structured as follows. Section 7.2 further describes the research problem and the case study. Section 7.3 presents the method used to predict bus travel time, number of transferring passengers and demand, as well as the passener cost estimation and transfer decision making framework. Section 7.4 provides a transfer coordination framework in operational control, follows by the simulated sensitivity analysis in Section 7.5. Finally, Section 7.6 sums up the findings, constributions and knowledge gained from this chapter.

7.2 **Problem and case study**

7.2.1 **Research problem**

ONTF is a real-time problem involving two transit vehicles of different routes, where passengers from the feeding route are transferring to the receiving route. The problem arises when the RV arrives at the transfer stop before the arrival of the FV. It is then broken down to a binary problem of whether the RV should wait for the coming FV, so that passengers can make transfers, or leave the transfer stop as scheduled. The coordination problem could also be defined as a vehicle holding problem, where the RV is held at the transfer stop to allow passenger transfers (Chung and Shalaby, 2007; Dessouky et al., 2003; Hadas and Ceder, 2010a).

This chapter assumes the following

- Automatic Vehicle Location (AVL) and Automatic Fare Collection (AFC) data are available in real-time. Although AFC data is traditionally not available in real-time, the advancement of communication technology would soon enable transit agencies to dynamically access passenger travel pattern through Smart Cards. The Automatic Passenger Counter data, which was also developed for ticketing purpose, has been widely available in real-time (Chen et al., 2004).

- RV always departs the transfer stop as scheduled, except as otherwise explicitly planed by the online coordination framework, or already arrived later than the scheduled departure time. All passengers boarding at the first stop are done before the dispatch time, so that vehicle can depart on-time. This assumption is equivalent to the transfer stop being the time-point of the RV, which makes the prediction of next coming RV obsolete. Prediction of the next coming RV is only necessary in high frequency system where the next RV is predicted to arrive within a short time and it is therefore not worthwhile to coordinate transfer. However, frequent RV does not require transfer coordination at the first place because transfer waiting time is always low. The set-up of this dissertation includes a high frequency FV (Route 555 with 15 minutes headway) and a low frequency RV (Route 572 with 30 minutes headway). In this case transfer coordination brings significant benefits, as discussed in the introduction.
- Transit vehicle is only held at the studied transfer stop, as no advantage is gained otherwise
- Holding the RV for ONTF will not affect its travel time downstream of the transfer stop

Figure 7.2-1 demonstrates the coordination problem in a time-space diagram. Here, at current time A_r the RV has just arrived at the transfer stop, while the FV is currently travelling to the stop. The ONTF framework will have to decide whether the RV should be held until the FV arrives- coordinated transfer decision, or leave as scheduled at S_r -no coordinated transfer decision. While offline transfer coordination does not increase the waiting time of non-transferring passengers because only the schedules of the two transit lines are adjusted, both coordinated and no coordinated decision in ONTF will induce some Extra Waiting Time (EWT) into transferring or non-transferring passenger. In coordinated transfer decision, transferring passengers will have zero transferring time, but non-transferring passenger of the RV may have EWT, depends on whether the arrival time of the FV is before or after the scheduled departure time of the RV. Therefore in this chapter we use EWT as one of the criteria for evaluating ONTF strategies, instead of just transfer time as in Chapter 4. EWT is defined as the total additional time cost induced by the transfer coordination/no coordination decision to transferring and non-transferring passengers. In no coordinated transfer decision, transferring passenger will have to wait for the next service, while non-transferring passenger will have no EWT.

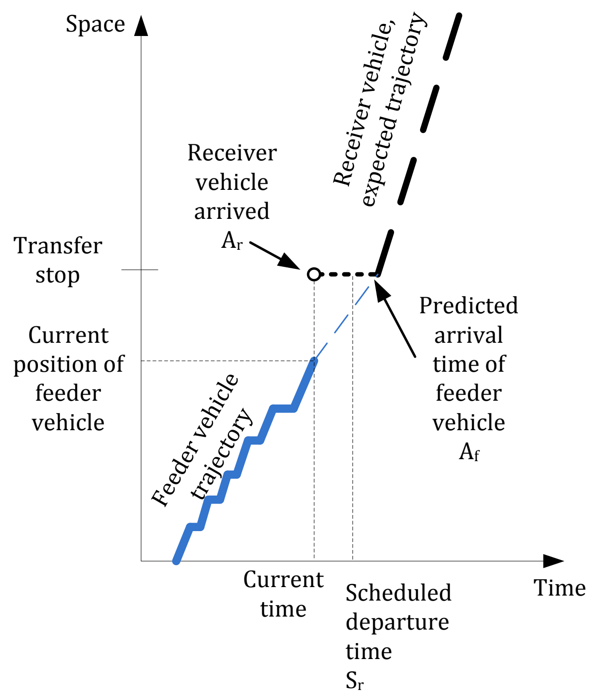


Figure 7.2-1 ONTF problem

The ONTF framework aims to estimate these costs in real-time to issue a decision that will induce the least EWT to transferring and non-transferring passenger. It is assumed that RV arrives earlier than FV ($A_r<A_f$). There are generally two cases where the RV arrived earlier or sooner than its schedule.

1) Case 1: RV arrived sooner than its schedule ($A_r < S_r$)

The EWT_r (min) for non-transferring passengers of the RV, once transfer coordination decision has been issued

$$EWT_r = \begin{cases} \left(\bar{A}_f - S_r + \overline{LT}_e / 60\right) \times \bar{N}_r & if \;\; \bar{A}_f > S_r \\ 0 & \bar{A}_f \le S_r \end{cases} \qquad (36)$$

Where EWT_r = total EWT of non-transferring passengers of the RV at transfer coordination strategy (min)

$\bar{A}_f$ = estimated arrival time of the FV to the transfer stop (min from 0:00)

S_r = schedule departure time of the RV from the transfer stop (min from 0:00)

$\bar{N}_r$ = estimated number of non-transferring passengers of the RV

$\overline{LT}_e$ = extra loading time induced by extra passengers (transferring passengers) boarding the RV (seconds). $\overline{LT}_e$ is the compilation of the lost time of FV stopping, passenger alighting time from FV, passenger walking time to RV, and passenger boarding time to RV.

Conversely, if no transfer coordination has been issued, the EWT for transferring passenger to wait for the next service could be calculated as

$$EWT_f = \begin{cases} \left(S_r + H - \bar{A}_f\right) \times \bar{N}_f & if \ \bar{A}_f > S_r \\ 0 & \bar{A}_f \leq S_r \end{cases} \tag{37}$$

Where EWT_f = total EWT of transferring passengers at no transfer coordination strategy (min)

H = schedule headway of the RV (min)

Figure 7.2-2 illustrates the case 1 of the ONTF problem

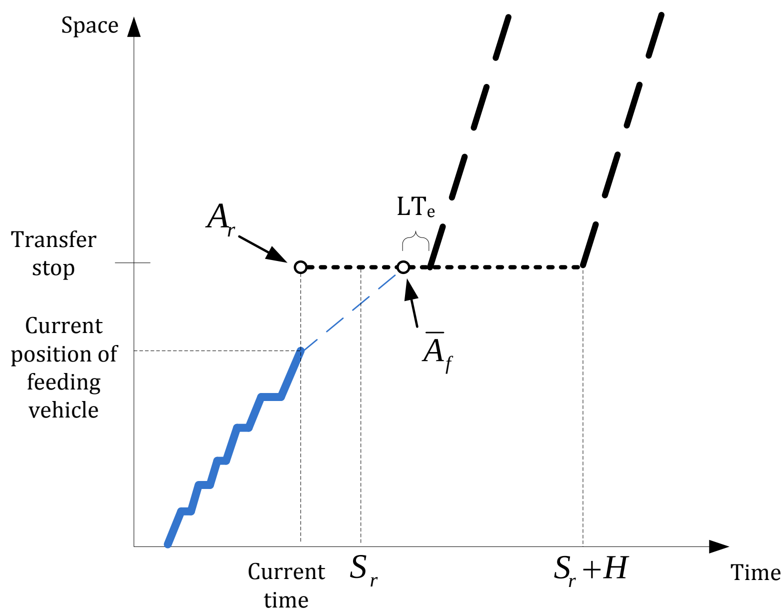


Figure 7.2-2 ONTF Case 1 ($A_r < S_r$)

2) Case 2: RV arrived later than its schedule ($S_r \le A_r < A_f$)

The EWT_r (min) for non-transferring passengers of the RV, once transfer coordination decision has been issued

$$EWT_r = \left(\bar{A}_f - A_r + \overline{LT}_e / 60\right) \times \bar{N}_r \qquad (38)$$

Where A_r = actual arrival time of the RV to the transfer stop (min from 0:00)

Conversely, if no transfer coordination has been issued, the extra cost for transferring passenger to wait for the next service could be calculated as

$$EWT_f = \left(S_r + H - \bar{A}_f\right) \times \bar{N}_f \qquad (39)$$

Figure 7.2-3 illustrates the Case 2 of the ONTF problem.

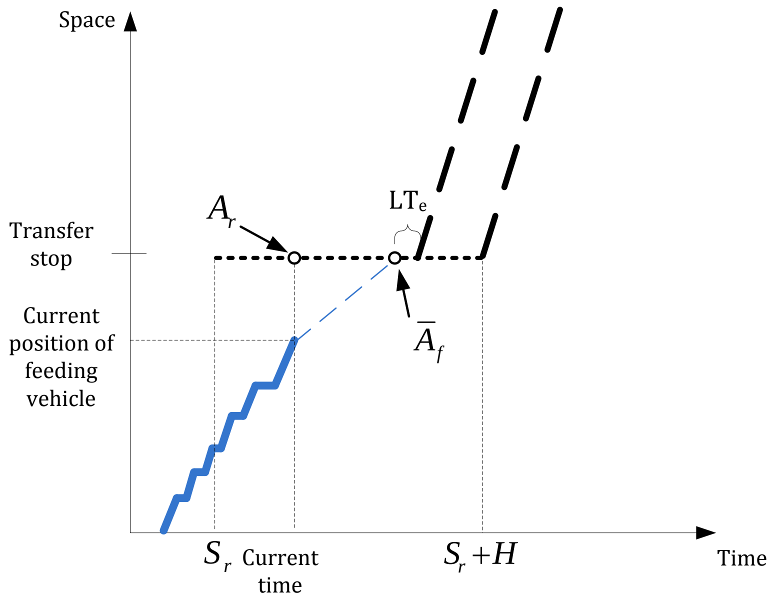


Figure 7.2-3 ONTF Case 2 ($S_r \le A_r < A_f$)

ONTF framework issues the yes-or-no coordinated transfer decision by comparing EWT_r and EWT_f.The online coordination framework will be further developed later in this chapter.

7.2.2 **Case study**

The ONTF – also named "connection protection" in previous studies (Chung and Shalaby, 2007) generally involves the transfer from a feeding transit line to another receiving transit line. This chapter uses the same study site and set of AVL and AFC data as Chapter 4. Figure 4.2-2 illustrates the case study in this chapter.

For online coordination, we only focus on the case where the Route 572 (RV) vehicle arrives to the Springwood station earlier than Route 555 (FV) vehicle, and the gap between these two arrivals are equal to or less than 10 minutes. Online coordination is defined as the control strategy where RV is held to wait for the arrival of FV. Since there are two Route 555 services for every Route 572 service, this chapter focuses on the transfer coordination of the direct-transfer service of Route 555 (similar to the Chapter 4). The threshold of 10 minutes is chosen because the frequency of Route 572 is 30 minutes, so a gap of 15 minutes or more means that the passengers should wait for the next Route 572 service, rather than making any transfer coordination.

There is no ONTF currently employed at Route 555 and 572. We develop the online coordination framework using the AVL and AFC data of July to September 2013 and test it using the data of October 2013.

7.3 **Methodology**

Section 7.2.1 describes the ONTF problem. This section develops the predictive method to supply the parameters $\bar{A}_f$, $\bar{N}_f$, $\bar{N}_r$ to estimate EWT_r and EWT_f. The prediction process is as follows

1) At current time A_r when the Route 572 vehicle arrives at the transfer stop, the system enquires the last known location of the Route 555 vehicle (last dwelling at transit stops), and the *CardID* of all passengers inside the Route 555 vehicle
2) Three predictors forecast the values of arrival time of the Route 555 vehicle ($\bar{A}_f$), number of transferring passengers ($\bar{N}_f$), and number of non-transferring passengers ($\bar{N}_r$) from the information of last known location of the Route 555 vehicle
3) The three predicted values and observed values are supplied into the EWT estimator to compare EWT_r and EWT_f and issue the binary $decision_{transfer}$

The following sub-section describes the predictors of $\bar{A}_f$, $\bar{N}_f$, $\bar{N}_r$

The models are developed from 3 months of Smart Card AFC and AVL data from July to September 2013, and tested using another month of AFC and AVL data of October 2013. This chapter focuses on working days only, i.e. weekdays except public holiday and school holiday. Table 7.3-1 describes the training and testing dataset used in this chapter.

Table 7.3-1 Dataset description

Model	Training dataset	Testing dataset
$\bar{A}_f$	AVL (Jul-Sep 2013)	AVL (Oct 2013)
$\bar{N}_f$	AFC (Jul-Sep 2013)	AFC (Oct 2013)

$\bar{N}_r$	AFC (Jul-Sep 2013)	AFC (Oct 2013)

7.3.1 Predicting the bus arrival time $\bar{A}_f$

Introduction

The travel time, as defined in the passenger view's in Transit Capacity and Quality of Service Manual (TRB, 2003) is the total time it takes to travel from the origin to the destination. In this study, we define the travel time as the total time it takes to travel from one bus stop to another i.e., the time difference of the arrival time of a bus at upstream and downstream bus stops. The travel time definition is illustrated in the Figure 7.3-1.

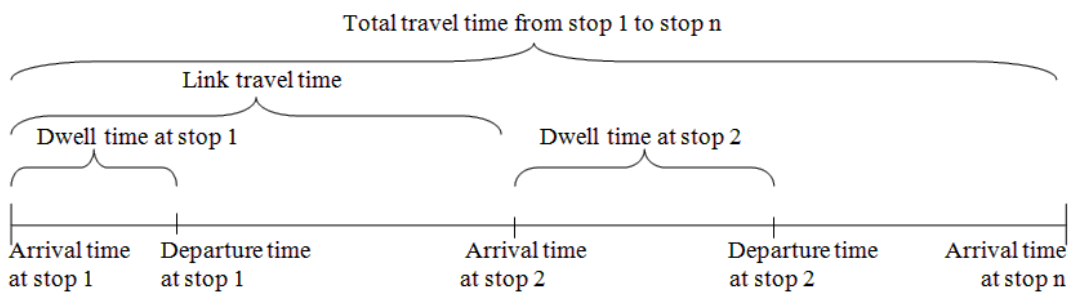


Figure 7.3-1 Travel time and related glossary

The travel time prediction model in this sub-section aims to predict the link travel time from the arrival time to the last known stop to the arrival time at the transfer stop.

$$\bar{A}_f = TT + Arr_i \qquad (40)$$

Where $\bar{A}_f$ is the estimated arrival of the studied Route 555 vehicle at the transfer stop

Arr_i = last observed arrival at a transit stop *i* of the studied bus

TT = predicted link travel time

The problem of bus travel time prediction has been extensively studied in the literature. This sub-section develops ANN models to predict bus travel time from last known position to the transfer stop. Interested readers of this problem could find the literature review of bus travel time prediction on APPENDIX B.

Methodology

This sub-section develops different types of ANN to predict the bus travel time. Table 7.3-2 shows the descriptive statistic of the variables used in the models proposed here.

Table 7.3-2 Descriptive statistic of variables using in bus travel time prediction models

Dependent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
TT	14606	363.01	290.52	60	1529	Observed bus travel time (s)
Independent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
1.Time_of_day	14606	11.49	3.97	0	23	Time of day in hour
2.Number_of_stop	14606	2.76	1.48	1	5	Number of stop from the last known location to the transfer stop
3.LastSpeed	14606	40.08	5.3	17.5	62.2	Last known link speed (km/h)
4.PriorTT	14606	361.09	286.19	60	1010	Last observed travel time of preceding bus on same link (s)
5.Headway	14606	10.49	5.87	0.017	29.98	Headway to the preceding bus (min)
6.Day_of_week	14606	4.27	1.4	2	6	Day of week (2-Monday to 6-Friday)
7.SchedTT	14606	414.96	222.66	120	840	Schedule travel time of the studied link

We develop 3 types of ANN for predicting the bus travel time: the conventional Multi-Layer Perceptron (MLP) feedforward-network, Cascade Correlation Neural Network (CCNN) and Bagging Ensemble Feedforward Network. The developments and descriptions of these models could be found on APPENDIX B.

Numerical experiment

This section compares the predicting accuracy of MLP feedforward, CCNN and Bagging ensemble feedforward networks in bus travel time prediction. The AVL data of October 2013 has been used to test those models. Table 7.3-3 shows the descriptive statistic of the testing data.

Table 7.3-3 Descriptive statistic of the testing data for bus travel time prediction

Dependent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
TT	4932	359.76	295.68	60	1537	Observed bus travel time (s)
Independent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
1.Time_of_day	4932	11.47	3.95	0	23	Time of day in hour
2.Number_of_stop	4932	2.74	1.47	1	5	Number of stop from the last known location to the transfer stop
3.LastSpeed	4932	39.89	5.4	16.8	61.7	Last known link speed (km/h)
4.PriorTT	4932	357.61	281.45	60	996.14	Last observed travel time of preceding bus on same link (s)
5.Headway	4932	10.06	5.95	0.014	30.24	Headway to the preceding bus (min)
6.Day_of_week	4932	4.26	1.35	2	6	Day of week (2-Monday to 6-Friday)
7.SchedTT	4932	409.15	219.9	120	840	Schedule travel time of the studied link

The models are compared by calculating their prediction error, quantified by Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(o_i - m_i)^2} \qquad (41)$$

Where N = number of testing data

o = observed bus travel time

m = model output value

Figure 7.3-2 compares the prediction error of the 3 aforementioned models and the schedule-based travel time prediction.

Schedule-based model is the prediction of travel time solely base on the schedule of Route 555. The three proposed models provide a significantly better predicting power than the schedule-based model, especially when the number of stop is large. The MLP feedforward and CCNN model show similar prediction error of approximately 105s for 5-stop prediction and 45s for next stop prediction. Bagging ensemble feedforward network provides the best prediction in terms of RMSE, especially at next stop prediction, where the RMSE could reach as low as 38s.

The comparison of prediction error between MLP feedforward, CCNN, Bagging ensemble feedforward network and schedule-based model shows that Bagging ensemble feedforward network has the lowest prediction error. Therefore, bagging ensemble feedforward network is used for further analysis.

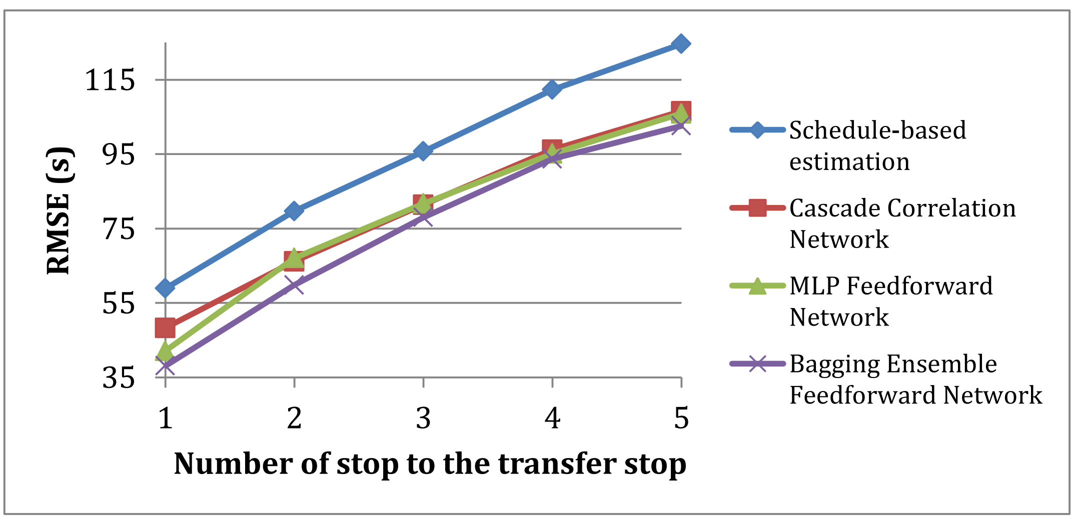


Figure 7.3-2 Comparison of bus travel time prediction models

7.3.2 Predicting the number of transferring passengers $\overline{N}_f$

Introduction

The number of transferring passengers is the amount of passengers who transfer from a running Route 555 vehicle to a Route 572 vehicle. As described in Section 1.2 of this thesis, the central issue in ONTF of public transit is the lack of passengers transferring plan due to the anonymousness of passengers and the stochasticity of their behaviours. Therefore, among the three predictions of $\overline{A}_f$, $\overline{N}_f$, $\overline{N}_r$, the number of transferring passengers is the most challenging. Previous research has concentrated on predicting the short-term passenger demand or vehicle occupancy, rather than the number of transferring passenger from a moving vehicle in real-time.

Although considerable research has been devoted to long-term passenger demand prediction, the problem of short-term demand forecasting has only investigated in recent studies. Tsai et al. (2003) developed three structures of neural network to predict the total passenger volume at a railway system for revenue management. The prediction results showed that both Multiple Temporal Units Neural Network (MTUNN), and Parallel Ensemble Neural Network (PENN) outperform the conventional Multilayer Perceptron (MLP) in predicting the passenger demand. Ma et al. (2006) proposed an Interactive Multiple Model-based Pattern Hybrid (IMMPH) framework based on three time-series models and an online amended IMM algorithm to predict the short-term demand of a transit system. The IMMPH approach is showed as more accurate, robust and has more explanatory power than statistical methods and neural networks. While Tsai et al. (2003) and Ma et al. (2006) aimed to forecast the total demand volume of a whole transit system, Chen et al. (2011) aimed to predict the actual passenger boarding at each transit stop. The authors developed a Least Squares Support Vector Machine (LS-SVM) model to predict the passenger flow for a bus route in Changchun, China. The proposed methodology also includes a Genetic Algorithm to optimise the parameters of the LS-SVM.

As far as the author's knowledge, there is not yet any full insight into the short-term transferring passenger prediction. However, the existing studies in short-term demand prediction provide some ideas for the proposed transferring passenger model in this chapter.

Methodology

This chapter defines the transferring passenger prediction problem as a common multivariate count regression problem of a single dependent variable ($\overline{N}_f$) and multiple independent variables describing $\overline{N}_f$. This section prepares the dependent and independent variables for transferring passenger prediction. The prediction model in this section is developed using the AFC data.

The dependent variable $\overline{N}_f$ is a common count data variable. Count data is a statistical data type in which the observations are non-integer values. Figure 7.3-3 illustrates the CDF of the number of transferring passengers from a Route 555 to a Route 572 service, and the total number of alighting passengers at the Springwood station from a Route 555 service

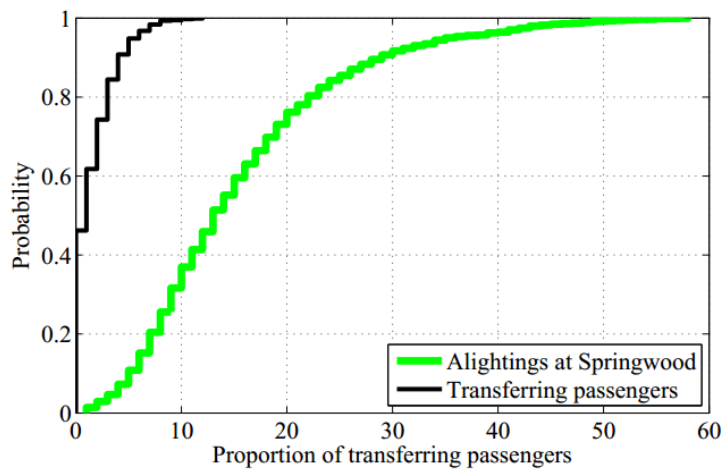


Figure 7.3-3 Cumulative density function of the number of transferring passengers and number of alighting passengers from a Route 555 service

Springwood station as a major bus stop attracts a high volume of alighting passengers, which could be up to nearly 60 passengers. However, the number of transferring passengers is generally less than 10, with 60% of chance being zero. Figure 7.3-3 verifies that $\overline{N}_f$ is a count data, and also suggests that it has a zero-inflated probability distribution.

Among the factors that could affect $\overline{N}_f$, the passengers-behaviour-related factors are the most important. Chapter 5 and 6 proposed algorithms to mine individual travel pattern and segment transit passengers into 4 identifiable types. Based on the methods proposed in these Chapters, this chapter develop $\overline{N}_f$ prediction models using two classes of passengers:

- Spatially Regular Passenger (SRP): Passenger who has regular pattern spatially, i.e. regularly travel between fixed places.
- Spatially Irregular Passenger (SIP): Passenger who do not have spatial regular pattern.

The SRP class is basically the combination of *Regular OD* and *Transit Commuters* segment, and SIP class is the *Habitual time* and *Irregular passenger* segment. *Habitual time passengers* are indeed not *Irregular passengers,* but also grouped in the same SIP group because here we only consider spatial travel pattern. These two classes can be found using the methods proposed in Chapter 5 and 6. Figure 7.3-4 classifies transit passengers into SRP and SIP.

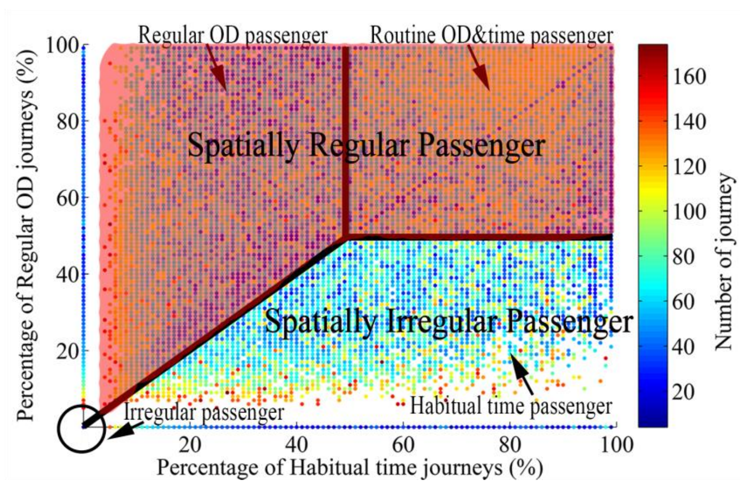


Figure 7.3-4 Passenger classification into SRP and SIP

The figure is similar to the original Passenger Segmentation Heuristic in Chapter 6. Although SRP is accommodated for only 21% of the total passenger population, more than 80% of the 555 journeys are from SRP passengers. Therefore, if we assume that SRP passenger will follow their usual spatial behaviour, we would have more than 80% confidence in predicting the number of transferring passengers. Approximately 14.52% of Route 555 passengers would transfer to a Route 572 service. On the other hand, we found on average 29.44% of Route 572 passengers have transferred from a Route 555 service. Table 7.3-4 shows the descriptive statistic of the dependent and independent variables.

Table 7.3-4 Descriptive statistic of variables using in transferring passenger prediction models

Dependent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
$\bar{N}_f$	3243	1.25	1.66	0	12	Number of transferring passengers from a Route 555 service
Independent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
1.SRP	3243	7.43	6.77	1	60	Number of SRPs
2.SIP	3243	1.75	2.06	0	16	Number of SIPs
3.HProbTransfer	3243	0.9	1.39	0	11	Number of SRP that has high probability of transferring
4.MeanTransfer	3243	1.19	1.51	0.74	1.35	Mean number of transfer at the time period (30mins window)
5.MeanSIPTransfer	3243	0.17	1.16	0.02	0.42	Mean number of SIP that transfer at the time period (30mins window)
6.AM	3243	0.31	0.46	0	1	1 if AM peak, 0 otherwise
7.MID	3243	0.26	0.45	0	1	1 if Midday period, 0 otherwise

HProbTransfer is the count of SRP passengers who are likely to transfer. They are the SRP passengers that in their historical travel pattern have more than 50% chance of transfers. The following sections develop simple analytical model, statistical model and data mining model to predict $\bar{N}_f$.

Simple analytical model

Analytical model has a mathematical closed form solution, which is tractable and high explanatory power. It is therefore the preferable type of modelling whenever it is possible. This section aims to develop a Simple Analytical (SA) model to predict $\bar{N}_f$ only by using *HProbTransfer* and *MeanSIPTransfer*. The idea is that if all SRP who is likely to transfer would make the transfer, then we only need to add the average number of transferring SIP within the same period to make up the $\bar{N}_f$.

$$\bar{N}_f = HProbTransfer + MeanSIPTransfer \quad (42)$$

The model has no intercept because when *HProbTransfer* and *MeanSIPTransfer* are both zero, we should have no transferring as well. While *MeanSIPTransfer* solely depends on the input data, the value of *HProbTransfer* depends on how much of probability is defined as "likely to transfer". For instance, if "likely to transfer" is defined as 20%, an individual regular passenger must have at least 20% of trips that s/he transferred at the Springwood station among the total trips in the historical dataset to be considered as "likely to transfer". In that case the value of *HProbTransfer* will be added by 1. *HProbTransfer* could be calculated as

$$HProbTransfer = \sum_{i=1}^{N} (\Pr(\text{transfer})_i \geq T) \quad (43)$$

Where T is the "likely to transfer" definition, $\Pr(\text{transfer})_i$ is the probability that passenger i among the total N passengers inside the feeding vehicle will transfer at the upcoming transfer stop. Table 7.3-5 shows an example of "likely to transfer" definition and how *HProbTransfer* is calculated.

Table 7.3-5 Examples of transfer probability

Passenger ID	Probability of transfer	T= 20%	T= 40%	T= 60%	T= 80%
X1	79%	1	1	1	0
X2	45%	1	1	0	0
X3	25%	1	0	0	0
HProbTransfer		3	2	1	1

As we increase the value of T, *HProbTransfer* reduces. Figure 7.3-5 shows that with different definition of high transferring probability, accuracy of the SA model changes.

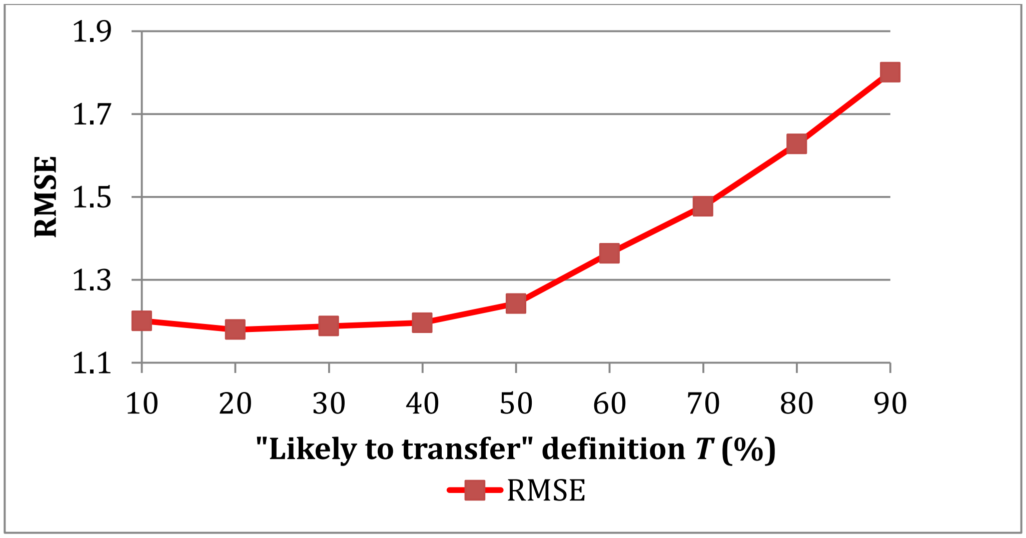


Figure 7.3-5 Root Mean Squared Error (RMSE) of SA model at different definition of "likely to transfer"

Figure 7.3-5 shows that the high transferring probability definition of 20% yields the lowest RMSE. Therefore, *HProbTransfer* values with this definition will be used throughout this chapter for predicting the number of transferring passengers.

The variable *HProbTransfer* in Equation (42) predicts the number of transferring SRP by assuming that all SRP who are likely to transfer will transfer. The variable *MeanSIPTransfer* predicts the number of transferring SIP. However, Figure 7.3-5 shows that the lowest RMSE the SA model can reach is 1.2 passengers, which is quite large since the average number of total transferring passengers in 1.25 (See Table 7.3-4). Figure 7.3-6 and Figure 7.3-7 investigate the relationship between *HProbTransfer* & the observed count of SRP transferred and *MeanSIPTransfer* & observed count of SIP transferred. Figure 7.3-6 shows that *HProbTransfer* represents well the observed count of SRP transferred. We can fit a *y equals x* linear regression line between these two variables and get very high R-squared value of 0.92. It confirms that simply using *HProbTransfer* to predict the observed count of SRP transferred will yield good results. However, Figure 7.3-7 shows that the observed count of SIP transferred has a much larger spread than the value of *MeanSIPTransfer*. While *MeanSIPTransfer* is approximately 0 – 0.4 at all time periods, the observed values of SIP transferred range from 0 to 6 passengers. Therefore, the use of *MeanSIPTransfer* limits the prediction accuracy of the SA model.

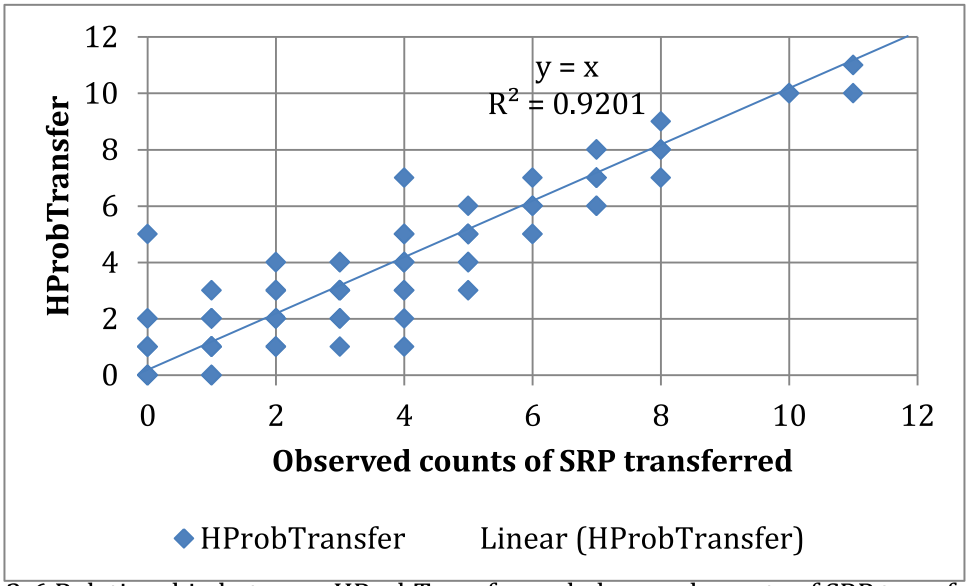


Figure 7.3-6 Relationship between HProbTransfer and observed counts of SRP transferred

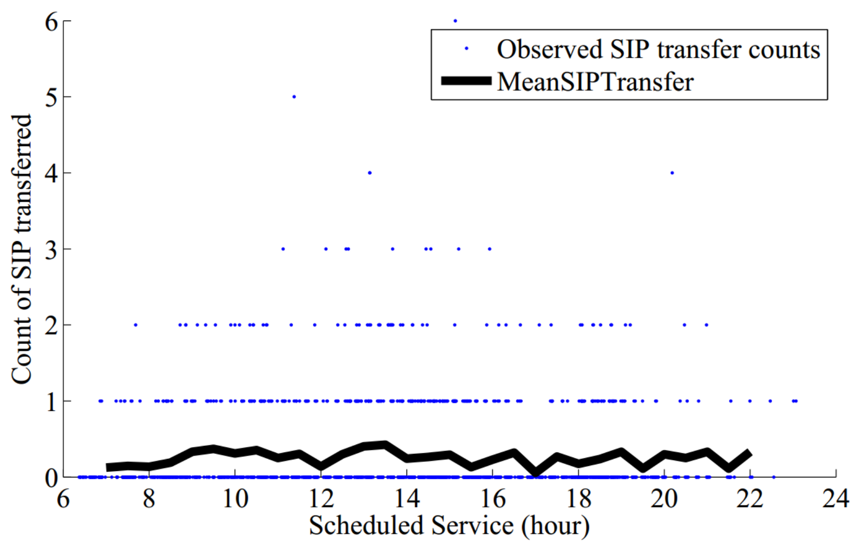


Figure 7.3-7 Value of *MeanSIPTransfer* and observed number of SIP transferred

Although SA offers a simple method to predict the number of transferring passengers, Figure 7.3-5, Figure 7.3-6 and Figure 7.3-7 demonstrates that the prediction accuracy of SA model is limited. The next sub-sections will investigate other predicting methods.

Statistical model

Linear regression, particularly Ordinary Least Squares (OLS) regression is often first considered to model non-categorical data. The OLS regression is one of the most common statistical models in statistic. However, OLS regression assumes that the dependent variable is continuous and linearly related to the independent variable; the residual is normally distributed and homoscedastic. Count data variables often lead to a violation of these assumptions.

Count data is common in many disciplines including transportation engineering. Quddus (2008) adopted Integer-Valued AutoRegressive (INAR) Poisson time series model to estimate the traffic accidents counts in Great Britain. Frondel and Vance (2011) surveyed adult members of German households to examine the determinants of public transport ridership. Zero-inflated models were developed to quantify the effects of fuel price, fare, personal and transit system attributes, as the ridership counts was modelled as count data. Fuel price was identified as having a positive impact on the ridership. This sub-section develop statistical count data model to predict the number of transferring passengers.

Poisson or Negative Binomial distribution is often assumed for modelling the distribution of observed count data. A random variable Y is said to have a Poisson distribution with parameter μ if it takes integer values y= 0,1,2,… with probability

$$P\left(y|\mu\right)=\frac{e^{-\mu}\mu^{y}}{y!} \qquad (44)$$

μ = both mean and variance of this distribution, or in other words, "equi-dispersed" (μ >0)

In our specific problem, μ refers to the expected transferring passengers, whereas y refers to the observed (real) number of transferring passengers. Poisson Regression models log of μ as a function of independent variable X_j.

$$\ln\left(\mu\right)=\sum_{j=1}^{K}\beta_j X_j \qquad (45)$$

In this form, the Poisson Regression is relatively similar to the OLS, with the log form of the dependent variable to avoid negative values. The formula can be rewritten as

$$\mu=e^{\sum_{j=1}^{K}\beta_j X_j} \qquad (46)$$

Where X_j independent variables (predictors) and regression coefficients β_j are to be estimated using Maximum Likelihood estimation.

However, Poisson regression relies on a strong assumption that the variance of the dependent variable equals its mean. This assumption is often not met in observed data due to its skewness. If the transferring passenger variable is "over-dispersed" or in other words, its variance exceeds the mean, we could also use the Negative Binomial distribution to model the dependent variable. Negative Binomial distribution describes "over-dispersed" count data better but has one more parameter compared to the Poisson Distribution. Its probability function could be written as

$$\Pr\{Y = y\} = \frac{\Gamma(y+1/\alpha)}{\Gamma(y+1)\Gamma(1/\alpha)}\left(\frac{1}{1+\alpha\mu}\right)^{1/\alpha}\left(\frac{\alpha\mu}{1+\alpha\mu}\right)^{y} \quad (47)$$

Where y= 0,1,2,… in this case it is the number of transferring passengers

μ = mean of this distribution (μ >0)

α = dispersion or heterogeneity parameter, where $\mu + \frac{\mu^2}{\alpha}$ is the variance of this distribution

If the dependent variable has excessive zeros, both the Poisson and Negative Binomial model will under-predict zeros. In this case, a zero-inflated Poisson (ZIP) or Negative Binomial (ZINB) model will be needed. This type of model assumes two distinct groups of observed dependent variables:

- Type 0 contains only zero – no probability of non-zero values
- Type 1 contains only positive count values, probability is varied but not zero

Zero-inflated model is a mix of two processes-one that determines if the individual is eligible for a Type 1 response, and another that determines the count of that response for eligible individuals. The first process uses a logit model to quantify the probability of being eligible for a Type 1 response, whereas the second process is a regular Poisson or Negative Binomial Regression model.

We adopt Vuong test to decide if ZIP and ZINB models are used instead of the classical Poisson and Negative Binomial Regression model or not. The Vuong test (Vuong, 1989) is designed to test the fitness of two different models on the same dataset using maximum likelihood. It tests the null hypothesis that the two models fit the observed data equally well. The Vuong test results of the data in this study show that ZIP and ZINB should be used instead of the classical Poisson and Negative Binomial Regression model.

The modelling results of ZIP and ZINB regression could be found in Table 7.3-6 and Table 7.3-7.

Table 7.3-6 Zero-Inflated Poisson Regression results (ZIP)

(a) Count model coefficients (Poisson with log link):

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.575046	0.003254	176.737	< 2e-16	***
SRP	0.001522	0.000181	8.404	< 2e-16	***
HProbTransfer	0.110855	0.000423	261.975	< 2e-16	***
SIP	0.085221	0.000528	161.339	< 2e-16	***
MeanSIPTransfer	0.017729	0.001579	11.229	< 2e-16	***
AM	-0.10031	0.003171	-31.629	< 2e-16	***
MID	-0.05308	0.003428	-15.483	< 2e-16	***
MeanTransfer	0.07844	0.0011	71.283	< 2e-16	***

(b) Zero-inflation model coefficients (binomial with logit link):

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	2.686003	0.02368	113.43	< 2e-16	***
SRP	-0.11389	0.002107	-54.054	< 2e-16	***
SIP	-0.15448	0.005978	-25.842	< 2e-16	***
AM	-0.27301	0.022234	-12.279	< 2e-16	***
MID	-0.43215	0.021415	-20.179	< 2e-16	***
MeanTransfer	-2.42785	0.023943	-101.403	< 2e-16	***

Vuong test of ZIP vs. standard Poisson: z = 137.8 (Pr>|z| = 0)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 7.3-7 Zero-inflated Negative Binomial Regression results (ZINB)

(a) Count model coefficients (negbin with log link):

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.431744	0.004062	106.298	< 2e-16	***
SRP	0.0017	0.000205	8.3	< 2e-16	***
HProbTransfer	0.146872	0.000657	223.632	< 2e-16	***
SIP	0.095082	0.000686	138.556	< 2e-16	***
AM	-0.09999	0.003524	-28.378	< 2e-16	***
MID	-0.02685	0.003772	-7.118	1.09E-12	***
MeanTransfer	0.065339	0.00134	48.748	< 2e-16	***
Log(theta)	2.94032	0.013883	211.798	< 2e-16	***

(b) Zero-inflation model coefficients (binomial with logit link):

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	2.729512	0.026063	104.729	< 2e-16	***
SRP	-0.12527	0.002465	-50.825	< 2e-16	***
SIP	-0.1366	0.006681	-20.446	< 2e-16	***
AM	-0.09999	0.003524	-28.378	< 2e-16	***
MID	-0.02685	0.003772	-7.118	1.09E-12	***
MeanTransfer	-2.79011	0.030786	-90.628	< 2e-16	***

Vuong test of ZINB vs. standard Negative Binomial: z = 142.04 (Pr>|z| = 0)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta = 18.9219

Table 7.3-6 and Table 7.3-7 show the statistical regression modelling results of ZIP and ZINB. We only discuss the parameters for ZIP because parameters of ZINB are similar.

Table 7.3-6a (Count model coefficients (Poisson with log link)) describes the prediction model of transferring passengers for passengers in the Type 1 group. Column Estimate shows the regression coefficients from a standard Poisson Regression model: the logarithm of expected number of transferring passenger changes by Estimate for each unit increase in the corresponding predictor. For instance, the expected change in log(transferring passenger) for one unit change in SRP is 0.001522 while holding all other variables constant. A morning period (AM=1) has expected log(transferring passenger) of 0.10031 less than a non-morning period (AM=0) while holding all other variables constant. If all of the predictor variables are zero, the predicted number of transferring passengers would be exp(Intercept)=exp(0.575046)=1.78 passengers. The Pr>|z| column shows that all the listed variables are significant in Poisson Regression. This is the probability of z test statistic under a null hypothesis that a predictor coefficient is zero, given that the other predictors exist in the model and 95% confidence interval.

Similarly, Table 7.3-6b (Zero-inflation model coefficients (binomial with logit link)) shows the prediction model of transferring passengers for passengers in the Type 0 group. There are less variables in the Zero-inflation model because HProbTransfer is now not significant. This is because an existence of a HProbTransfer passenger will likely lead to at least a transferring passenger.

The Vuong test suggests that the Zero-inflated Poisson Regression is a significant improvement over the classical Poisson Regression model.

Data mining model

In transportation engineering, the most commonly applied data mining paradigm in prediction is backpropagation learning method using ANNs (Smith and Demetsky, 1994; Dougherty, 1995; Jeong, 2004). Vlahogianni, Golias and Karlaftis (2004) thoroughly reviewed papers in short-term traffic forecasting and indicated that neural networks are the most potential techniques. ANN model the complex nonlinear relationship between the dependent variable and its independent variables. ANN can be built without the need of specifying the exact formulation, unlike the other models described here. While other types of data mining model such as Support Vector Machines could also be used, this sub-section develops an ANN model to predict the number of transferring passengers from independent variables.

A three-layered, multilayer perceptron ANN model, with back propagation algorithm was constructed for predicting the number of transferring passengers. Among the three layers of the ANN model, the first layer is the input layer, where the observed data is presented to the neural network. The input data is normalized numerical value or a binary code (AM and MID). This data is presented to a 7 neurons input layer, where each neuron holds an independent variable. The last layer is the output layer, producing the estimated response for the input. The output layer has only a single neuron, representing the estimated number of transferring passengers. The intermediate layer is the hidden layer, where nonlinear pattern associations between the input and output variables are established. A single hidden layer with 9 nodes has been found to be satisfactory by experimentation. Figure 7.3-8 illustrates the structure of proposed ANN model.

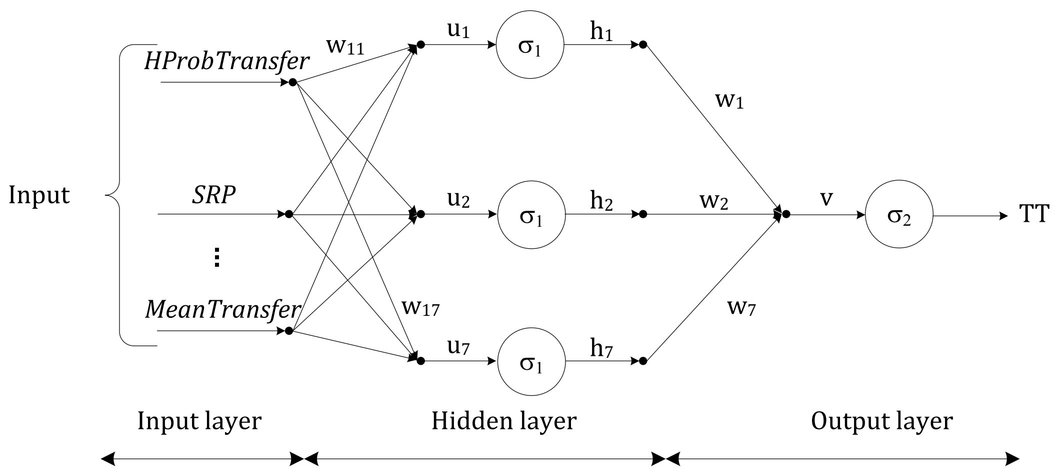


Figure 7.3-8 Structure of ANN model for N_f prediction

The training data (Jul-Sep 2013) is divided to 70% of “developing dataset” and 30% of “cross-validating dataset”. We built different MLP model with 1 to 20 neurons in the hidden layer from the developing dataset and calculate their prediction error MSE using the cross-validation dataset. Figure 7.3-9 shows the predicting accuracy in terms of predicting power and root mean squared error (RMSE) when the hidden layer has different number of nodes.

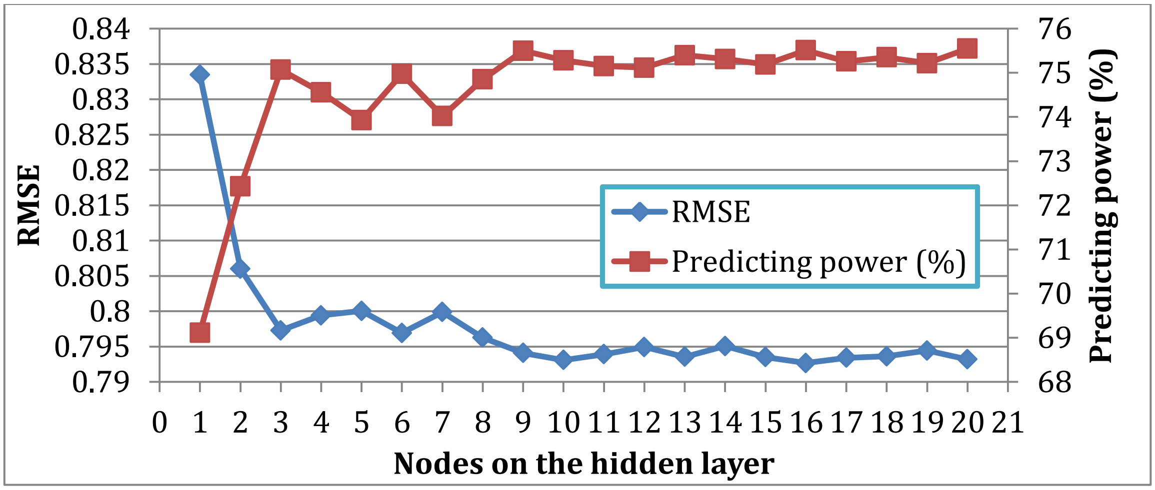


Figure 7.3-9 Root mean squared error and predicting power with different number of nodes on a single hidden layer

The predict power *PP* measures the probability that the prediction model would yield exactly the same number of transferring passengers as the observed data.

$$PP = \frac{\sum_{j=1}^{N} Y_j}{N} \times 100\% \qquad (48)$$

$$\text{where } Y_j = \begin{cases} 1 & if\ t_j = m_j \\ 0 & otherwise \end{cases}$$

Where *N* = number of testing data

t = target output value

m = model output value

Figure 7.3-9 shows that the predicting accuracy does not increase significantly as the number of nodes increases to more than 9 nodes. The final ANN model then has 9 nodes in a single hidden layer. Sigmoid transfer function is used in the hidden layer and linear transfer function is used in the output layer. The neural network is trained by the most common training algorithm: the backpropagation rule, where the maximum iteration is set as 1000, learning rate as 0.1 and training goal as 0.001.

The backpropagation algorithm minimises the output error, as described by the value of Mean Squares Error (MSE)

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(t_j - m_j)^2 \qquad (49)$$

Where N = number of testing data

t = target output value

m = model output value

Numerical experiment

This sub-section compares the proposed analytical, statistical and data mining models in predicting the number of transferring passengers. The testing dataset is Smart Card AFC data of October 2013. Table 7.3-8 shows the descriptive statistic of the dependent and independent variables. *HProbTransfer* is calculated with "likely to transfer" definition of 20%.

Table 7.3-8 Descriptive statistic of the testing dataset

Dependent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
$\bar{N}_f$	1031	1.34	1.73	0	14	Number of transferring passengers from a Route 555 service
Independent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
1.SRP	1031	5.64	5.18	0	50	Number of SRPs
2.SIP	1031	3.14	2.93	0	25	Number of SIPs
3.HProbTransfer	1031	1.21	1.57	0	14	Number of SRP that has high probability of transferring
4.MeanTransfer	1031	1.41	1.58	0.77	1.69	Mean number of transfer at the time period (30mins window)
5.MeanSIPTransfer	1031	0.19	1.21	0.02	0.43	Mean number of SIP that transfer at the time period (30mins window)

6.AM	1031	0.32	0.47	0	1	1 if AM peak, 0 otherwise
7.MID	1031	0.25	0.43	0	1	1 if Midday period, 0 otherwise

The 4 models developed for predicting the numbers of transferring passengers are: ANN, Zero-inflated Poisson Regression (ZIP), Zero-inflated Negative Binomial (ZINB) and Simple Analytical model (SA). Table 7.3-9 compares these 4 models in terms of RMSE and predicting power (PP).

Table 7.3-9 Comparison of 4 prediction models of $\bar{N}_f$

Model	RMSE	PP (%)
ANN	0.75	58.39
ZIP	0.90	51.70
ZINB	0.91	51.31
SA	1.18	54.61

Overall, ANN shows the lowest prediction error and highest predicting power compared to all other models. ZIP is slightly better than ZINB in predicting the value of $\bar{N}_f$, whereas SA shows the highest error in the same prediction. Figure 7.3-10 compares the 4 models in terms of their prediction errors RMSE.

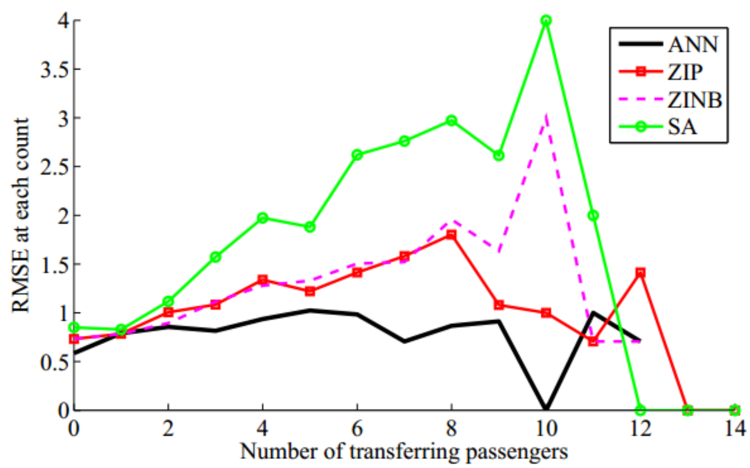


Figure 7.3-10 Comparison of RMSE

Figure 7.3-10 shows that ANN has significantly lower RMSE than all other 3 models, especially at high counts of transferring passengers. The RMSE of ANN is also relatively stable, whereas RMSE of other 3 models increases as the counts increases. Other non-data mining models, especially SA, predict poorly at large counts, where the RMSE could be up to 4. Figure 7.3-11 compares the predicting power of the models.

Figure 7.3-11 illustrates that ANN has much higher predicting power than the other three models, especially at high counts. While all models have the predicting power of 70-75% at zero count, only ANN maintains the predicting power of around 50% at counts of 1-9. Because counts 10-14 contribute to very little sample size, the models show fluctuations in predicting power. See Figure 7.3-3 for a CDF of transferring passengers.

The comparisons in deviation of probability at each count, RMSE and predicting power demonstrate that ANN is superior to ZIP, ZINB and SA in predicting the number of transferring passengers.

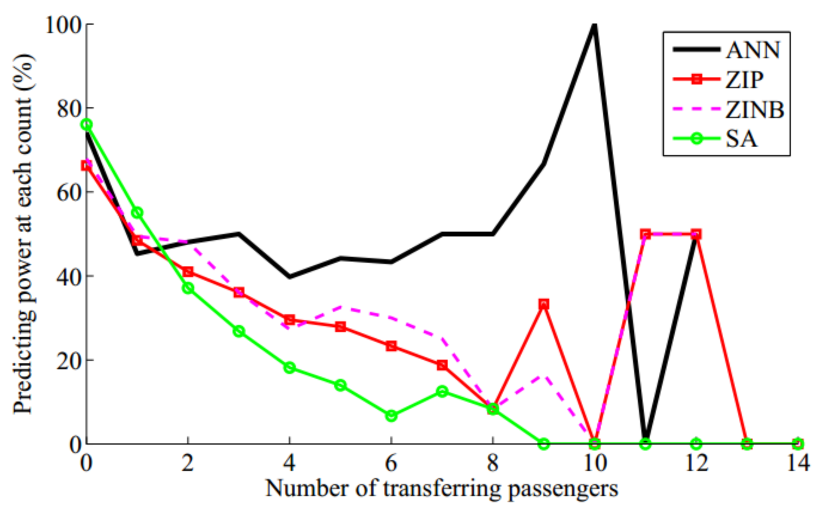


Figure 7.3-11 Comparison of predicting power

7.3.3 Predicting the number of non-transferring passengers $\bar{N}_r$

Introduction

The number of non-transferring passengers is the number of boarding passenger to a Route 572 service from the transfer stop, who has not transferred from a Route 555. The problem of predicting the $\bar{N}_r$ could be broken down to a short-term demand prediction. The literature of short-term demand prediction has been reviewed in Section 7.3.2.

Besides of being predicted by a neural network model (Meireles et al., 2003), support vector machine (Chen et al., 2011), hybrid pattern recognition model (FHWA, 2006), the short-term passenger demand has also been estimated by using simply arrival or boarding rate of passengers. Shalaby and Farhan (2004b) predicted the bus dwell time by multiplying the predicted passenger arrival rate with the predicted headway. A Kalman filter algorithm was developed to predict the passenger arrival rate using APC and AVL data.

On the other hand, a number of other studies assumed a probability distribution model for the arrival of passengers at transit stop. The assumptions include uniform distribution (Chang and Hsu, 2001; Zhao et al., 2003; Zolfaghari et al., 2004), or homogenous Poisson process (Hickman, 2001) (Liu and Wirasinghe, 2001). These studies also generally assumed that the passenger arrival rate is unchanged during the study period. However, whether these assumptions are also valid for real-time prediction is untested.

$\bar{N}_r$ represents the passengers who physically come to the transfer stop to wait for an arriving Route 572 service, who did not transfer from a Route 555 service. $\bar{N}_r$ is a fraction of the total passenger demand at the transfer stop. It is not correlated to the demand transferred from Route 555. $\bar{N}_r$ is also a typical count data of positive discrete values.

Methodology

The prediction of $\bar{N}_r$ is also a count regression problem, similar to the previous sub-section. Figure 7.3-12 shows the CDF of $\bar{N}_r$.

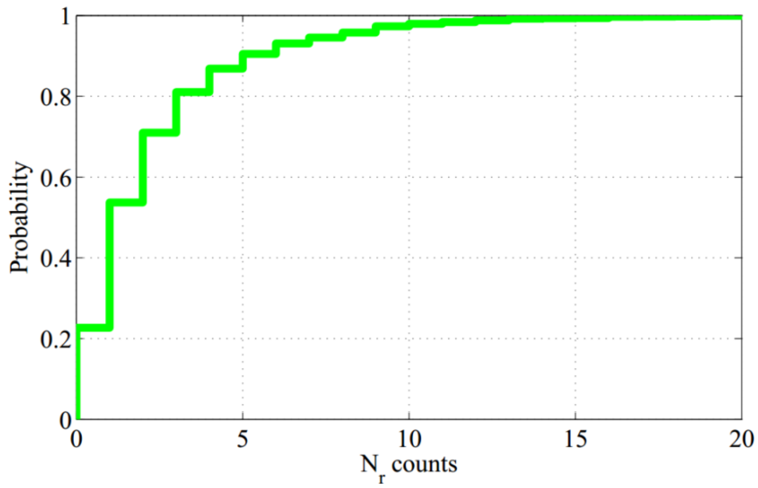


Figure 7.3-12 CDF of non-transferring passengers counts

There is more than 20% of chance that there is no non-transferring passenger boarding at the transfer stop. Although the value of $\bar{N}_r$ could be up to 20 passengers, the probability of $\bar{N}_r$ being less than 5 is 90%. Count regression techniques such as Poisson and Negative Binomial Regression could estimate the value of $\bar{N}_r$ using a set of independent variables. A variety of other methods in the literature could also be applied to this problem. However, the last sub-section has already showed that data mining model outperforms count regression model in similar problem. Therefore, this sub-section compares the probability distribution and data mining models in predicting the value of $\bar{N}_r$. Table 7.3-10 lists the used dependent and independent variables using in this sub-section.

Table 7.3-10 Descriptive statistic of variables using in non-transferring passenger prediction

Dependent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
$\bar{N}_r$	1611	2.71	3.43	0	20	Number of non-transferring passenger who will board the studied Route 572 service
Independent variables						

Name	Sample size	Mean	Std. Dev	Min	Max	Description
1. S_n	1611	14.95	3.78	7.3	23.58	Scheduled departure time of the studied Route 572 service
2.EstimatedHeadway	1611	31.71	11.15	5.48	59.98	Time gap between the schedule departure time of the studied Route 572 service with the previous arrival at the transfer stop ($[S_n - AT_{n-1}]$) in real time
3.MeanPass	1611	2.03	0.78	1.15	4.49	Day-to-day average $\bar{N}_r$ per trip of the same scheduled service
4.Day_of_week	1611	4.27	1.33	2	6	Day of week (2-Monday to 6-Friday)

Probability distribution models

Shalaby and Farhan (2004b) estimated the bus dwell time using the following equation

$$DWT_{n(i+1)} = \lambda_{(i+1)} * [AT_{n(i+1)} - AT_{n-1(i+1)}] * \rho_{avg(i+1)} \tag{50}$$

Where

$DWT_{n(i+1)}$ is the predicted dwell time for bus *n* at stop (*i*+1)

$\lambda_{(i+1)}$ is the predicted arrival rate at stop (*i*+1), predicted by a Kalman Filter algorithm (passengers/second)

$AT_{n-1(i+1)}$ is the actual arrival time of bus *n-1* at stop (*i*+1) in seconds

$[AT_{n(i+1)} - AT_{n-1(i+1)}]$ is the predicted headway for bus *n* at stop (*i*+1) in seconds

$\rho_{avg(i+1)}$ is the average boarding time at stop (*i*+1), assumed to be 2.5 sec/passenger

Similarly, $\bar{N}_r$ could be estimated by the following equation

$$\bar{N}_r = \lambda_0 * [S_n - AT_{n-1}] \qquad (51)$$

λ_0 is arrival rate at the transfer stop

AT_{n-1} is the observed arrival time of the previous bus *n-1* of Route 572 at the transfer stop

S_n is the scheduled departure time of bus *n* of Route 572 from the transfer stop

The aforementioned equation of $\bar{N}_r$ could be used to estimate $\bar{N}_r$ if the arrival rate λ_0 is fixed and the passenger arrival is assumed as uniformly distributed. Figure 7.3-13 shows the passenger arrival rate λ_0 per minute, where λ_0 is assumed as fixed and similar to the boarding rate for the same period of an hour. Because we have no information on passenger arrival, Figure 7.3-13 uses the boarding rate per hour as a proxy for passenger arrival rate at the transfer stop.

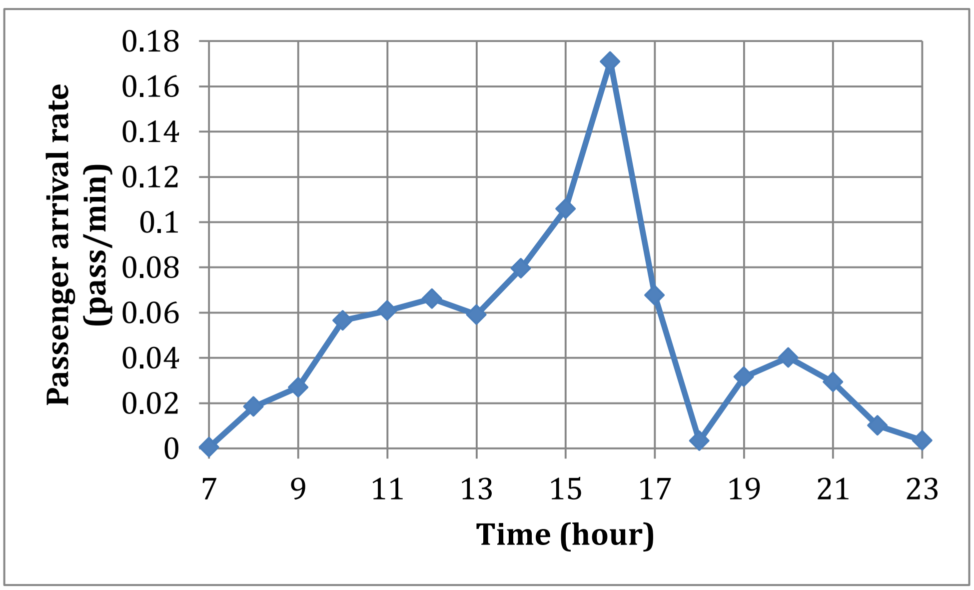


Figure 7.3-13 Passenger boarding rate per minute within 60 minutes window

Data mining model

This section develops a MLP feedforward network to predict the non-transferring demand $\bar{N}_r$ that will board on a Route 572 service. The MLP feedforward network is developed through a trial-and-error process, aiming to build a network that provides the lowest MSE in prediction of $\bar{N}_r$. Observed data is again randomly divided into 70% of "developing dataset" and 30% of "cross-validating" dataset. The best set of parameters is chosen by experimenting, i.e. developing the network by the "developing dataset" and then testing it by the "cross-validating" dataset. The final MLP network has a single hidden layer of sigmoid transfer function with 6 neurons, an input layer of 5 neurons and an output layer of a single neuron with linear transfer function. Backpropagation algorithm is chosen to train the MLP feedforward network, where the maximum iteration is set as 1000, learning rate as 0.1 and training goal as 0.001.

Numerical experiment

This sub-section develops numerical experiments using the testing dataset of Smart Card AFC data of October 2013 to investigate the prediction of $\bar{N}_r$ by the proposed probability distribution, statistical and data mining models.

Table 7.3-11 Descriptive statistic of the testing dataset in non-transferring passenger prediction

Dependent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
$\bar{N}_r$	514	2.67	3.29	0	19	Number of non-transferring passenger who will board the studied Route 572 service
Independent variables						
Name	Sample size	Mean	Std. Dev	Min	Max	Description
1. S_n	514	14.94	3.78	7.3	23.58	Scheduled departure time of the studied Route 572 service
2. EstimatedHeadway	514	31.68	11.09	5.51	59.57	Time gap between the schedule departure time of the studied Route 572 service with the previous arrival at the transfer stop ($[S_n - AT_{n-1}]$)
3.MeanPass	514	2.01	0.75	1.14	4.51	Average $\bar{N}_r$ per trip within same scheduled service
4.Day_of_week	514	4.26	1.35	2	6	Day of week (2-Monday to

		6-Friday)

Table 7.3-12 shows the comparison of RMSE and PP of the 2 proposed models in non-transferring demand prediction.

Table 7.3-12 Comparison of 2 prediction models of non-transferring passenger prediction

Model	RMSE	PP (%)
ANN	1.9	25.71
Probability model	3.02	21.08

The MLP feedforward ANN has lower predicting error (RMSE) and highest predicting power (PP) among the two tested techniques, whereas the probability model shows the worst predicting performance. The difference between these two techniques is significant, especially in terms of prediction error RMSE. Figure 7.3-14 clearly shows that the probability model could only predict 10 as the highest count of non-transferring passenger. This is because the prediction is only based on the passenger arrival rate λ_0 and value of $[S_n - AT_{n-1}]$, which means no extreme value is predicted. ANN shows the lowest RMSE at most of the count values.

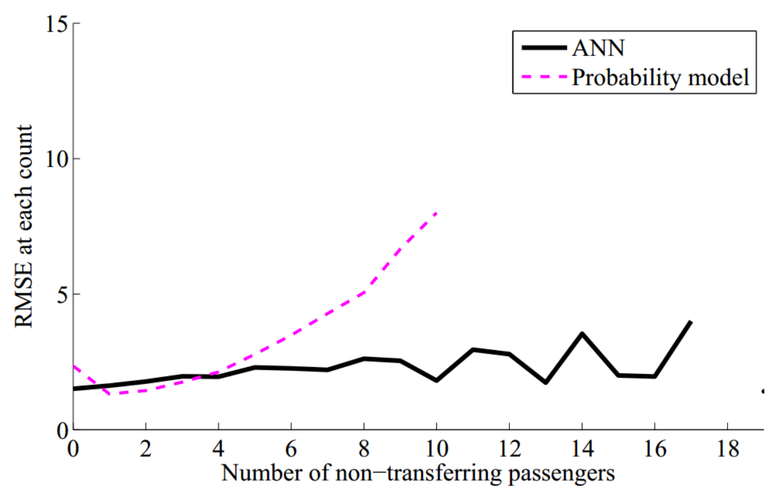


Figure 7.3-14 RMSE at each count

Figure 7.3-15 shows the predicting power at each count of ANN and probability model. Similar to the previous figure, both models has good predicting performance at low counts, while the PP is decreasing and fluctuating as the value of $\bar{N}_r$ is higher than 10. ANN could predict 55% times correct when the value of $\bar{N}_r$ is zero.

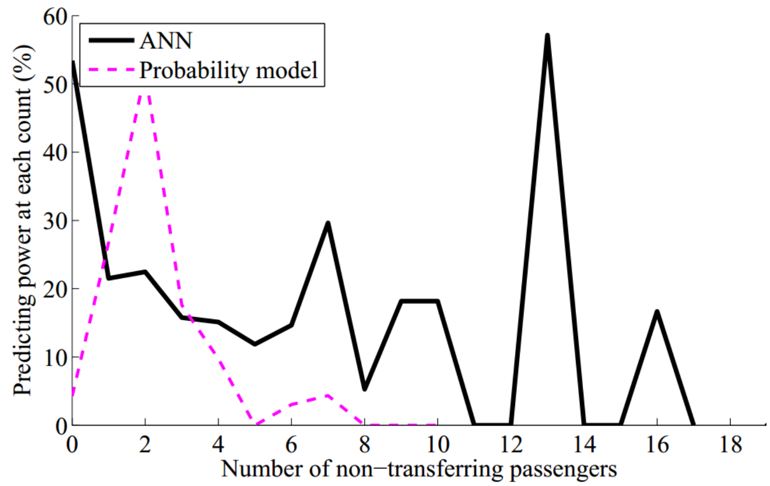


Figure 7.3-15 Predicting power at each count

To sum up, ANN shows a better predicting performance in term of probability deviation, RMSE and predicting power at each count than the probability model.

7.4 **ONTF control experiment**

This section aims to develop the online framework and test it using real AFC and AVL data of October 2013.

7.4.1 **ONTF control strategies**

This sub-section develops and tests different ONTF control strategies. As mentioned in Section 4.1, the successful of ONTF heavily depends of the availability of real-time information of (1) the delay of the FV, (2) the number of transferring and non-transferring passengers and (3) the frequency or schedule of the RV. In practice, we may not have data available in real-time due to technological or predicting limitations. This sub-section develops strategies that require different level of real-time information and compares them in terms of EWT and probability of missing a transfer.

The ONTF problem as described in Section 7.2.1 is a yes-or-no question of whether the RV should be held until the FV arrives or leave as scheduled, in case the RV arrives earlier to the transfer stop. The online coordination problem could also be defined as a real-time vehicle holding problem, where the RV is held at the transfer stop to allow passenger transfers. In practice, there could be a maximum holding time *MH*, which limits the amount of time the RV could be held beyond scheduled departure time. *MH* is less than or equal to the amount of slack time in the RV schedule, allows the RV to be held without negatively affect the on-time performance downstream of the transfer stop. Therefore, the proposed strategies in this sub-section are executed in three possible control decisions: (1) depart the RV immediately, (2) hold up until the FV arrives and (3) hold up but only until a maximum holding time *MH* beyond the scheduled departure time.

The following symbols are used to define the strategies, where some of them have already been defined in Section 4.3 but restated here for clarification.

r index of the RV being controlled at the transfer stop

f index of the FV approaching the transfer stop

CD_r controlled departure time of the RV after transfer decision

A_f actual arrival time of the FV at the transfer stop

S_r scheduled departure time of the RV from the transfer stop

$\overline{A}_f$ predicted arrival time of FV at the transfer stop

$\overline{N}_f$ predicted number of transferring passengers from the feeding to RV

$\overline{N}_r$ predicted number of non-transferring passengers that will board on the RV

A_r current time, also the arrival time of the RV at the transfer stop

MH maximum allowed holding time beyond scheduled departure time

TT_{Af} Time gap from the current time A_r to the arrival of FV A_f, equals A_f-A_r

$SchedDev_r$ Schedule deviation of the RV, equals A_r-S_r

(1) *Always-holding* : Hold the RV until the FV has arrived

$$CD_r = Max(\mathrm{A}_f, S_r) \tag{52}$$

(2) *No-holding*: Do not hold and dispatch the RV as scheduled – this is the current strategy at Route 555 and 572.

$$CD_r = Max(\mathrm{A}_r, S_r) \tag{53}$$

(3) *MH-holding*: Hold the RV but no more than the maximum holding time

$$CD_r = Min(Max(\mathrm{A}_f, S_r), Max(\mathrm{A}_r, S_r + MH)) \tag{54}$$

(4) *MH-Travel time holding*: Hold the RV if the predicted arrival time of the FV $\overline{\mathrm{A}}_f$ is within the maximum holding time *MH*

$$CD_r = Max(S_r, \mathrm{A}_r, \overline{\mathrm{A}}_f : \text{if } \overline{\mathrm{A}}_f < S_r + MH) \tag{55}$$

(5) *Predictive-holding*: Hold the RV if $\overline{EWT_r} <= \overline{EWT_f}$

$$CD_r = \begin{cases} Max(\mathrm{A}_f, S_r) & if \quad \overline{EWT_r} <= \overline{EWT_f} \\ Max(\mathrm{A}_r, S_r) & if \quad \overline{EWT_r} > \overline{EWT_f} \end{cases} \tag{56}$$

Where $\overline{EWT_r}, \overline{EWT_f}$ are the estimated EWT of non-transferring and transferring passengers, calculated using Equation (36) to (39), but using predicted values $\overline{N}_f$, $\overline{N}_r$,and $\overline{\mathrm{A}}_f$ instead of the real (unknown) values.

(6) *MH-predictive holding:* Hold the RV if $\overline{EWT_r} <= \overline{EWT_f}$, but no more than the maximum holding time

$$CD_r = \begin{cases} Max(S_r, \mathrm{A}_r, \overline{\mathrm{A}}_f : \text{if } \overline{\mathrm{A}}_f < S_r + MH) & if \quad \overline{EWT_r} <= \overline{EWT_f} \\ Max(\mathrm{A}_r, S_r) & if \quad \overline{EWT_r} > \overline{EWT_f} \end{cases} \tag{57}$$

While Strategy 2 is no-holding strategy, Strategy 1 is always-holding, an extreme case to maximise the probability of transferring for passengers in the FV. Strategy 3 introduces a slack time amount of *MH*, which makes it very similar to timed transfer coordination in offline planning process. Strategy 1 and 3 do not require any prediction, but the online coordination is only active if there is a FV scheduled to come within 10 minutes. Strategy

4-6 require the prediction of FV arrival time, which means AVL data should be available in real-time. Strategy 5-6 additionally require the prediction of transferring and non-transferring passengers, which means both AVL and AFC data should be available in real-time. Strategy 5 does not require the maximum holding time, but minimises the EWT induced by the coordination control strategy. Strategy 6 is similar to Strategy 5, but adds *MH* in case it is required as an operational constraint. Strategy 5 and 6 defines the transfer coordination problem as a global cost minimisation problem, where the coordination problem is a binary decisive question that minimises the EWT of transferring and non-transferring passengers. In Strategy 3, 4 and 6 (*MH*-enabled strategies), if the RV arrives later than the maximum holding time ($S_r + MH$), it will leave immediately.

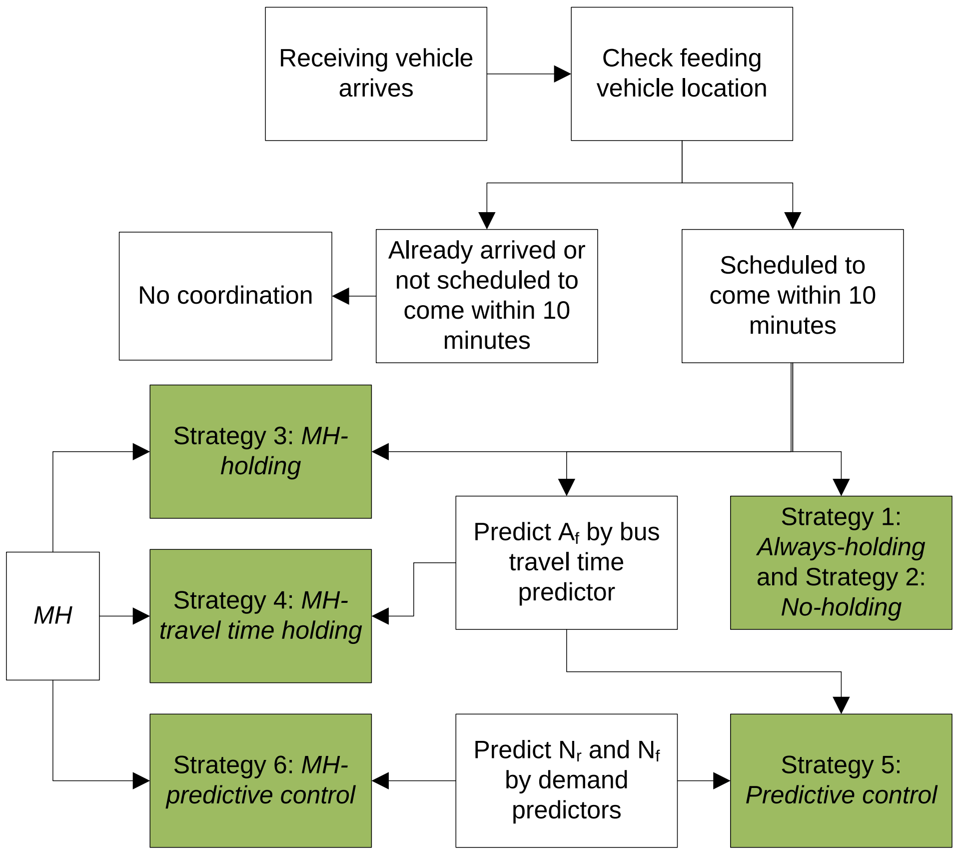


Figure 7.4-1 ONTF framework

At the current time A_r when RV arrives at the transfer stop, we check the last known location and timestamp of FV. If FV is scheduled to come in 10 minutes, the ONTF is activated. While Strategy 1, 2 and 3 could be directly executed, a prediction of A_f is needed for the Strategy 4 to be implemented. Further predictions of N_r and N_f are finally performed to run Strategy 5 and 6. The Strategy 3, 4 and 6 are under the influence of *MH*, where the holding time cannot exceed *MH* minutes from the scheduled departure time S_r. The algorithms for estimating the EWT of each strategy could be developed from the general algorithms in Section 7.2.1. Interested reader of these algorithms could refer to the pseudo-code in Appendix C.

7.4.2 **Online coordination testing results**

This sub-section compares the performance of different ONTF strategy. The two testing criteria are (1) total cost of transferring (EWT_f) and non-transferring passengers (EWT_r) and (2) the probability of missing a transfer when each strategy is executed over the testing data of October 2013. Table 7.4-1 shows an example of the testing dataset.

Table 7.4-1 Example of the testing dataset.

A_r (min)	N_r *	TT_{Af} (min) *	$SchedDev_r$ (min)	A_f (min) *	N_f *	# Stop **	LastTT (sec) **	…	HProbTransfer**
1126.2	0	6.30	-1.61	1132.5	2	2	512.5	…	2
925.8	6	1.94	8.00	927.74	0	2	491.9	…	0
738.12	0	9.32	-0.10	747.44	3	3	791.6	…	2
441	4	7.03	2.98	448.03	0	2	531.2	…	0
888.03	6	7.82	0.05	895.85	2	1	416	…	1

**These variables are not given to the ONTF control framework, but will be used for strategy testing.*

***These variables are presented to the prediction models of N_r, N_f and TT.*

There are in total 177 set of observations on the case where A_r<A_f and A_f is scheduled within 10 minutes from A_r, so that a transfer coordination may be feasible. The remaining 1312 set of observations are of the case where A_r>=A_f, or A_f is not scheduled within 10 minutes from A_r, so no coordination is needed. To emulate a real-time working environment, each set of A_r and schedule deviation (A_r-S_r) along with other dependent variables to predict N_r, N_f and A_f are presented. The values of N_r, N_f and A_f are forecasted and EWT_r and EWT_f are calculated. Each strategy issues its transfer coordination control decision using these predicted values. The observed values of N_r, N_f and A_f are then used to calculate the EWT induced by the coordination decision to transferring and non-transferring passengers. Figure 7.4-2 compares the 6 strategies in terms of total EWT (equals $EWT_r + EWT_f$).

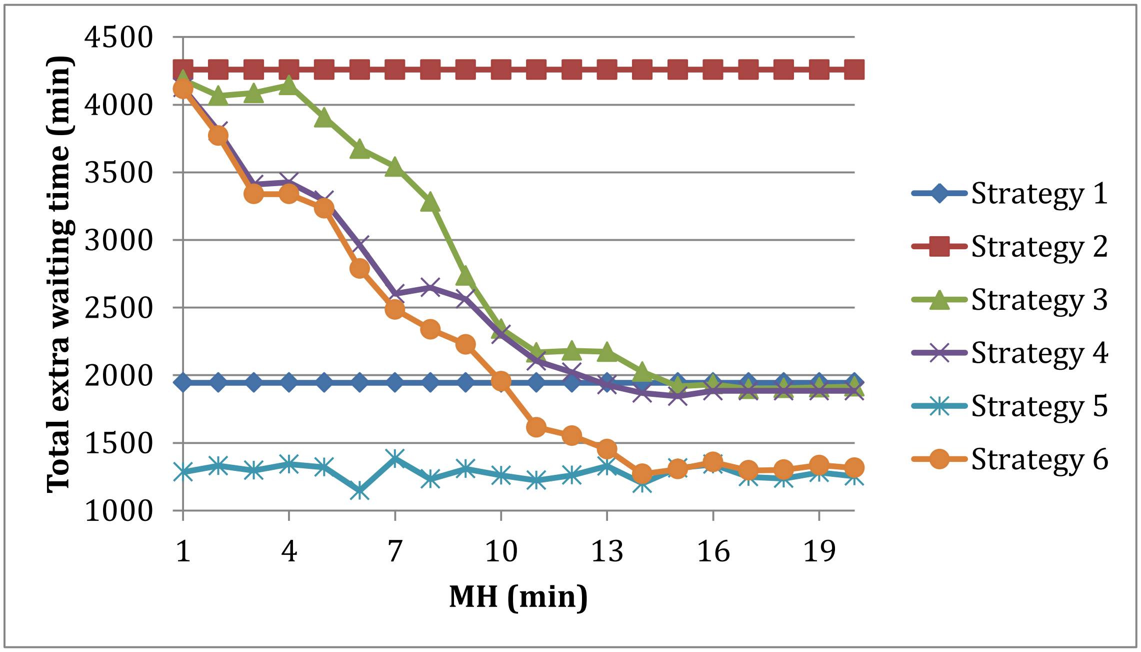


Figure 7.4-2 Comparison of EWT by different strategies

Strategy 2 (no-holding) is by far the worst strategy with the highest total EWT. That is because the frequency of Route 572 is low (30 minutes per service), which makes the sum of total EWT experience by transferring passengers (EWT_f) much higher than the sum of non-transferring passengers (EWT_r). While non-transferring passengers generally have to wait for a few minutes in case of transfer coordination, transferring passengers would have to wait for nearly a full headway in case of no-holding. Therefore, in this particular case study the Strategy 1 (always-holding) seems to be an effective strategy. The total EWT of Strategy 1 and 2 are fixed because no prediction or consideration of *MH* is required.

The introduction of *MH* limits the effectiveness of Strategy 3, 4 and 6. Because of this operational constraint, RV may not be able to be held until the FV arrives, because FV arrives after $MH + S_r$. In that case, the non-transferring passenger will have to wait until $MH + S_r$, while the transferring passenger will have to wait for the next Route 572 service, because the coordination was not successful. If the RV arrives after *MH*, it will have to depart immediately and no coordination could be formed.

The performance of Strategy 4 shows that only the prediction of bus travel time would not much enhance the ONTF performance. The introduction of travel time prediction only improves the coordinating performance at low MH compares to the Strategy 3, but much worse than the always-holding Strategy 1. This is because the balance between total EWT of transferring and non-transferring passengers has not been examined in Strategy 4.

Strategy 5 in general outperformed other Strategies. This is the most advance strategy with predictions of N_r, N_f, A_f and no MH constraint. The performance of Strategy 5 demonstrates that integrating the real-time information of passengers and transit vehicles would significantly benefit ONTF control. The EWTs in Figure 7.4-2 are calculated for the case where RV arrives earlier than FV. In October 2013, there are in total 1386 passengers transferred from Route 555 to Route 572 in the outbound direction in working days. Among them, only 194 passengers experienced the situation where their Route 572 (RV) vehicle arrives earlier than a Route 555 (FV) vehicle. Compared to the current strategy in SEQ (no-holding or Strategy 2), Strategy 5 shows a reduction of 16.24% on average in terms of total EWT. The effectiveness of Strategy 5 comes from the comparison between $\overline{EWT_r}$ and $\overline{EWT_f}$ where the transfer decision is issued with regard to the lowest EWT. Figure 7.4-3 shows the values of EWT_r and EWT_f at all 177 cases of transferring where A_r<A_f and A_f is scheduled to come within 10 minutes from A_r. Figure 7.4-3 demonstrates that the spread of EWT_f is clearly larger than EWT_r, denoting that issuing transfer coordination would generally induce less extra waiting time to passengers than not issuing. This is the reason why Strategy 1 and 5 generally outperform other strategies.

However, while RV is held until FV arrival, the holding time could be excessively long for non-transferring passengers of RV. Figure 7.4-4 demonstrates this issue by plotting the CDF of holding time and excessive holding time when implementing Strategy 5 on the data of October 2013. Excessive holding time is defined as the amount of time the RV is held beyond MH minutes from its scheduled departure time S_r (thus Excessive holding time equals A_f – (S_r + MH)).

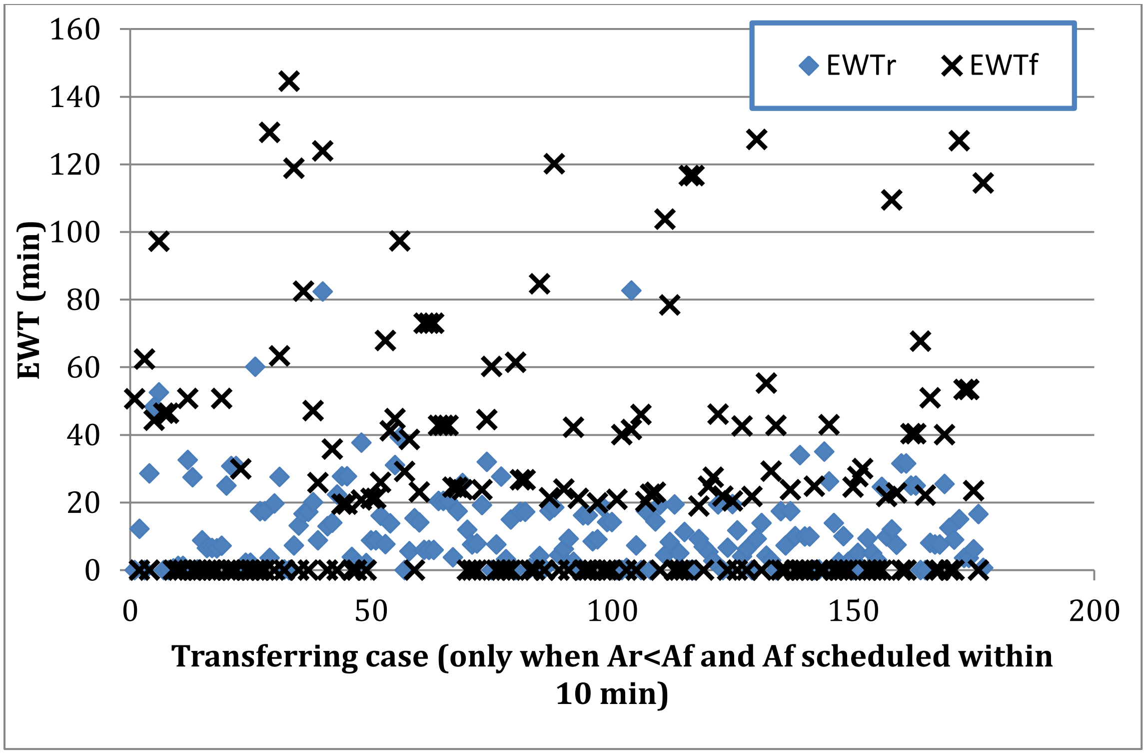


Figure 7.4-3 EWT_r and EWT_f at each transferring case

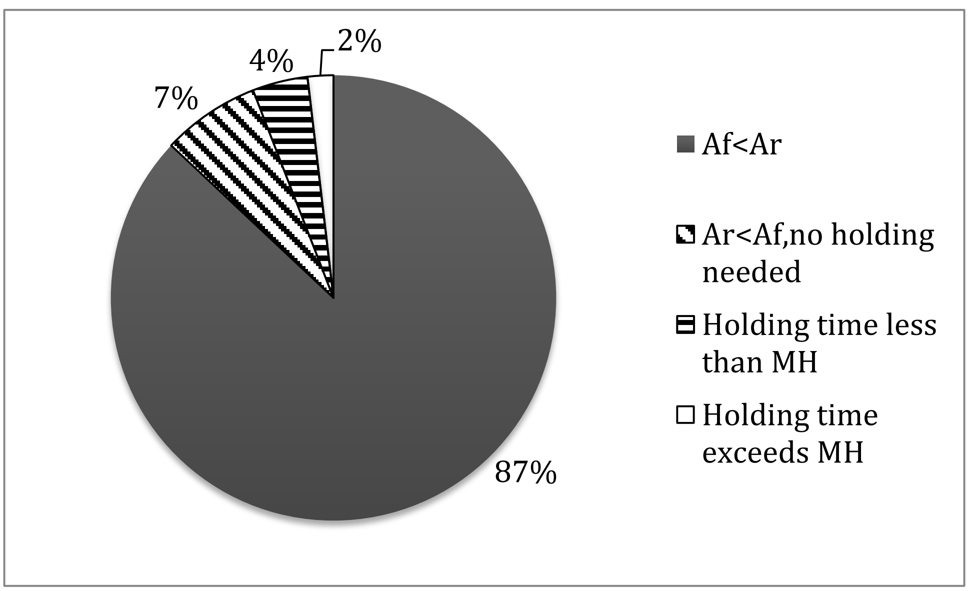


Figure 7.4-4 Pie chart of holding time and excessive holding time at Strategy 5

Figure 7.4-4 shows that over the testing dataset of October 2013, there is only around 13% of time when RV arrives earlier than FV. Around half of these cases, Strategy 5 issued a holding control, where most of them time the holding time was less than MH. There is 2%

of all the dataset where Strategy 5 issued a holding time that exceeded MH. Figure 7.4-4 demonstrates that even though Strategy 5 outperforms other ONTF strategies, transit operators still need to carefully examine its operational characteristic to avoid the circumstances where the holding time is too long.

On the other hand, Figure 7.4-5 compares the probability of missing a transfer among the control strategies.

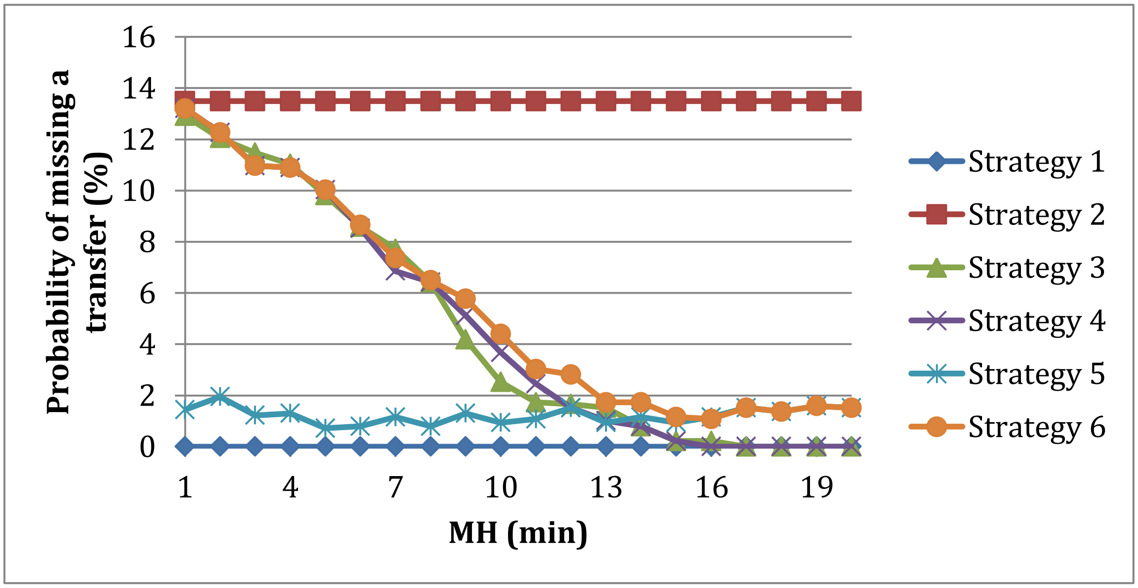


Figure 7.4-5 Probability of missing a transfer

Without any ONTF control, approximately 13.49% of passengers will miss the transfer and have to wait for the next Route 572 service. The always-holding Strategy 1 does not let any passengers to miss a transfer. By executing the Strategy 1 the probability of missing a transfer can be reduced from 13.49% to 0%. At *MH* larger than 15 minutes, Strategy 3 and 4 will also allow 100% of passengers to make the first transfer. Strategy 5 allows 99% of passengers to make the first transfer at any value of *MH*, which makes it the best strategy overall when considering this criteria with the total EWT.

7.4.3 Sensitivity of N_r, N_f and A_f prediction

The coordination performance of Strategy 5 depends on the predicting power of N_r, N_f, A_f. The Strategy 5 in the last sub-section has been executed by using the best proposed predictors. It is necessary to investigate the performance of Strategy 5 with different predictors to get an idea of a required predicting power to operate Strategy 5. Section 7.3.1

shows that the differences between proposed bus travel time prediction models are not significant, and travel time predictors have also been extensively studied in literature. Therefore, this sub-section focuses on the performance of Strategy 5 with different predicting models of N_r and N_f. Figure 7.4-6 compares different Strategy 5 implementation using different predictors of N_r and N_f, where the model name is (Predictor of N_r – Predictor of N_f). For instance, Prob-ZIP means that N_r has been predicted by Probability distribution model and N_f has been predicted by Zero-Inflated Poisson model. There is also a special case where we assume perfect information of N_r and N_f.

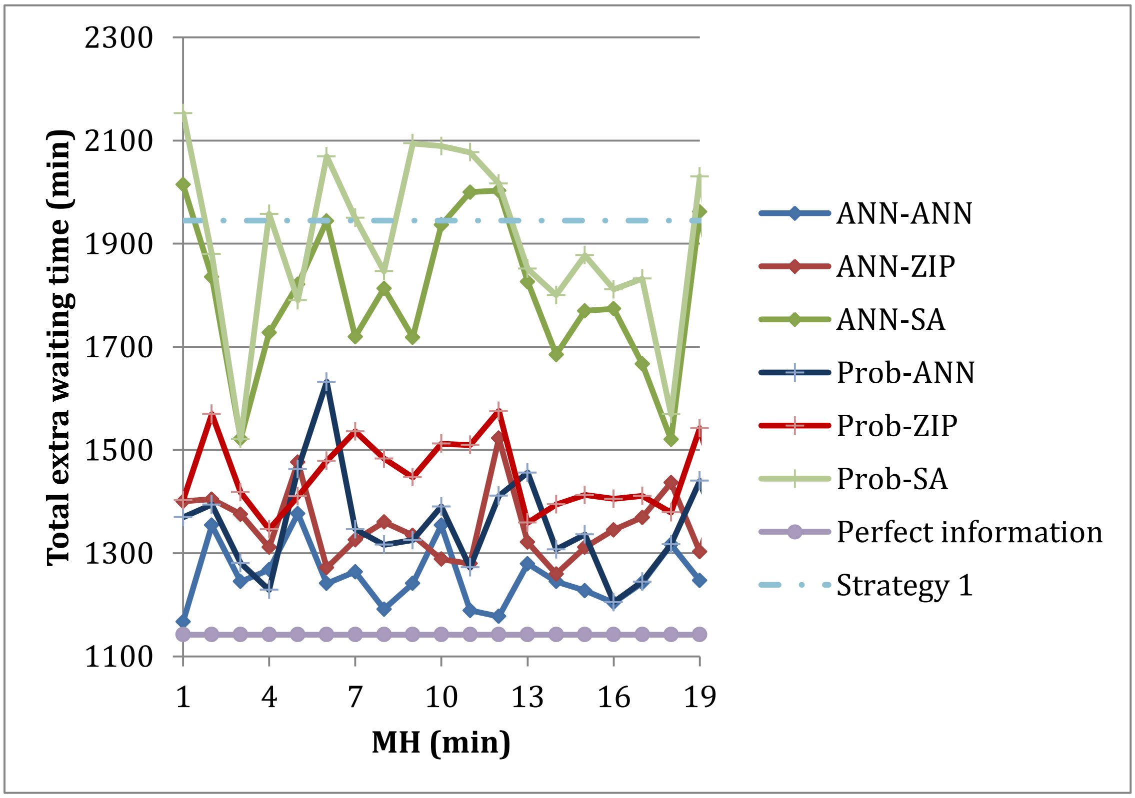


Figure 7.4-6 Comparison of total EWT between Strategy 5 with different predictors and Strategy 1

Figure 7.4-6 shows that if we have perfect information of N_r, N_f and A_f, we can provide a transfer coordination strategy that yields the least EWT. However, the predictive ONTF framework also works effectively using the proposed predictors of N_r, N_f and A_f. The prediction of N_f and is generally more important than the prediction of N_r in deciding the overall coordinating performance, as Figure 7.4-6 shows that the worst model of N_f (SA-Simple Analytical model) also yields the worst coordinating performance. Transfer coordination model with SA predictor is generally not satisfactory, as it may provide larger total EWT than the always-holding Strategy 1. Models with ANN are slightly better than models with ZIP as the predictor of N_f. It means that using the right predictor is essential in the implementation of the predictive control strategy.

The examination of ONTF strategies show that the Predictive-holding Strategy 5 outperformed other strategies in providing least total EWT and probability of missing a transfer. Perfect information of N_r, N_f and A_f in real-time would even yield a better result, but the current predictive mechanism of Strategy 5 also provide a satisfactory coordination.

7.5 **Simulated sensitivity analysis**

The previous section demonstrates that the predictive control Strategy 5 outperforms other strategies in ONTF. The testing dataset is the observed AVL and AFC data of October 2013. However, the data consists of only a single receiving transit route. The Strategy 5 works well for the case study of Route 572, but may not yield similar performance at different operational conditions. This section investigates the performance of the transfer coordination control strategies at different arrival profile, transferring demand and scheduled headway of the receiving transit route. To examine the sensitivity of each operational condition, the sensitivity analysis approach aims to test each variable one by one. We simulate the changes in N_r, N_f, S_r and A_r by changing only the studied variable and keep other attributes as the observed data of October 2013. The value of MH is 5 minutes for all simulations in this section. The prediction of N_r, N_f, S_r or A_r is also assumed 100% prediction accuracy if the value has been modified by the simulation scenario. This section only tests Strategy 1 (always-holding), Strategy 2 (no-holding) and Strategy 5 (predictive control) because these 3 are extreme cases of transfer coordination. Interested readers could find full tests of these simulated sensitivity analysis including all 6 strategies from APPENDIX D.

7.5.1 **Sensitivity of arrival profile**

The time gap between A_r and S_r defines the requirements for transfer coordination. If the RV arrives much earlier than the scheduled departure time S_r, there will not likely be any transfer coordination needed because the vehicle has to wait for the schedule. On the other hand, if the RV arrives too late compared to its schedule, it is likely that it arrives even later than the maximum holding time MH and no transfer coordination could be executed using Strategy 3,4 and 6. More importantly, the RV may be close to the next Route 572 service, which makes transfer coordination futile because transferring passengers from the FV can wait for the next service for less EWT than transfer coordination.

This sub-section tests the sensitivity of the time gap between A_r and S_r ($SchedDev_r$) in the transfer coordination performance of the proposed strategies. As $SchedDev_r$ equals A_r minus S_r, we can shift A_r or shift S_r and keep all operational attributes such as of N_r, N_f and A_f exactly the same as the observed set of variables used in Section 7.4. Shifting S_r means changing the scheduled departure time of the RV, while shifting A_r means testing different operational arrival profile of the RV.

Sensitivity of operational arrival profile (A_r) of the RV

For each simulation run, we keep all operational attributes such as of Nr, Nf, Sr and Af exactly the same as the observed set of variables used in Section 7.4. Only Ar is shifted so that SchedDevr ranges from -15 to 15 minutes, representing the arrival of the RV 15 minutes earlier to 15 minutes later than its fixed scheduled departure time. For each value of SchedDevr tested, the ONTF simulation is run 177 times for 177 observed set of variables. The time gap between Sr and Af remains similar to the observed data. The objective of this test is to examine the transfer coordination performance when the RV arrives 15 minutes earlier to 15 minutes later than a fixed schedule S_r. Figure 7.5-1 compares the total EWT induced by online coordination controls.

Figure 7.5-1 shows that Strategy 5 is the best strategy for all cases. However, all strategies produce similar EWT when the RV arrives more than 10 minutes later than S_r, because the RV arrives later than the FV. There is no coordination needed for that case, which result in exactly the same EWT for all strategies.

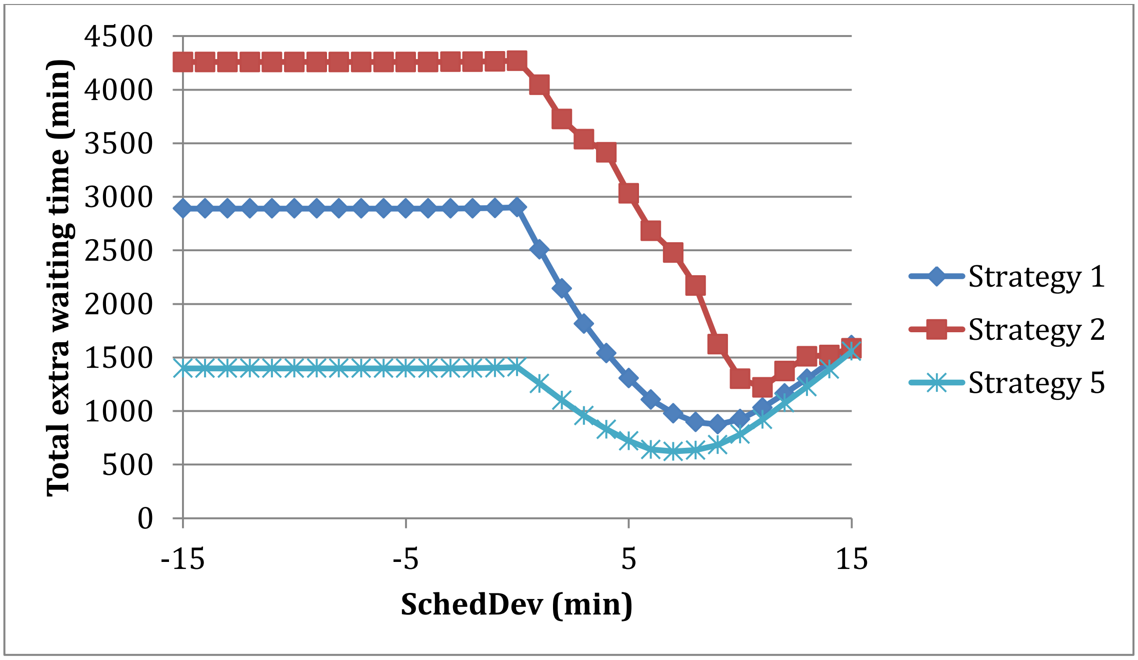


Figure 7.5-1 Operational arrival profile sensitivity analysis

Sensitivity of scheduled departure time (S_r) of the RV

For this test, we only shift S_r and keep we keep all other operational attributes such as of N_r, N_f, A_r and A_f exactly the same. *SchedDev*$_r$ also ranges from -15 to 15 minutes. The time gap between A_r and A_f remains similar to the observed data. The objective of this test is to examine the case where the arrival profiles of both vehicles are the same, but the schedule is changed from 15 minutes earlier to 15 minutes later than the existing schedule. In this case *SchedDev*$_r$ equals -15 minutes means that S_r has been shifted 15 minutes ahead of the existing schedule and *vice versa* for *SchedDev*$_r$ equals 15 minutes. Figure 7.5-2 compares the total EWT of the proposed coordination strategies.

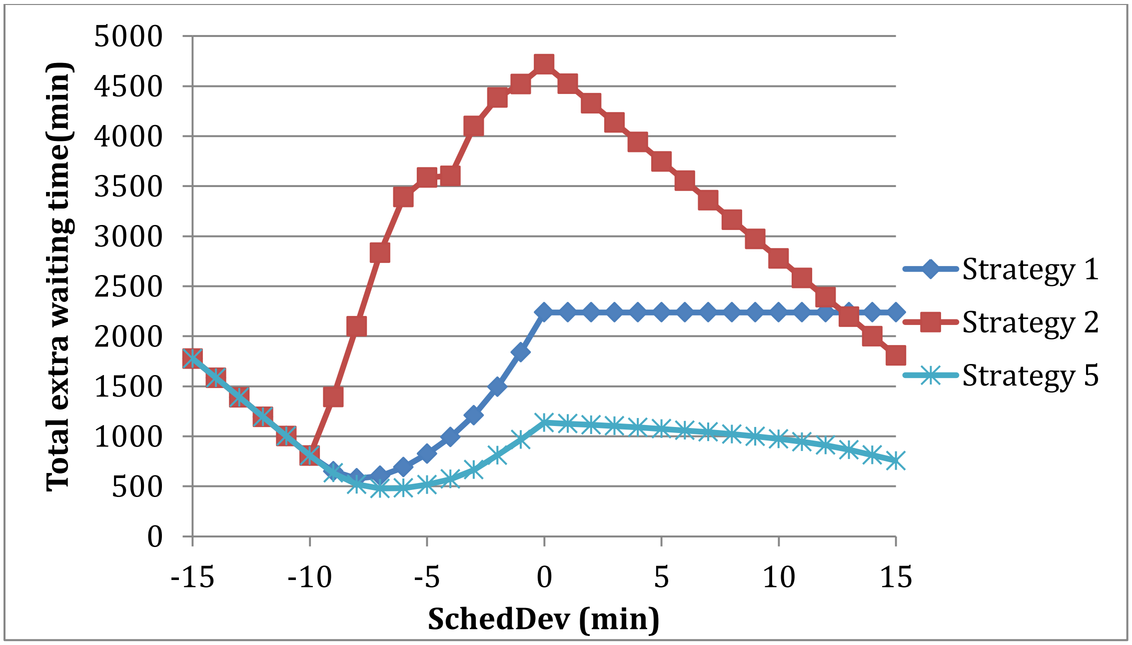


Figure 7.5-2 Scheduled departure time (S_r) sensitivity analysis

Figure 7.5-2 shows that all strategies would yield similar EWT when S_r has been shifted more than 10 minutes ahead (*SchedDev$_r$* is smaller than -10) because when S_r is far ahead of A_f, the only EWT is for transferring passengers from A_f to S_r. When S_r has been shifted more than 12 minutes back (*SchedDev$_r$* is larger than 12), the always-holding Strategy 1 costs more than all other strategies. That is because S_r is too far back from A_r that the EWT for holding is actually smaller than the EWT for the next service at $S_r + H$. This test infers that if we shift the schedule S_r far away from the actual arrivals A_f and A_r, there would be no coordination needed. However, this would be a waste of resources because of too much slack/recovery time. Predictive online coordination control such as the Strategy 5 is important for the current schedule (*SchedDev$_r$* is around 0), as could clearly be seen from Figure 7.5-2.

7.5.2 **Sensitivity of transferring demand**

The share of transferring passengers N_f among the total number of passenger in Route 572 decides whether transferring coordination is necessary. If N_f is large N_r and is small, a transfer coordination will be preferable, and *vice versa*. The objective of this sub-section is to test the applicability of the proposed transfer coordination framework under different share of transferring demand. Figure 7.5-3 illustrates the total EWT in Strategy 1, 2 and 5 when the share of transferring passengers is from 0 to 100% of the total demand of Route 572.

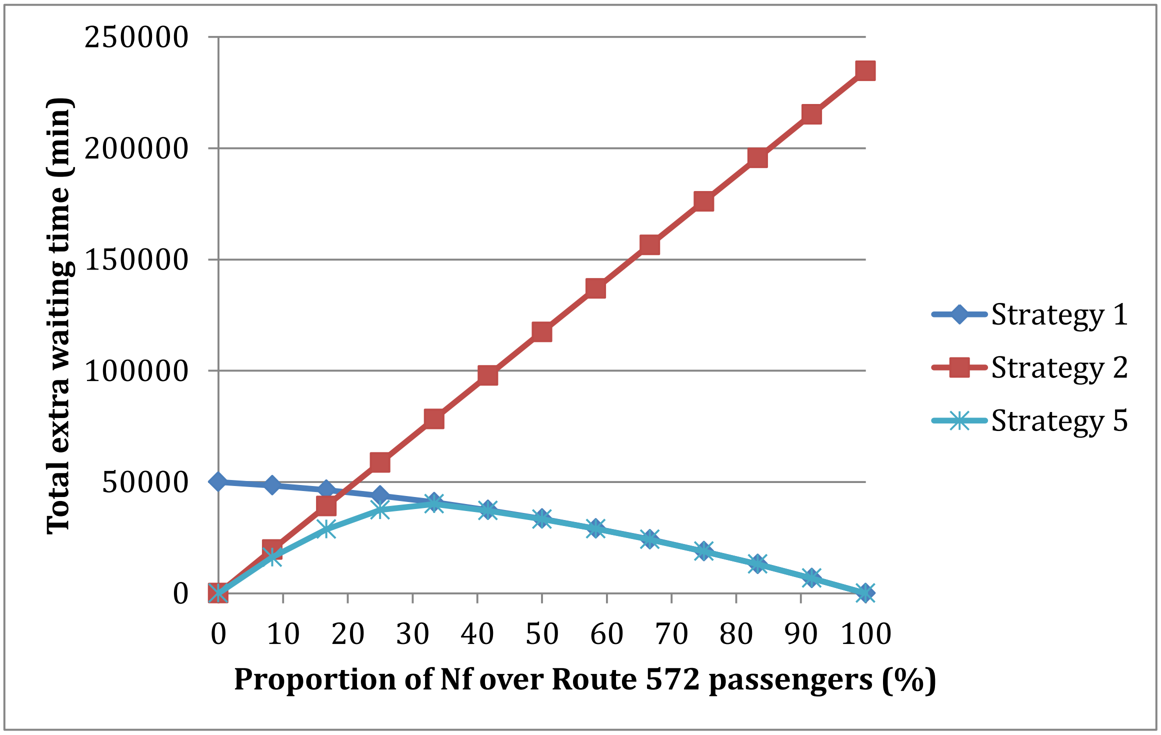


Figure 7.5-3 Transferring demand sensitivity analysis

Transfer coordination is generally not necessary when the share of transferring demand is less than 20%. The always-holding strategy actually costs the most in that case. When the share of transferring exceeds one-third of the total demand, always holding becomes the best strategy. Therefore, the predictive Strategy 5 is again the best coordination control strategy, because the EWT of each type of passengers is estimated and the best control is chosen.

7.5.3 **Sensitivity of scheduled headway**

The scheduled headway of the RV is also one of the determinants of ONTF systems (Dessouky et al., 1999). The aim of this section is to examine the proposed coordination strategies when the scheduled headway is small to large. Figure 7.5-4 compares the total EWT when the scheduled headway is from 5 minutes to 90 minutes.

Figure 7.5-4 shows that no transfer coordination is needed when the scheduled headway is smaller than 15 minutes. When the scheduled headway is 20 minutes onwards, holding becomes more than more essential. Overall, Strategy 5 is the best control framework for all scheduled headway.

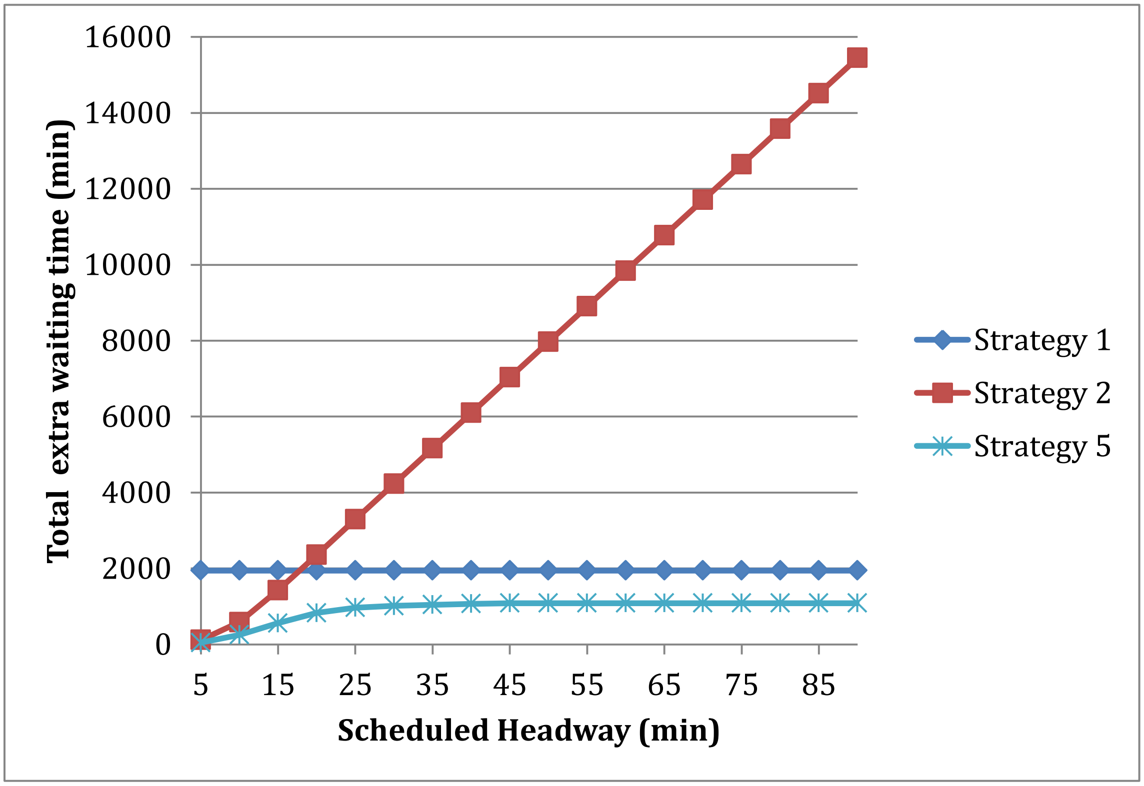


Figure 7.5-4 Scheduled headway sensitivity analysis

7.6 **Summary of Chapter 7**

Due to the lack of passengers' transferring plan data, the recent advances in ONTF in the literature have not been satisfactory. The transfer coordination framework has been developed and tested using simulated data, leaving the question of their practical applicability unanswered. Most of the existing studies also forecast the transferring demand using deterministic assumptions of transferring faction of the demand, rather than examining the transferring behaviour of each individual passenger. This chapter fill these gaps by predicting the number of transferring, non-transferring passengers and bus travel time using observed AVL and AFC data of SEQ, Australia. The models are developed using the data of July to September 2013 and tested using data of October 2013. The knowledge gained from Chapter 5 and 6 facilitates the understanding of individual passenger travel pattern and segment to forecast each passenger transferring plan. The transfer coordination results are tested using observed and simulated data under 6 control strategies. The strategy with predictions of travel time and demand (Strategy 5) outperforms all other strategies on every test of observed data, different arrival profile, transferring demand and scheduled headway.

However, Strategy 5 assumes no applied *MH*, which could be unrealistic in practical application of the framework. In real-world implementation of any transfer coordination control, there should be a maximum holding time because unexpected incidents may lead to excessive holding time of the RV. Moreover, holding RV too far beyond the scheduled departure time causes frustrations for on-board passengers, even if they are being informed about the coordination strategy. If *MH* is an operational constraint that has to be in transit operation control, the *MH*-predictive control Strategy 6 outperforms the Strategy 3 and 4.

7.6.1 Scientific and practical contributions

This chapter provides an ONTF framework that is ready to be implemented in practice. The framework is transferable, in which the forecasting of passenger demand and travel time could be performed by any prediction model. The predictive transfer coordination strategy (Strategy 5) reduces the total EWT for both transferring and non-transferring passengers by 70% compared to the existing strategy of no coordination control. The probability of missing a transfer also reduces from 13.49% to around 1%. This chapter also provides two scientific contributions: (1) the integration of passenger travel pattern to predict the number of transferring passengers; and (2) the development and testing of the ONTF control framework using real world AVL and AFC data.

7.6.2 Knowledge gained

The following knowledge could be gained from the development and implementation of the ONTF framework in this chapter

7) The most prediction-enabled transfer coordination strategies (Strategy 5 and Strategy 6-if *MH* is required) outperform other coordination strategies in both observed data and simulated scenarios. This finding is consistent with other studies in literature (Chung and Shalaby, 2007; Dessouky et al., 1999; Dessouky et al., 2003). We also found that having perfect information will improve the

coordination performance by at least 10% compared to the predictive transfer coordination, leaving the avenue to enhance the performance of the proposed predictive coordination framework by using better predictors of demand and travel time. In fact, the sensitivity analysis of these predictors performance shows that the forecasting accuracy is essential for the overall coordination framework performance.

8) For the current situation at Route 555 and 572, the always-holding strategy is an effective control method if no MH is required. This is the best control strategy without any prediction and outperforms the current no-holding control. The reduction in terms of EWT from the current strategy of no-holding to the simple always-holding strategy is 12.61%.
9) If we have less than 30% of transferring demand at the receiving transit vehicle, or less than 15 minutes in scheduled headway, the no-holding strategy is actually more beneficial than always-holding strategy. This is similar to the case when the RV arrives more than 12 minutes later than its schedule, or the schedule departure time is too far from its arrival. Therefore, examining the passenger demand, vehicle arrival time and schedule is essential before developing any transfer coordination control.

8 Conclusion

Transfer coordination is essential to enhance the transit quality of service and attract ridership. However, the problem of online and offline transfer coordination in public transit is complicated mainly due to (1) the complexity of public transport travel time variability (PTTV) in offline transfer coordination and (2) the unavailability of passenger transferring plan in online transfer coordination. Therefore, the primary objectives of this dissertation are to propose a comprehensive and effective framework in both offline and online transfer coordination.

Stage 1 meets the first sub-objective: **improving offline transfer coordination by understanding travel time variability**. Chapter 3 established the transit-oriented definitions of PTTV, proposed a comprehensive methodology to model and indicate PTTV using a probabilistic approach. Chapter 3 also reveals that the travel time of transit vehicle on arterial roads follows a log-normal distribution. Chapter 4 utilised these knowledge to develop an Event-based Multi Agent Simulation (EMAS) model to balance the trade-off between average transfer time and probability of missing a transfer in offline transfer coordination. There is no best value of the Planned Transfer time (*PTT*) that minimises both mean transfer time and probability of missing a transfer, but the EMAS model could be used to find an acceptable balance between these two values. However, transit operators could reduce both mean transfer time by 20% and probability of missing a transfer by 80% only by making all transit vehicles to dispatch on-time.

Stage 2 fulfils the second sub-objective: **enhancing online transfer coordination in real-time by exploiting individual travel pattern and passenger segmentation**. Chapter 5 proposed a comprehensive approach to mine individual passenger travel pattern from Smart Card AFC transactions and a new algorithm named WS-DBSCAN to detect & update the changes in passenger travel pattern. Chapter 6 further augmented the passenger characterisation by introducing *a priori* market segmentation based on the travel pattern of individual passenger. Chapter 6 shows that transit commuters though account for 14% of the sold Smart Cards, but they are covering nearly 50% of the fare revenue. Therefore, the fare revenue from a single Transit commuter is over 10 times that from an Irregular passenger. Chapter 7 developed a predictive technique to coordinate the transfer between two transit lines in real-time using the knowledge of individual passenger travel pattern.

The most prediction-enabled or technology enabled transfer coordination strategy outperforms other coordination strategies, especially the current strategy of no-holding. Having perfect information will improve the coordination performance by at least 10%, leaving the avenue to enhance the performance of the proposed predictive coordination framework by using better predictors of demand and travel time. There will be no coordinated control needed if we have less than 30% of transferring demand at the receiving transit vehicle, or less than 15 minutes in scheduled headway. Therefore, examining the passenger demand, vehicle arrival time and schedule are essential before developing any transfer coordination control.

8.1 **Contributions**

Within its primary objective of transfer coordination, this research provides the following contributions:

1) Stage 1 proposes **an Event-based Multi Agent Simulation (EMAS) model** that integrates the knowledge of travel and dispatching time variability with observed passenger demand to simulate the real world empirically and examine different offline coordination strategies. The EMAS model provides a new flexible approach to make the best use of travel time variability knowledge and real passenger demand data to enhance offline transfer coordination.
2) Stage 2 provides **an online transfer coordination framework** which was developed and tested using observed data. As far as the author's knowledge, this is a first online transfer coordination approach based on actual prediction of transfer demand in real-time. The framework enables transit operators to provide seamless transfer coordination. The method is practical ready and transferable, in which better predictors could be used to improve the coordination performance.

Within its secondary objectives of understanding travel time variability & passenger travel pattern and as supportive knowledge for transfer coordination studies, this research provides the following contributions:

1) This research *establishes the definitions and models public transport travel time variability.* The definition of PTTV is significantly different to its private counterpart, which assists travel time variability understanding. We also proposed

a new probabilistic approach to facilitate the measuring of PTTV and transit timetabling. The findings also contribute to the EMAS model to investigate offline transfer coordination strategies.

2) This research introduces a comprehensive method to mine individual travel patterns from only Smart Card Data. Without a costly passenger survey, transit operators can study their customer transit usage using the dynamic and large scale Big data. More importantly, *this research develops a new algorithm named WS-DBSCAN to observe and update daily changes in individual passenger travel pattern.* The existing algorithms in travel pattern analysis have high computing complexity, which limits their implementation on daily travel pattern analysis. WS-DBSCAN is approximately 200 times faster than the classical DBSCAN in detecting & updating individual travel pattern. The understanding of travel pattern obtained from this method facilitates online transfer coordination.
3) This research provides *automatic a priori market segmentation based on transit individual travel pattern* that further enhances passenger characterisation and profiling, which in turn is important for online transfer coordination strategies.
4) This research proposes *a novel method to predict the number of transferring passengers using passenger travel pattern.* The method facilitates multiple operational strategies such as occupancy prediction, incident management and especially online transfer coordination.

These contributions have been reported in 5 journal articles and 4 conference proceeding papers. The publication plan described in Section 1.4.4 has been met.

8.2 **Response to the research questions**

The knowledge gained from Stage 1 and 2 provides the answers for the research questions of this research.

8.2.1 **How to understand and model public transport travel time variability?**

In transfer coordination, PTTV is essential to anticipate the travel time variation and foresee the possibility of successful connection. Knowledge of PTTV facilitates the allocation of Planned transfer time (PTT). A too short PTT between the arrivals of the FV to the departures of the RV may lead to missed connection, whereas a too long PTT would lead to reduced commercial speed of transit services. Notwithstanding the importance of PTTV, there is a lack of understanding on the definitions, modelling and measurement of PTTV. The definition of Travel Time Variability (TTV) in literature is more relevant with private transport than public transport.

In this research we exploited the Big public transport data to better understand PTTV. The Vehicle Identification (VID) data of SEQ enables us to establish two definitions of PTTV, one derived from the common definition of TTV in private transport and one used additional data of public transport vehicle. The later definition is the better representative of PTTV and distinguishes PTTV from its private counterpart. The public transport data therefore was exploited by each service from multiple day of the same transit line.

A comprehensive 7-step approach was developed to investigate the distribution of travel time, enable us to observe the nature and shape of PTTV. By exploiting the VID data using this approach, we confirmed that the bus travel time in arterial roads follows a log-normal distribution. A probabilistic indicator of PTTV was proposed using log-normal PDF function. The indicator provides a measurement of PTTV similar to the classical Coefficient of Variation method, and also facilitates transit timetabling and slack time optimisation.

8.2.2 How to improve transfer coordination in offline strategic planning?

Offline transfer coordination, in particular "timed transfer coordination" (TTC) is the problem of coordinating the schedule of two transit routes so that passengers can make transfers. A value of PTT between the arrival of FV to the departure of RV at transfer stop is chosen with two principal objectives: minimising average transfer time and PMT. However, there is no PTT that minimises both average transfer time and PMT, because PMT is large while average transfer time is small and *vice versa*. This research develops a framework to examine and find a balance between this trade-off.

EMAS model was developed in this research to firstly simulate the observed transit operations and passenger demand and secondly to examine the impact of different values of PTT, dispatching time and travel time to average transfer time and PMT. The EMAS model integrated the knowledge of travel time variability from Chapter 3 with the observed passenger demand from AFC data. The verification results of total travel time and transfer time of passenger agents confirmed that the EMAS model represent the real-world passengers.

The EMAS model facilitates the selection of PTT to balance between average transfer time and PMT. On-time dispatching reduces average transfer time by 20% and PMT by 80%. However, transit operators have to carefully examine the current travel time and travel time variability to maintain high transfer services. Interested readers could find more information from Chapter 4 of this dissertation. This findings also subject to the study case of a single transfer stop between 2 connecting transit routes.

8.2.3 **How to mine individual passenger travel pattern?**

Notwithstanding the importance of the transfer demand variable in estimating the cost induced by a transfer coordination control to transferring and non-transferring passengers, the existing Online Transfer coordination (ONTF) strategies in literature have not described a method to forecast the transfer demand in real-time. This research solves this problem by exploiting Big public transport data to augment individual passenger characterisation through travel pattern. Travel pattern is defined in this research as the regular times and places of passenger transit travels. Understanding the individual travel pattern equals to understand how each passenger regularly travels, which enables us to predict the probability of transferring for each of them.

To mine travel pattern from each passenger, we developed a comprehensive approach to reconstruct full travel itineraries from AFC transactions and analyse travel pattern using DBSCAN algorithm. Then, a new algorithm named WS-DBSCAN was also proposed to improve the computing performance of DBSCAN, and enable daily travel pattern analysis. Interested reader could find more information from Chapter 5.

To further enhance the characterisation of each individual passenger, an automatic passenger segmentation framework was introduced. Transit passengers were grouped into 4 identifiable segments of similar travel patterns, revealing each segment characteristics and behaviours. Chapter 6 provides more details about this market segmentation study.

8.2.4 **What strategies could enhance online transfer coordination in transit operational control?**

The lack of information on passenger transfer plan is one of the principal reasons why ONTF in public transit is not as successful as its air transportation counterpart (Dessouky et al., 1999). In order to overcome this issue, this research uses passenger travel pattern to forecast the number of transferring passengers. This variable along with the bus travel time and the number of non-transferring passengers are the core components of a predictive ONTF framework. The EWT induced by the transfer coordination or no transfer coordination decision to transferring and non-transferring passengers are estimated and compared to find a global minimisation in the total passenger cost.

Six ONTF strategies were proposed and tested on observed and simulation scenarios. The strategies ranged from very simple without any prediction strategies (Always-holding Strategy 1 and No-holding Strategy 2) to strategy that required all forecasted variables (Predictive control Strategy 5 and MH-Predictive control Strategy 6). The examination of observed and simulated scenarios showed that the most prediction enabled strategies outperform other strategies in EWT and PMT.

However, the simulation scenarios also showed that before implementing any coordination strategies, transit operators should carefully examine the existing transit demand, vehicle arrival time and schedule. There would be no transfer coordination needed if the transferring demand is less than 30%, or the scheduled headway is 15 minutes.

8.2.5 **What are the benefits of transfer coordination?**

Transfer extends the existing transit coverage by omnidirectional connections of lines. However, poorly coordinated transfer is also one of the major disutility of public transport (Creutzig and He, 2009). A seamless interconnected transit system is essential to attract ridership.

The quality of transfer service could be improved by offline transfer coordination in strategic planning phase and online transfer coordination in real-time operational control. Figure 8.2-1 compares the extra waiting time (EWT) and probability of missing a transfer (PMT) between the current situation and the proposed offline and online transfer coordination strategies in this research, where the EWT and PMT of the current situation are valued as 100%.

Figure 8.2-1 clearly shows the reduction in both EWT and PMT when we apply transfer coordination strategies compared to the current situation. By simply dispatching transit vehicles as scheduled in offline transfer coordination, we can reduce EWT by 20% and PMT by 80%. Assuming all vehicles are dispatched on-time, modifying the value of *PTT* brings minor improvement in terms of EWT compared to the on-time dispatch implementation, but will triple the value of PMT. In online transfer coordination, if we always hold the receiving vehicle (RV) until the feeding vehicle (FV) arrival, there will be no missed connection and the EWT will be reduced by approximately 12%. The predictive control is perhaps the best online coordination strategy, which reduces EWT by 16% and only allows around 1% of missed transfer.

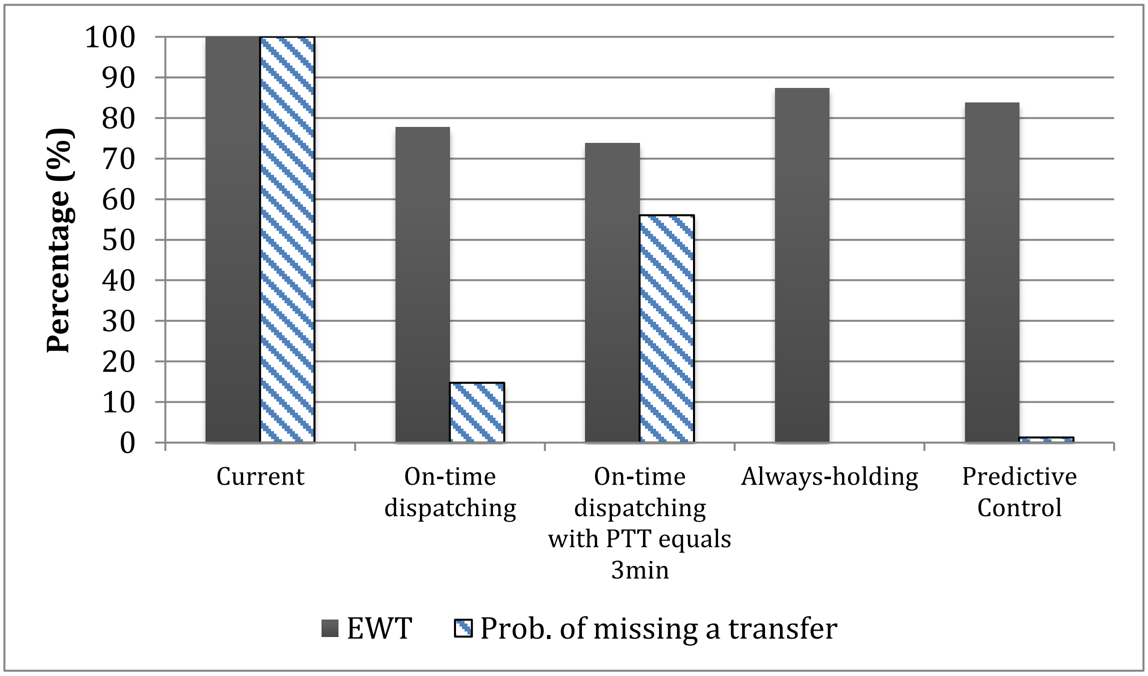


Figure 8.2-1 Comparison of offline and online transfer strategies to the current situation

Offline and online transfer coordination strategies are both helpful in reducing EWT and PMT. It is difficult to justify whether offline or online transfer coordination is more beneficial in providing seamless transfer service, because they are designed for cooperative purposes. Offline transfer coordination optimises the schedule, in particular the Planned Transfer Time to minimise EWT and PMT. In some occasion where there is still a possibility of missed connection for instance RV arrives earlier than FV, online transfer coordination is implemented to minimise the missed transfers.

8.3 **Limitations**

This research investigates the use of Big Transit Data for enhancing the planning and execution of passenger transfer coordination. It establishes fundamental understanding of PTTV, passenger travel pattern mining and segmentation, as well as provides novel and practical ready transfer coordination frameworks. However, various limitations may exist in this study.

The transfer coordination case in this thesis has a simple set-up of two transit lines connection at a single transfer terminal. The transfer coordination methodology of this research is therefore applicable to only similar case, which is in reality similar to the connection between a high frequency transit lines (subway, BRT lines, frequent bus, etc) and local low frequency lines in practice. Figure 8.3-1 illustrates an applicable case.

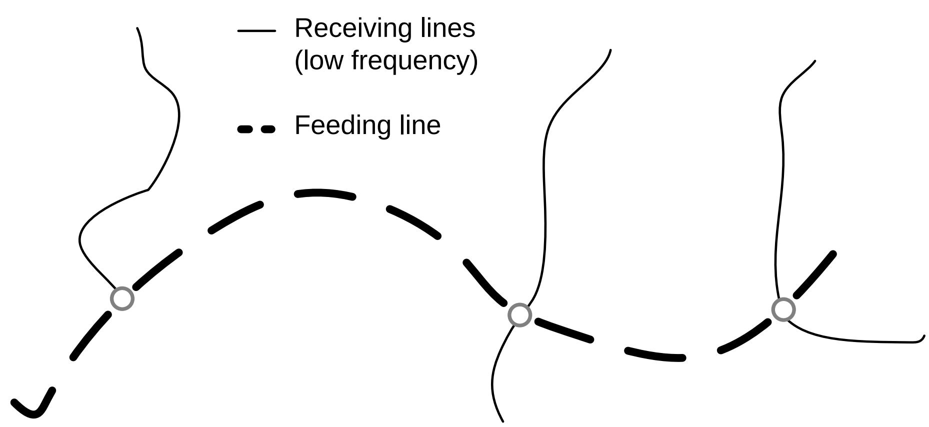


Figure 8.3-1 Connection between receiving and feeding lines

While this research has been developed for the simple set-up of only two transit lines and a single transfer stop, it is easily extendable to the case of a single feeding line and multiple receiving lines because both offline and online transfer coordination only apply to the receiving lines. The transfer is limited to time-point stop, uni-directional transfer from feeding to receiving lines and no control is applied to the feeding line.

8.4 **Recommendations for future research directions**

The knowledge gained in this research enables the following future research directions to be investigated.

8.4.1 Offline strategic planning and online predictive control strategy for bus bunching prevention

Headway deterioration leads to uneven passenger loadings, because a late bus has to pick up more passengers due to the long headway from its leading vehicle, which would result in further delay downstream of the trip. The following vehicle conversely has fewer boarding passenger and tend to run ahead of schedule, further reducing the headway between it and the late bus (TRB, 2013). This “bus bunching” phenomenon increases the passenger waiting time, bus travel time and deteriorates the scheduled headway or timetable. The problem has been addressed by many authors in the literature and different strategies have been proposed for solving it, which mainly have been associated with dynamic scheduling such as stop skipping (Liu et al., 2013; Sun and Hickman, 2005) or bus holding (Bartholdi III and Eisenstein, 2012; Cats et al., 2012; Cats et al., 2011; Daganzo, 2009; Sun and Hickman, 2008; Toledo et al., 2010; Xuan et al., 2011) and other strategies such as Transit Signal Priority (Currie and Shalaby, 2008; TRB, 2013). However, very limited studies aimed to empirically analyse the bus bunching problem to understand the phenomenon and develop proactive methods to solve it.

The conceptual knowledge of PTTV and passenger travel pattern gained from Chapter 3, 5 and 6 of this research could be used to address those gaps. The proposed EMAS model can integrate PTTV, dispatching time variability and observed passenger demand in order to simulate the bus bunching phenomenon and its impacts to transit passengers. Passenger travel pattern and segmentation can be used to develop predictive control strategies to prevent the bus bunching problem in real-time. In particular, the bus travel time, number of boarding and alighting passengers can be forecasted in real-time to anticipate the possibility of bus bunching and issue appropriate prevention strategies. The proposed methodology in this thesis will facilitate the investigation of bus bunching impact to passengers and bus bunching prevention strategies.

8.4.2 The use of maximum holding time (MH) in operational strategies

Holding is a common operational strategy in bus bunching prevention, headway regularisation and transfer coordination. Holding allows transit vehicle to stay beyond its scheduled departure time to wait for, or adjust the headway with another coordinated vehicle. MH prevents any passengers from experiencing the frustration of staying in stationed vehicle after its scheduled departure time. Even though the modern technology enables transit operators to inform the involved passengers about the holding strategy, the optimal value of MH that will be acceptable to passengers is still unknown.

MH has seldom been addressed in literature. Most of the studies on holding strategies overlooked the importance of MH as a practical operation constraint to limit the amount of waiting time for individual passenger. Only a few studies have used MH in vehicle holding problem. Van Oort et al. (2010) examined different values of MH in scheduled-based and headway-based holding strategies to improve system reliability. The authors showed that MH of 1-3 minutes is optimal for most of the tested scenarios. However when MH equals 1 minute, the performances of scheduled-based and headway-based holding strategy in reliability improvement are similar. Dessouky et al. (1999 and 2003) claimed that MH of 3 minutes minimised the passenger average trip time.

The value of MH should be considered in future studies of holding strategies as an operation constraint according to on-board passenger acceptance. The time lost due to vehicle holding could be perceived as unacceptable if the holding time is too long. Conversely, Chapter 7 shows that increasing MH will reduce the EWT of MH-enabled transfer coordination strategies. A survey of passengers could reveal the optimal value of MH that is perceived as acceptable for transit passengers.

8.4.3 Inference of travel purpose from Smart Card AFC data

Smart Card AFC data provides a rich and new data source of spatial and temporal characteristic of travel pattern on a multi-day period. The thesis exploits this data source to reveal meaningful travel patterns, passenger segmentations and transferring probability from individual passengers. The new methodologies developed in this thesis such as WS-DBSCAN, transferring passenger prediction facilitate further inference of travel purpose from Smart Card data. In particular, the following research directions can be examined using Smart Card data

- The current journey reconstruction method uses a threshold of an hour to define passenger transfers. This threshold originates from the transit usage rules in South East Queensland, where passengers are allowed to have up to an hour time limit between transfers (Translink, 2007). That is why the trip constructing algorithm has a one-hour limit constraint because outside that one hour the passengers are assumed not to have an intention of transferring. However, within that one hour this thesis assumes that passengers do not make any intermediate activities, because transfer time is simply calculated as the time gap between the alighting time from feeding vehicle to boarding time to receiving vehicle. The trip purpose inference can be further extended to separate actual time spent on waiting for a transfer and intermediate activities.

- Smart Card AFC data can be used to infer trip purpose, e.g. differentiating work, study-based journeys to recreational journeys. The travel purpose information from individual passengers replaces the costly manual travel survey method to support operators' decision on a timely manner. An extension of WS-DBSCAN can be proposed to infer individual trip purpose dynamically at the time of passenger boarding to adaptively aid the decision makers in real-time.

8.4.4 On-line transfer coordination by connected vehicles

The proposed ONTF framework in this research works only when RV arrives at transfer stop earlier than FV. While it has been confirmed as effective in reducing EWT and PMT, the framework has two main limitations:

- If FV arrives much earlier than RV or vice versa, the EWT of passengers would still be high due to the uncontrolled arrival time of both vehicles.
- Passengers perceive the holding time for transfer coordination at the transfer stop as time lost. As mentioned in the previous sub-section, too long holding time is unacceptable for on-board passengers.

These two limitations are unavoidable for the current implementation of the proposed ONTF framework. Future studies could address these issues by developing a connected controlling framework that synchronise RV and FV operations to guarantee simultaneous arrivals at transfer stop. If transit vehicles are held little by little at upstream stops, or their operating speeds are continuously adjusted, then passenger would not perceive the time lost for transfer coordination. However, this framework requires very precise information on vehicle positions and passenger's movements in real-time, which would complicate this connected control problem in both development and implementation.

APPENDIX A

Automatic Data Collection System Review

A.1 Automatic Data Collection Systems

This section provides an overall view on the available and useful data to be explored in this research. The data has been collected using three commonly used Big Public transport data: Automatic Vehicle Location (AVL), Automatic Fare Collection (AFC) and Vehicle Identification Data (VID). Table 8.4-1 illustrates the availability of each data source at arterial intersections and transit stops.

Table 8.4-1 Characteristic of data sources

Location	AVL	AFC	VID
Arterial intersections	Available	Not available	Available
Bus stops	Available	Available, but not at all stops	Not available

The fundamental of AVL system is on the instalment of GPS devices on transit vehicle to track its location. Generally, AVL data is available at both arterial intersections and bus stops. AFC system has been developed for automatic ticket collections. It is only available at bus stops of passengers dwelling where there are passenger boarding/alighting activities. VID data is based on the RFID technology, where a sensor is installed to identify transit vehicle holding RFID tags. For that reason, VID sys is normally available at signalised intersection and is used for Transit Signal Priority purpose. The following sections described each data source in details.

A.2 Automatic Vehicle Location (AVL) system

AVL is the technology that automatically locates the geographic location of a vehicle and transmitting the information to a central computer. The location is commonly identified by GPS and the information is send back by SMS, GPRS, satellite, radio or simply by offline connection. There are two main types of AVL systems: the real-time operated one and the offline archived one designed purposely for data analysis (Furth and Muller, 2006).

The archived AVL vehicle generally uploads the location data at the end of the scheduled day (Pu et al., 2009). The archived data is usually more detailed than the real-time AVL and sometimes also consists of detailed bus operations data such as travel time, distance, dwell time, number of stops served or even the number of passengers on-board (Furth et al., 2003). The timestamp, GPS coordinates, odometer of the bus and door open time are expected in any achieved AVL data. The travel time could be calculated by taking the difference of timestamps, the distance could be found from odometer values at two specific location and dwell time could be estimated from door opening time of the bus. Furth et al. (2003) provided a detailed review of the practices of using AVL data in the U.S.

The real-time AVL vehicles transmit their operation data to a central computer in real-time (Pu et al., 2009). The data is send periodically and includes timestamp, location (GPS coordinates), instantaneous speed and direction of the bus. Because of the limitation in data bandwidth, the real-time AVL data is usually less detailed than the achieved one, but the real-time fashion makes it feasible for real-time transit and traffic information studies.

Achieved and real-time AVL data provide a rich source of information on the bus journey. The Figure 8.4-1 presents an example of the bus space-time trajectories that are generated from the AVL data. The trajectories provide the delays of the bus on each stage: dwell time, acceleration/deceleration time, signal delay, etc. in which the delays are caused by the interactions with modes of transport.

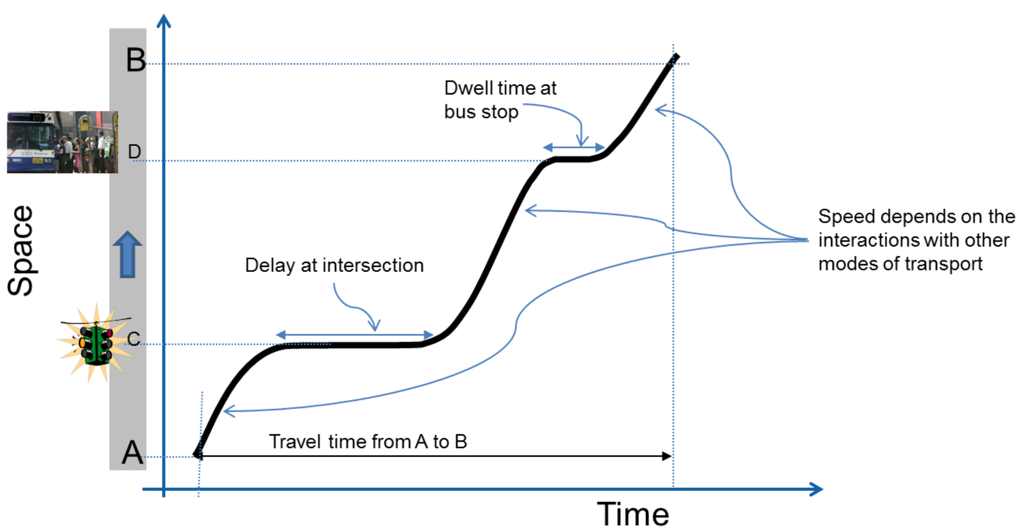


Figure 8.4-1 Example of bus trajectories generated from AVL data

Each component of the bus operations could be explored and modelled. Among the studies on bus operations that have been reviewed in the previous section, the majority of the studies utilised AVL data for a complete picture of the bus operations. AVL data is also used for bus travel time estimation (Bae, 1995; Tétreault and El-Geneidy, 2010) and prediction models (Jeong and Rilett, 2005; Shalaby and Farhan, 2004a). However, the following issues need to be addressed when examining the AVL data:

1) The first problem related to the GPS technology. Vehicle with GPS requires a line of sight to the satellites to be located. GPS can be blocked by canyons such as buildings and mountains. The signal can also reflected by those obstacles causing erroneous location estimation for the system (Furth et al., 2003)
2) The processing of AVL data is not really an issue, but a challenge for traffic engineers in utilising the data. The majority of AVL data has only location in the form of GPS coordinates, so a map matching algorithm is needed to find the exact location of the bus on the map. The algorithm should also consider the error in GPS coordinates. For some AVL dataset where the schedule and route information is not included, matching the bus location to the route and find the schedule adherence is also a challenging task for the analyser.
3) At this moment, the on-board GPS equipment for bus is still expensive. AVL system is not available globally, and usually GPS equipment is also not installed on all vehicles in the system which can limit the sample size of study.

Translink, the transit service providers in SEQ has installed GPS into buses operating in Logan City, and some bus routes in Brisbane City, Queensland to provide AVL data to service monitoring and research purposes. The archived AVL data in SEQ has been stored at bus stops only.

A.3 Automatic Fare Collection (AFC) system

AFC system has been increasingly used in major cities in the world as a new media for transit fare payment. Up to 2008, more than 30 cities in Asia were using AFC in ticketing (Park et al., 2008). It usually embedded with integrated circuits to store data and communicate with an on-board card reader via radio waves. Each AFC card has a unique serial number. It could be registered to an individual person or anonymous. The card normally stores debited value to be used for transit fares along with other fare payment products such as travel passes and tickets (Bagchi and White, 2004).

In terms of transit data analysis, AFC data provides a larger volume of travel data from longer travelling periods by an automatic collection method compared to the traditional on-board survey. AFCs data can be easily classified into several groups (senior, student/concession, adult etc.) and analysis of passengers using the system could be easily carried out. Finally, passengers using AFCs are usually required to touch it to the card reader during boarding and aligning the bus. A transit Origin-destination (OD) study is feasible if the AFC data for all trips within an area is provided.

Some authors in the literature explored the AFC data in many different purposes. Chu and Chapleau (2008) estimated the bus arrival time and identify linked trips by using temporal concepts. Agard et al. (2006) classified the passengers into typical types and analysed variability according to the day, week or season of trip. Park and Kim (2008) carried out an interesting study predicting future trend of passengers demand on AFC data of Seoul, Korea. Although AFC data could provide useful information for transit analyser, the followings are the limitations of this data source.

- Compared to traditional survey method, AFC data cannot provide trip purpose and final destination of the passengers (Bagchi and White, 2004). In order to find individual journeys of each passenger, algorithms need to be developed for linking several AFC transactions and identify the alighting points from the data.
- The penetration rate is not 100%. The presence of unrecorded paper ticket or travel pass could negatively affect the modelling effort. AFC data has only information at the bus stops, hence other delays along the bus route cannot be found. Moreover, the bus might skip some stops, which will add some complexities for mining the necessary data.
- Privacy is also a noteworthy issue when analysing AFC data. The individual movements of AFC holder could be tracked by exploring the data.

Translink launched the AFC system in South East Queensland from 2008. The card is called Go Card and it classified the passengers into 6 main types: Adult, Child, Tertiary Student, School Student, Pension and Senior. Translink has introduced some policies to increase the use of Go Card such as lower journey fare, automatic top up and account registering via internet and phones.

A.4 Bus Vehicle Identification (VID) data – Public Transport Priority System data

Automatic identification procedures have been very popular in providing information about movement of people, animals and goods. One of the popular technologies in automatic identification is Radio Frequency Identification (RFID) technology. RFID is the technology that uses radio-frequency magnetic or electromagnetic for communication between a tag attached device and a reader (Finkenzeller and Muller, 2010). Unlike the bar code or AFCs technology, the tag does not need to be in direct contact or within line of sight of the reader and could be installed in the tracked object.

In traffic engineering, RFID technology could be used in Public Transport Priority System (PTPS), toll application, parking management, vehicle identification, traffic control and theft protection of cars due to its ability in identifying and tracking of vehicles. Blythe (1999) provides a detailed review of the practices and issues of RFID applications in road tolling, road-use pricing and vehicle access control. Some other authors (Chon et al., 2004; Lee et al., 2012a) explored the possibility of using RFID for replacing or improving the accuracy of GPS in positioning.

Since each vehicle also has a unique ID tagged to its RFID device, this data could also be used for matching vehicle locations and estimating travel time between the locations similar to the Bluetooth technology (Bhaskar et al., 2014a; Bhaskar et al., 2014b). Researchers have utilised the RFID technology to estimate travel time between toll gates (Swedberg, 2004) and OD matrices on motorway networks (Baek et al., 2010). Sriborrirux et al. (2008) also explored the possibility of using RFID technology in monitoring and scheduling of the bus fleet in Bangkok, Thailand. Their study described the communication protocols, formats and functions in the design and development of the system. However, the performance of the system in terms of travel time estimation was not mentioned. Seo (2008) proposed a simulation study of a "futuristic study" where RFID tagging of cars is used for traffic data collection. Every car was assumed to have its own RFID tag and RFID readers were installed at intersections for collecting link velocity and travel time between the readers. The study was conducted on simulation without validation using observation data.

The RFID technology was invented a long time ago, from the World War II when it was used to differentiate between friendly and enemy aircrafts (Stockman, 1948). Even though the technology improvements have increased the detecting range, accuracy and reduced the equipment's price, RFID technology has not been widely used in travel time estimation. The problems related to RFID technology could be classified into technical problems and security problems.

On technological issues, the RFID technology has been implemented in different fields and by different ways. An official international standard is still missing, which could cause problems on conversions and upgrades. Secondly, the system could be jammed relatively easy both from the reader side (because of too many signals from tags) and tags side (because tags cannot response to simultaneous queries from readers). Finally, the costs of tags are still relatively high compared to other automatic vehicle identification systems

The security and privacy concerns are the principal issues in the development of RFID technology in private vehicles. The RFID tags could be read from distance and without the knowledge or approval of the tag bearer. More importantly, unlike the Bluetooth technology, where each device has a unique MAC address but there is no MAC address database for matching and find information of the devices; for the RFID case because of the purpose of identification, there is always a RFID ID database. These two characteristics could lead to serious security and privacy problems for RFID tagged vehicles' owners.

The Brisbane City Council has installed RFID scanners at intersections of the major bus routes in Brisbane for PTPS (Kieu et al., 2015a). The VID data includes the Vehicle ID of an in-service or not-in-service bus, vehicle tag, intersection ID and the timestamp when the vehicle is identified. Table 8.4-2 shows an example of VID data.

Table 8.4-2 Sample VID data

Timestamp	Intersection Id	Vehicle ID	Vehicle tag
2011/08/04 09:15:24	1	X1	BBT696,623700I103301
2011/08/04 09:42:58	1	X2	BBT697,589000I103531
2011/08/04 10:54:11	1	X3	BBT1878,622200I353011

The vehicle tag includes the bus identification number (e.g. BBT696), service number (e.g. 623700), start time (e.g. I10, which means 9:10:00) and bus route number (e.g. 330).

APPENDIX B

Bus Travel Time Prediction models

B.1 Literature Review

The problem of travel time prediction has been extensively studied in the literature. Table summarises the recent advances in travel time prediction.

Table A-1 Literature review on bus travel time prediction

Method	Literature	Data source	Data collected
Historical average model	Jeong and Rilett (2005)	AVL	arrival time, dwell time, and schedule adherence at each stop
	Chen et al (2011)	AVL	Link travel time, arrival time, section travel speed
Time series models	Rajbhandari (2005)	AVL	Arrival time, delay, travel time
	Suwado *et al.* (2010)	Handheld GPS	Arrival time, departure time
Regression model	Abdelfattah and Khan (1998)	AVL	Traffic information, bus schedules, road geometrics, signalization, accident data, bus survey
	Lin and Zeng (1999)	AVL	GPS data, time table, delay
	Patnaik et al. (2004)	APC	GPS data
Artificial Neutral Network (ANN)	Kalaputapu and Demetsky (1995)	AVL	Bus arrival time, time table
	Chien *et al.* (2002)	Simulation data	traffic data, passenger arrival rate, bus arrival time
	Chen *et al.* (2004)	APC	historical arrival time clustered by day-of-week, time-of-day, segment and weather, recent running time of the current bus
	Mazloumi *et al.*	SCATS, AVL	Real-time traffic flow, degree

	(2011)		of saturation, schedule adherence
Kalman Filter	Reinhoudt and Velastin (1997)	On-board radio, platform beacon	Link journey time
	Wall and Dailey (1999)	AVL	Historical travel time, current location data from AVL
	Shalaby and Farhan (2004)	AVL & APC, microsimulation	Running time, departure time, arrival time
Pattern recognition	Yu et al. (2006)- Support vector machine learning method	No information	The travel time of current segment and the historical travel time
	Chang et al. (2010) – Nearest Neighbour Non-parametric Regression	AVL	Current and historical bus travel time
	Vu and Khan (2010)- Statistical pattern recognition	AVL,APC, simulation	Historical travel times, travel time of current and preceding buses on the last segment

The recent advances in bus travel time prediction could be classified into 6 major approaches: Historical Average, Time Series, Regression, Kalman Filter, ANN and other Pattern Recognition methods. Each method has its own disadvantages and advantages and has been proven as satisfactory in bus travel time prediction in the literature. This sub-section develops an ANN to predict the link travel time. ANN has been commonly believed as having more potential in travel time prediction than other modelling methods (Park and Rilett, 1999; Jeong and Rilett, 2005; Chang et al., 2010). ANN models could also be incorporated with other method such as time series models, statistical models (Chien et al., 2002) or Kalman Filter models (Chen et al., 2004). ANN models are suitable to find complex nonlinear relationship between the dependent variable bus travel time and the independent variables that influence the travel time.

ANN has been applied to transportation since the early 90s (Faghi and Hua, 1992; Dougherty, 1995) as the application of artificial intelligence in transportation engineering. Through many researches since 1990, ANN was demonstrated as a potential method for predicting the traffic conditions accurately (Smith and Demetsky, 1994; Kalaputapu and Demetsky, 1995; Chien *et al.*, 2002; Chen *et al.*, 2004). ANN emulates the learning procedure of the human brain. It is formed by a number of artificial neutrons, which are processing units that are strongly connected with each other by synaptic weights (Chien et al., 2002).

In transportation engineering, the most commonly applied paradigm is supervised learning, backpropagation learning method (Smith and Demetsky, 1994; Dougherty, 1995; Jeong, 2004). Kalaputapu and Demetsky (1995) proposed ANN models for predicting the bus schedule deviations. Three ANN architectures in backpropagation learning were investigated: feedforward and two recurrent networks: the Jordan networks and the Elman recursive networks. The data were collected from Tideware Regional Transit's AVL system in Virginia, U.S. The results of the three architectures were moderately different to each other. This study gave an initial insight into the application of ANNs to bus travel time prediction by its encouraging results. However, the input data used in the three models are only historical time series data of the bus arrival times. The prediction of bus arrival could be calculated from the bus schedule deviation, the performances of the models are questionable, because of the lack of input data.

Chien *et al.* (2002) developed two ANNs models for predicting the bus arrival times with the case at New Jersey, U.S. The models are trained by link-based and stop-based data. The authors stated that the training processes for the ANN backpropagation models are lengthy and therefore, the models are not suitable for online prediction of bus arrival times. Hence, an adaptive algorithm was introduced to fine-tune the prediction based on real-time data. The input data for the models were derived from simulation data CORSIM. The evaluations of the models illustrated that the enhanced ANNs models outperformed the ANNs without the adaptive algorithms. The authors also concluded that the stop-based ANN was more suitable in network with many intersections between stops, while the link-based ANN was preferable in the other case. However, because of the lack of location-based and traffic data in the study site, the study used artificial data from microscopic simulation model CORSIM. Hence, the data used for the ANNs such as traffic volumes, speeds and delays and the real-time data used for the adaptive algorithm for enhancing the prediction are secondary data derived from CORSIM. The study, along with Abdelfattah and Khan (1998) gave motivations for later researchers to include dynamic real-time information in their models for predicting the bus travel time.

Chen et al. (2004) introduced an ANN model based on historical APC data, bus operation and weather data. Considering the influence of nonrecurrent situations which could affect the bus trip, the authors also developed a dynamic algorithm based on the Kalman filter for adjusting the prediction from the ANN model. The Kalman filter algorithm used the real-time observation of bus location for modifying the predicted bus travel time according to the most recent information of the bus trip. The authors used an assumption that the bus speed remained unchanged between the two consecutive time points for filling the missing data if the bus skipped a stop. The evaluation of the models showed that the proposed model outperformed the schedule-based method and the ANN model individually.

Mazloumi et al. (2011) developed the models that included real-time traffic flow data in their two ANN models. The traffic flow data was obtained from the Sydney Coordinated Adaptive Traffic Systems (SCATS) loop detectors in Melbourne, Australia. The authors proposed two ANN models to forecast the average and variance of bus travel time. The models are responsive to the dynamic changes in both traffic supply and demand. The evaluation of the models illustrated that the proposed models performed better than two alternative models: ANN model based on historical data with temporal variables, and timetable-based model.

B.2 Bus travel time prediction model development

Multi-layer perceptron feedforward ANN

Feedforward nets are the most common and widely-used class of neural network in the literature. It has been used and proved sufficiently effective in bus travel time prediction (Chen et al., 2004; Chien et al., 2002; Mazloumi et al., 2011). In feedforward ANN, the connections between the units do not form a directed circle, enables the information to move in only forward direction from the input to output nodes without any circle and loops.

There are two types of feedforward ANN: single-layer perceptron and multi-layer perceptron. Single-layer perceptron has only a single layer of output nodes, where input are fed directly via a set of weights. This type of neural network has limited computational power and generally capable for modelling a linear relationship between input and output nodes. Multi-layer perceptron (MLP) is the most commonly used type of feedforward neural network in the literature. It consists of multiple interconnected layers, where each neuron in a layer has direct connections with the neurons in subsequent layer. MLP network is more capable of capturing the complex relationship between input and output neurons than single-layer perceptron. This sub-section develops a MLP feedforward neural network to predict bus travel time.

Figure illustrates the structure of the proposed MLP feedforward network.

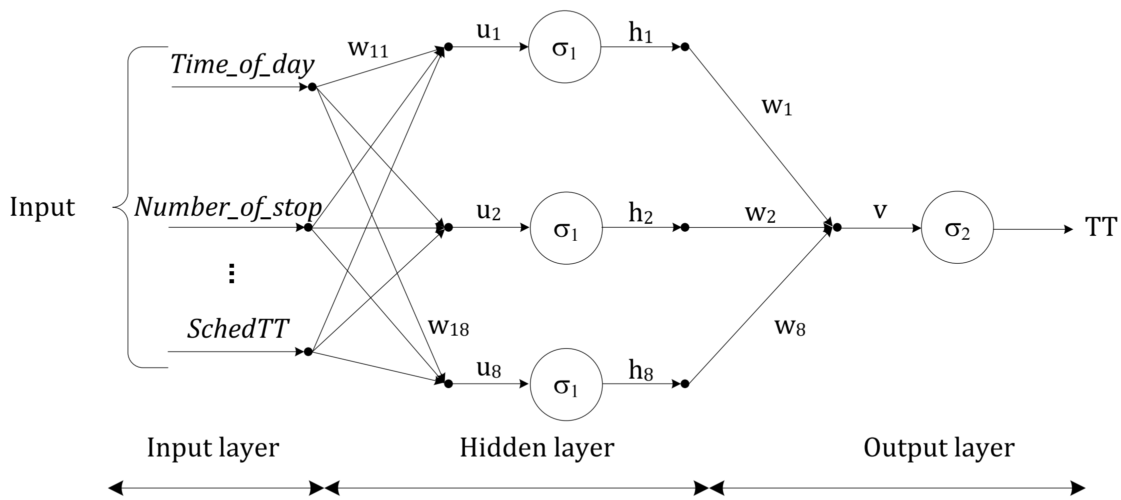


Figure A-1 MLP feedforward network structure

The network on Figure has three layers: input layer with 7 neurons (7 input variables), a single hidden layer and a single output layer. Each layer has its own role in the network operation

- Input Layer: A vector of independent variable ($x_1 ... x_7$) is standardised to values from -1 to 1 and is fed to the input layer. The input layer delivers the input values to each of the neurons in the hidden layer.
- Hidden Layer: The value from each input neuron is multiplied by a weight (w_{ji}). A constant input equals to 1.0, called the *bias* is also multiplied by a weight and added to the sum of w_{ji}. This weighted sum (u_j) is inputted into a transfer function σ_1, which yields a value h_j.
- Output Layer: Each value h_j from the hidden layer neuron is multiplied by a weight (w_k), and again combined to form a weighted sum v. The value v is then fed into another transfer function σ_2, which yields y as the output of the network.

The MLP is mainly developed by a trial-and-error process, where different options are tested and the one that yield the best results is chosen. The following issues are involved in designing and training a MLP network:

- Selecting the number of hidden layer: a MLP network with an input, an output and a single hidden layer is generally sufficient to most of the predicting task. Using two hidden layers in this bus travel time prediction MLP model does not significantly improve the model accuracy, but may introduce a greater risk of converging to local minima. Therefore, the proposed MLP network consists of a single hidden layer.
- Selecting the number of neurons in the hidden layer: If insufficient number of neurons are used the MLP network will not be able to capture complex in-output relationship. However, if too many neurons are used the network may "overfit" the data. It models the random noise in the dataset, fits the training data very well but generalises poorly to unseen data. To select the optimal number of neurons, the training data (Jul-Sep 2013) is divided to 70% of "developing dataset" and 30% of "cross-validating dataset". Different MLP model of 1 to 20 neurons in the hidden layer are trained using the "developing dataset". By calculating their prediction errors, we found that 10 neurons are sufficient to predict the bus travel time.
- Selecting other variables for MLP network: Backpropagation, the most common method of training ANN is chosen in this study. Sigmoid transfer function is used for hidden and linear transfer function is used for the output layer. The maximum iteration is set as 1000. The learning rate is set as 0.1 and the training goal as 0.001.
- A sensitivity analysis using a MLP feedforward network using different set of input variables reveals that the inclusion of *Headway* and *Day_of_week* would not significantly improve the accuracy of the prediction model. Therefore, these two variables are not included in the development of final MLP network in this section.

Cascade correlation network

Cascade Correlation Neural Network (CCNN) is a "self-organising" ANN. Instead of having a predetermined number of neurons in the hidden layer, CCNN starts with only input and output neurons. CCNN then selects neurons from a pool of candidates and adds one at a time to the hidden layer. Outputs from existing neurons are fed into new neurons, as the CCNN attempts to maximise the degree of correlation between the new neuron's output and the residual error of the CCNN prediction model.

The proposed CCNN has three layers: input, hidden and output.

- Input layer: A vector of independent variables ($x_1 \ldots x_p$) is fed into the input layer. There is also a constant C equals to 1.0 called the *bias* that is presented to each of the hidden and output neurons. C is given a weight during the training process.

- Hidden layer: Each variable from each input neuron is multiplied by a weight and accumulated to a combined value. The transfer function, in this case is a sigmoid function processes this sum into a value and presents it to the output layer.
- Output layer: There is a single neuron in the output layer, which is the bus travel time. The single output neuron receives values from all the input and hidden neurons. Each of these values is multiplied by a weight and added together to form a combined value. This weighted sum is again processed by a linear transfer function, and the output is the predicted bus travel time.

The CCNN has several advantages over the aforementioned MLP feedforward network

- The CCNN has a "self-organising" structure, which means there is no issue of selecting the number of layers and neurons in the network
- The training time is significantly faster than the common MLP feedforward network, especially for the large training dataset in this study
- CCNN training is more robust and less likely to converge to local minima than MLP feedforward network.

However, the CCNN also suffers from the following disadvantages

- CCNN has more probability of overfitting the training data. To prevent this issue, we also divide the training dataset (Jul-Sep 2013) to "developing dataset" and "cross-validation dataset". The "developing dataset" is used to train the CCNN while the "cross-validation dataset" is used to test the network.
- CCNN performs worse than MLP networks if the sample size is small. This is not a big problem in our predicting scenario because the sample size is sufficiently large.

Interested readers on CCNN could refer to the paper by Fahlman and Libiere (1989) for more detailed information.

Bagging ensemble MLP feedforward network

Supervised learning using ANN searches through a hypothesis space to find a set of weights that minimise the residual between predicted and observed values. However, even the best ANN could fall into local minima or overfit the training data. Ensemble learning is an effective technique that combines multiple base learners to form a strong learner. The strong learner integrates the predictions from base learners and provides a smoother combined prediction. The ensemble method has been proven as effective to produce a better predictor than a single prediction model (Breiman, 1996; Freund and Schapire, 1995; Wolpert, 1992).

Among a large number of ensemble techniques such as bagging (Breiman, 1996), stacking (Wolpert, 1992) and boosting (Freund and Schapire, 1995), bagging ensemble is one of the most intuitive and effective method. Bagging aims to produce a diversity of learners by using bootstrapped replicas of the training data. We adopt the following steps to predict bus travel time using bagging ensemble:

1) Training phase:
   In each iteration *m*, *m*=1,…,M
   - Randomly select with replacement N samples from the training dataset. *N* is chosen as half of the total training sample size to increase the generalisation of the prediction.
   - Train the "base MLP feedforward network" MLP_m
2) Testing phase
   - Start all trained base networks MLP_1 to MLP_m, each of those provides a prediction of bus travel time
   - Averaging the M predictions from the base networks to provide a single prediction of the bus travel time

$$TT = \frac{1}{M}\sum_{m=1}^{M} TT_m \qquad (58)$$

Where TT_m is the prediction output of base network m

M is the total number of base networks, in this case M equals to 10. If M is too low, the benefit of ensemble technique is insignificant. Conversely, if M is too large the computation time EWT would be too high for practical application. M equals to 10 has been chosen to balance this trade-off. The parameters and training of each base MLP feedforward network are similar to the MLP network in the previous sub-section.

APPENDIX C

Pseudo code for testing the 6 transfer coordination strategies using observed data of October 2013.

```
function online transfer coordination

load testing data of October 2013
Input MH

Initialize the extra waiting time of each strategy
    EWT1 = 0;
    EWT2 = 0;
    EWT3 = 0;
    EWT4 = 0;
    EWT5 = 0;
    EWT6 = 0;
    H = 30; //Scheduled headway 30 minutes

For each data line, obtain the observed Ar, Nr, TT, Af, Nf, SchedDev
and Sr from the observed data

if SchedDev<0 //the receiving vehicle arrives sooner than the schedule
   if Af>Sr
       //the extra waiting time for non-transferring and transferring
passengers, induced by the transfer coordination or no transfer
coordination decision
       EWTr = (Af-Sr+(5.8+3.6*Nf)/60)*Nr;
       EWTf = (Sr+H-Af)*Nf;
       //Strategy 1: always-hold until Af
       EWT1 = EWT1 + EWTr;
       //Strategy 2: no-hold
       EWT2 = EWT2 + EWTf;
       //Strategy 3: hold but no more than the maximum holding time MH
       if Af < MH + Sr //if feeding vehicle arrives earlier than the
maximum holding time
          EWT3 = EWT3 + EWTr;
       else
```

```
          EWT3 = EWT3 + (MH +(5.8+3.6*Nf)/60)*Nr + EWTf;
       end
       //Strategy 4: hold but only if predicted TT is less than MH
       Obtain TT_pred from the bus travel time prediction model
       // the predicted arrival time equals the last known arrival plus
the predicted travel time
       Af_pred =  TT_pred + Last known arrival
       if Af_pred <= MH + Sr //if the predicted arrival time is less
than the maximum holding time
          EWT4 = EWT4 + EWTr;
       else
          EWT4 = EWT4 + EWTf;
       end
       //Strategy 5: hold if EWTr_pred>EWTf_pred
       Obtain Nr_pred from the predictor of non-transferring passengers
       Obtain Nf_pred from the predictor of transferring passengers
       //calculate the predicted EWTr and EWTf
       EWTr_pred = (Af_pred-Sr+(5.8+3.6*Nf_pred)/3600)*Nr_pred*60;
       if EWTr_pred<0
          EWTr_pred=0;
       end
       EWTf_pred = (Sr+0.5-Af_pred)*Nf_pred*60;
       if EWTf_pred<0
          EWTf_pred=0;
       end
       if EWTr_pred<EWTf_pred
          EWT5 = EWT5+EWTr;
       else
          EWT5 = EWT5+EWTf;
       end
       //Strategy 6: hold if EWTr_pred>EWTf_pred, but only until MH
       if EWTr_pred<=EWTf_pred
          if Af_pred <= MH + Sr
             EWT6 = EWT6 + EWTr;
          else
             EWT6 = EWT6+EWTf;
          end
       else
```

```
          EWT6 = EWT6+EWTf;
       end
    end
else //receiving vehicle arrives later than its schedule
    EWTr = (Af-Ar+(5.8+3.6*Nf)/60)*Nr;
    EWTf = (Sr+H-Af)*Nf;
    //Strategy 1: always-hold until Af
    EWT1 = EWT1 + EWTr;
    //Strategy 2: no-hold
    EWT2 = EWT2 + EWTf;
    //Strategy 3: hold but no more than the maximum holding time MH
    if Af< MH + Sr
       EWT3 = EWT3 + EWTr;
       elseif Ar<= MH + Sr
              EWT3 = EWT3 + (Sr + MH-Ar+(5.8+3.6*Nf)/60)*Nr + EWTf;
       elseif Ar> MH + Sr
              EWT3 = EWT3 + EWTf;
    end
    //Strategy 4: hold but only if predicted TT is less than MH
    Obtain TT_pred from the bus travel time prediction model
    Af_pred =  TT_pred + Last known arrival
    if Af_pred <= MH + Sr
       EWT4 = EWT4 + EWTr;
    else
       EWT4 = EWT4 + EWTf;
    end

    //Strategy 5: hold if EWTr_pred>EWTf_pred
    Obtain Nr_pred from the predictor of non-transferring passengers
    Obtain Nf_pred from the predictor of transferring passengers

    EWTr_pred = (Af_pred-Ar+(5.8+3.6*Nf_pred)/3600)*Nr_pred*60;
    if EWTr_pred<0
       EWTr_pred=0;
    end
    EWTf_pred = (Sr+0.5-Af_pred)*Nf_pred*60;
    if EWTf_pred<0
       EWTf_pred=0;
```

```
    end
    if EWTr_pred<EWTf_pred
       EWT5 = EWT5+EWTr;
    else
       EWT5 = EWT5+EWTf;
    end
    //Strategy 6: hold if EWTr_pred>EWTf_pred, but only until MH
    if EWTr_pred<=EWTf_pred
       if TT_pred/60 + Ar <= MH/60 + Sr
          EWT6 = EWT6 + EWTr;
       else
          EWT6 = EWT6 + EWTf;
       end
    else
       EWT6 = EWT6+EWTf;
    end
end

output EWT1, EWT2, EWT3, EWT4, EWT5, EWT6
```

APPENDIX D

Simulated sensitivity analysis of 6 proposed online transfer coordination strategies

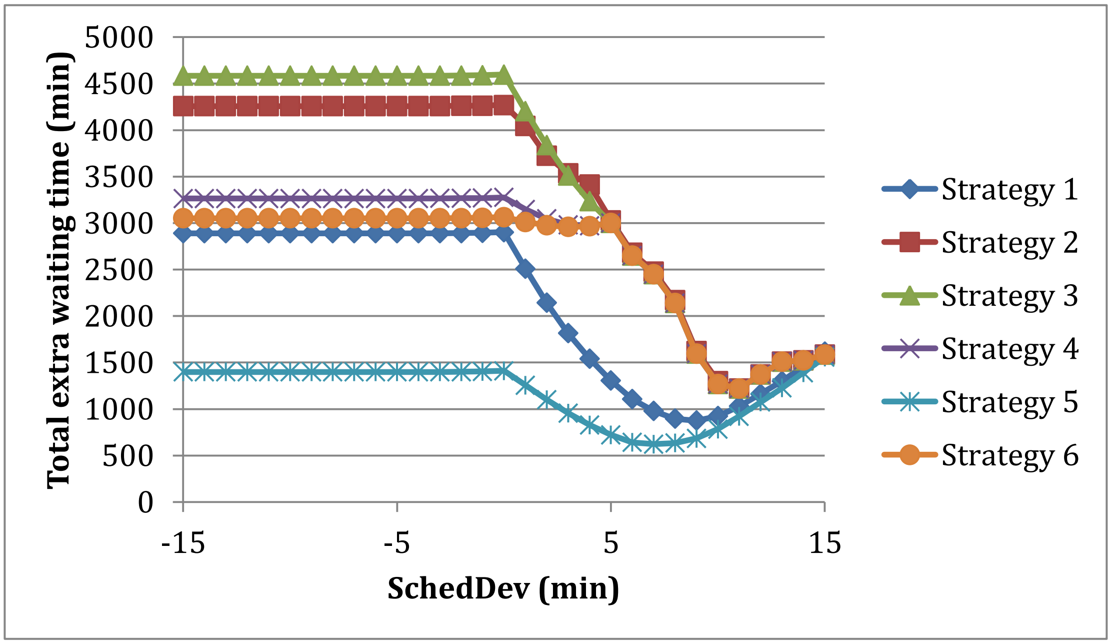


Figure C-1 Operational arrival profile sensitivity analysis

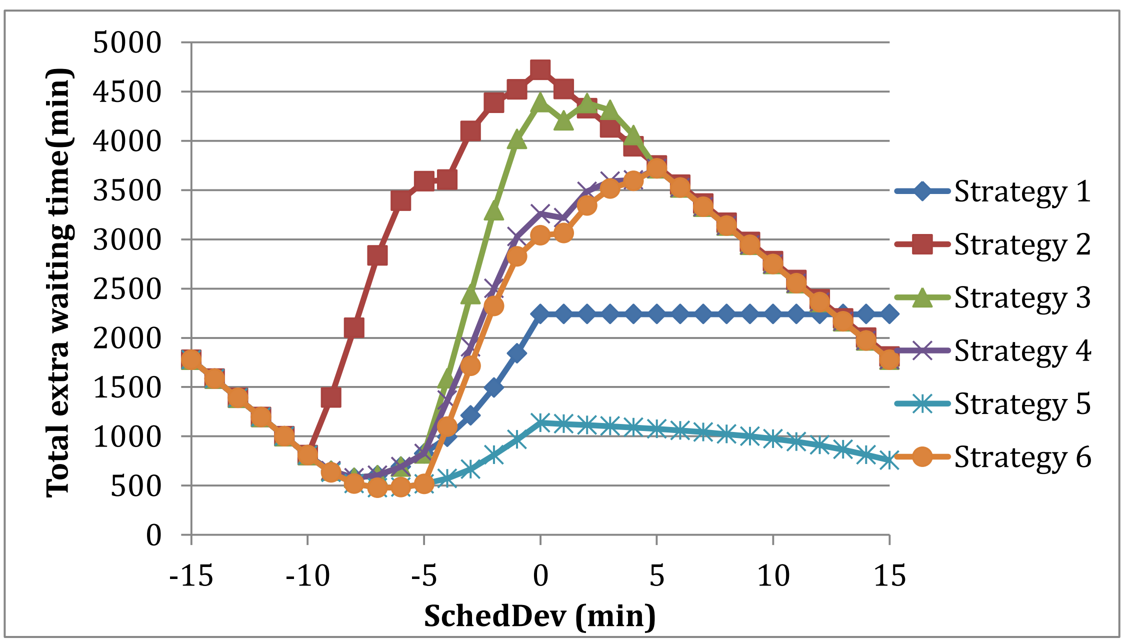


Figure C-2 Scheduled departure time (S_r) sensitivity analysis

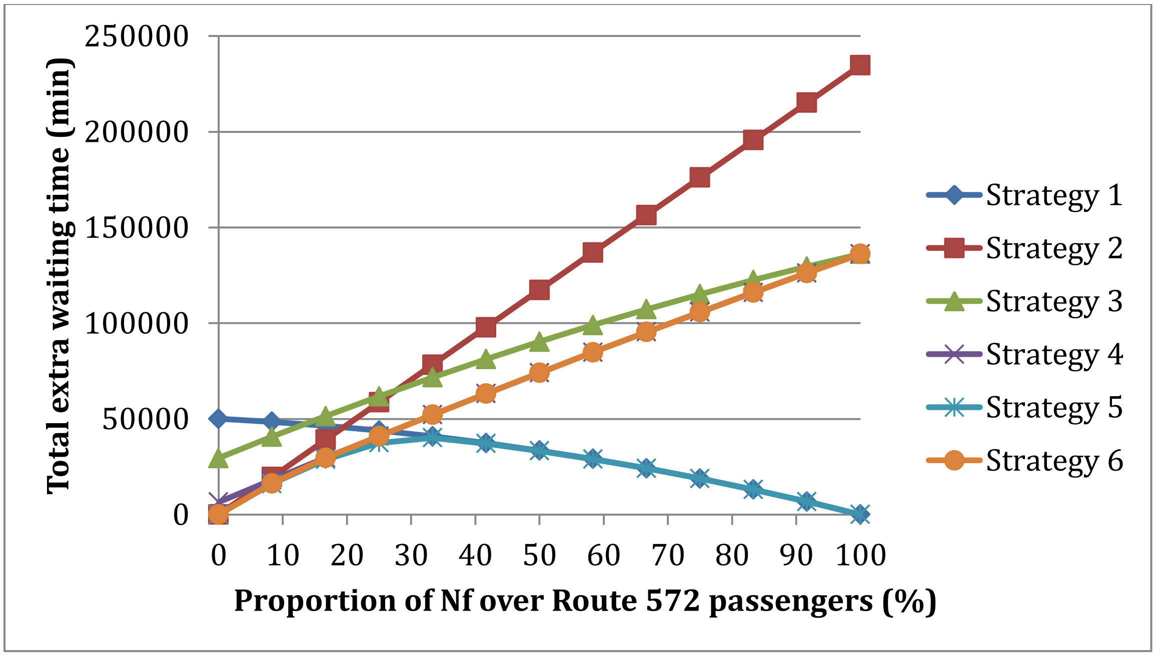


Figure C-3 Transferring demand sensitivity analysis

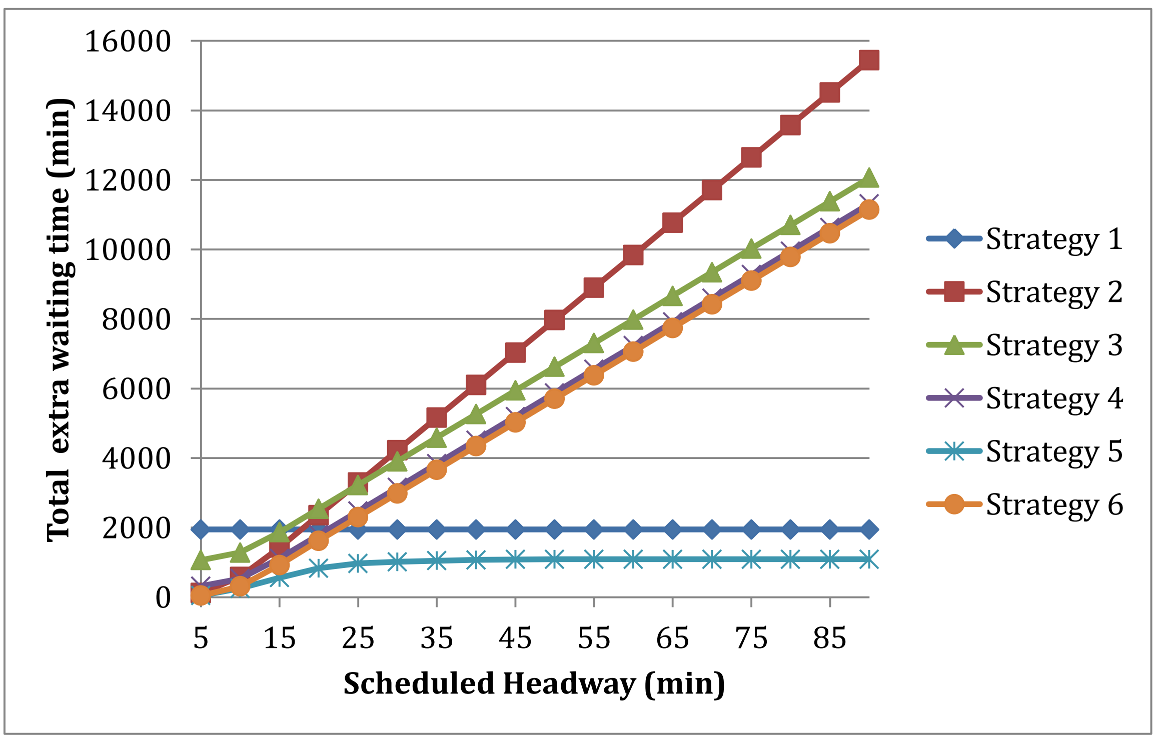


Figure C-4 Scheduled headway sensitivity analysis

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