Passenger-to-Train Assignment Model Based on Automated Data

by

Yiwen Zhu

Submitted to the Department of Civil and Environmental Engineering
in partial fulfillment of the requirements for the degree of

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Abstract

This thesis aims at developing a methodology for assigning passengers to individual trains using: (i) fare transaction records from Automatic Fare Collection (AFC) system and (ii) the train tracking data from Automatic Train Regulation (ATR) system. The proposed Passenger-to-Train Assignment Model (PTAM) can provide a better understanding of capacity utilization and help assess the service quality in underground rail systems.

PTAM is a probabilistic model that links each fare transaction to one (or multiple) feasible train itineraries. Key inputs to the model include the passenger walking speed distribution at stations. The thesis also develops methods to infer the parameters of the speed distribution using AFC and ATR data, while prior methods used either manually collected observations or statistically biased estimates.

PTAM is applied in the context of Hong Kong's Mass Transit Railway (MTR) system and a series of applications are developed using PTAM output to assess the capacity utilization of the network, including trainload estimation, crowding assessment at stations, and animation of passenger movements in a playback mode.

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Chapter 1

Introduction

Transportation plays an important role in serving a city and its mobility and contributing to its economic and social development. With constantly increasing travel demand, transit is gaining popularity because of its capacity, efficiency, and ability to reduce traffic congestion. Many major cities, especially in developing countries, make large investments in transit to offer alternative means of transportation and improve the quality of life (Vuchic, 2005). To support efficient management, performance measurement, analysis and planning, automated data holds great potential for analysts with its improved quantity, variety and quality (Furth, 2006).

This thesis develops a model to monitor operations of a rail transportation network using actual, detailed data based on the characterization of individual trips. By inferring the train boarded by each passenger, a Passenger-to-Train Assignment Model (PTAM) is developed in order to simulate the passengers and trains' movements in the network in detail, providing a convenient tool to evaluate tactical planning and operating strategies.

A statistical method is proposed as a building block using two automated data sources: (i) fare transaction records from the Automatic Fare Collection (AFC) system and (ii) train tracking data from the Automatic Train Regulation (ATR) system. By appropriately linking each fare transaction to one (or multiple) feasible train itineraries, the model is able to establish a quantitative assessment of the system's current state through a number of applications at the aggregate level.

The model is applied in the context of Hong Kong's Mass Transit Railway (MTR) system, which has a heavily used network. The method developed is applicable to any public transportation system with similar quality and availability of data.

1.1 Motivation

This research is motivated by three needs. First, there is a need to improve the capacity utilization of transit systems. The process of infrastructure expansion requires large capital investments and long construction times. Therefore, to cope with increasing travel demand, agencies are seeking approaches to better utilize the current transportation facilities through better planning and management strategies. With the emergence of automatic technologies, such as Automatic Fare Collection (AFC) and the Automatic Train Regulation (ATR) systems, massive amounts of data related to both demand and service have become available. This data has the potential to provide valuable insights into the actual operations of a system from both the operators' and the passenger's points of view. This understanding provides a solid basis for future investment decisions(e.g. network expansion), rolling stock allocation, scheduling, and identifying opportunities to improve capacity utilization.

Second, the work is motivated by the desire for tools to systematically measure and predict service quality and transit performance from the passenger's point of view. Quality of Service (QoS) has become a central concern for transit users, operators, and transport authorities (Aguiléra et al., 2013). Understanding and measuring customer experience in the system clearly helps address this concern. Measuring service quality from the passenger's point of view and capturing their actual experience when traveling through the system, can improve indicators currently used by agencies and also provide better information to customers.

Third, enhanced historical information based on longitudinal analysis can be provided about how the network performs in the face of unexpected events, delays, and increasing demand. This information can help operators make better decisions on how to maintain the transport system. Furthermore, using the model developed in this thesis, different scenarios can be tested to examine the effects on passengers of different interventions, which can assist operators in effectively responding to future events.

In order to provide efficient and high quality service, Mass Transit Railway (MTR), the rapid transit railway system in Hong Kong, is constantly making system improvements in terms of passenger communications, facilities and rolling stock, etc. In the short-term, MTR focuses on the challenge of accommodating the increasing travel demand, which is already very close to (or even exceeds) capacity during peak hours. This research is specifically motivated by the need for MTR to a) understand the system's ability to serve the rapidly growing demand in Hong Kong, b) assess how close to its limit the system is currently operating, and c) identify opportunities to further improve capacity utilization without negatively affecting service reliability.

1.2 Objectives

The broad goal of this research is to look at how transit systems operate near capacity by examining the capacity utilization of the network in detail. Automated data from various sources, supported by appropriate models, are used to provide insights into the usage of the system.

An important building block in achieving this objective is a Passenger-to-Train Assignment Model (PTAM) which aims at identifying passenger boarding events and inferring the specific train itineraries individuals took. With the advent of automated data, the tap-in and tap-out times of the passengers at stations and the arrival/departure times of trains at corresponding stations are recorded. By enumerating feasible itineraries, the model attempts to estimate the probabilities of each passenger boarding each train. Given this assignment, at the individual level, different journey time components (in-station access time, waiting time, in-vehicle time, transfer time and in-station egress time) can be computed for each passenger. The expected number of passengers left behind can also be inferred.

At the aggregate level, this information allows for accurate examination of the customer experience and the utilization of the network. A number of applications can result:

- Estimating individual train loads, which helps identify the hot spots in the network and the peak periods to inform the scheduling process
- Developing service quality metrics from the passenger's point of view, such as
  - Crowding on trains and at platforms/stations
  - Number of passengers left behind (denied boarding) at key stations
  - Travel time variability and overall service reliability
- Improving customer communication to enhance their experience in the system
  - Better inform customers with travel information (e.g. route suggestions, travel times at different times of day, crowding levels, etc.)
  - Expand real-time customer information services with predicted level of service attributes

1.3 Approach

The Passenger-to-Train Assignment Model (PTAM) serves as the most important building block for this research and has many potential applications.

The model utilizes and integrates two main data sources–AFC and ATR. The AFC data describes the passenger demand in the network by time of day and the ATR data provides detailed information about the transit service delivered. The model aims to capture the interaction between the demand and supply in the transit network and provide more detailed information on individual trips (e.g. the journey time components, crowding levels, etc.). It also enables a close examination of passenger movements in the system. The resulting output supports system monitoring and performance measurement from the customer's point of view, and assesses capacity utilization (see Figure 1-1).

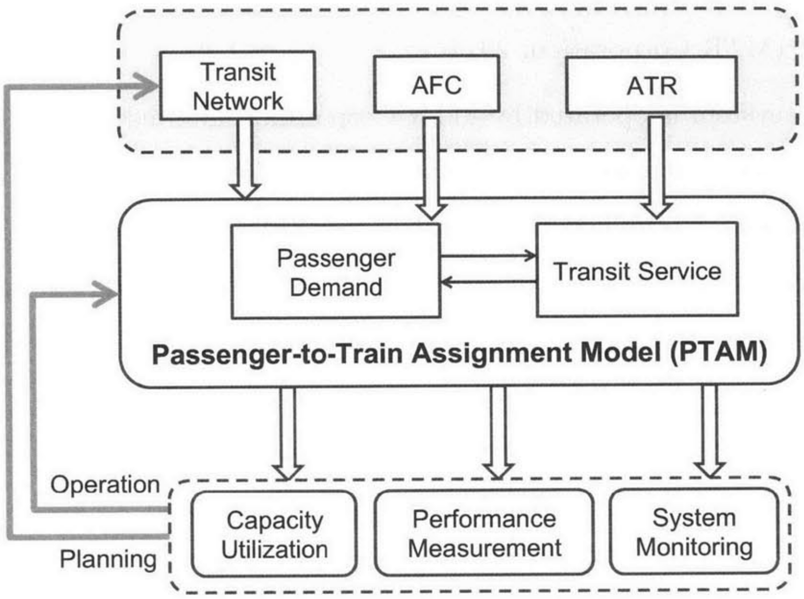


Figure 1-1: Passenger-to-Train Assignment Model (PTAM)

In the short run, a better understanding of the current system performance can lead to better operation and demand management strategies with better capacity utilization. More efficient network operation can improve customer experience, reduce crowding and, more importantly, accommodate increasing demand. In the long run, the results can support future planning and resources allocation by effectively identifying hot spots in the network and advising on future expansion and investments.

1.4 Introduction to MTR

Hong Kong, formally the Hong Kong Special Administrative Region (SAR) of the People's Republic of China, is an international metropolis and the world's third largest financial center after London and New York (Monetary and Economic Department, 2010). Known as one of the most densely populated cities in the world, it is located in southern China, east of the Pearl River estuary with a population of 7 million and a total area of 1104 km^2 (GovHK, 2013). Among the public transport modes, the Mass Transit Railway (MTR) is one of the busiest and most efficient systems in the world, serving nearly 5 million daily trips, or about 46% of the total Hong Kong travel market (MTR Corporation, 2014).

The MTR system is operated by MTR Corporation Limited (MTRCL), a privatized rail and metro company and a major property developer in Hong Kong. With total assets of HK$ 216 million, MTRCL has over 21,000 employees globally and operates rail service under contract in several cities around the world including London, Stockholm, Beijing, and Melbourne (MTR Corporation, 2011). The company was formed as a government-owned statutory corporation in 1975 and was privatized in 2000. The government still owns about 76% of the shares as the majority stakeholder (MTR Corporation, 2011). In 2007, the company merged with the Kowloon-Canton Railway Corporation (KCRC), in what is referred to as the MTRCL-KCRC merger, through a 50-year concession agreement and took over the operation of the KCR network, which includes the East Rail Line, West Rail Line and Ma On Shan Line (Hong Kong SAR Government, 2006). Figure 1-2 shows the current rail network of MTR.

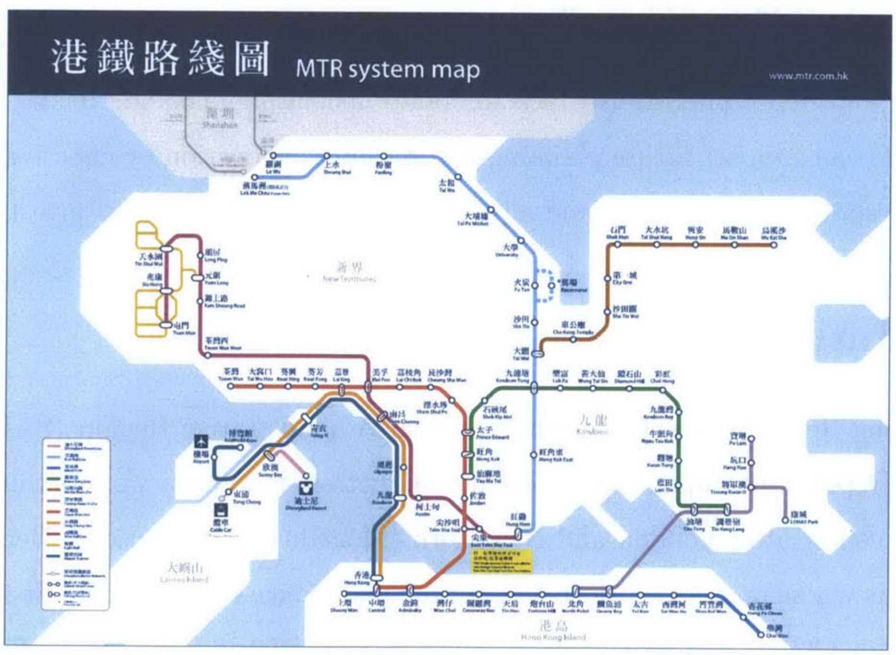


Figure 1-2: MTR Heavy Rail Network (MTR, 2014)

The construction of the MTR system started in the 1970s. In the early 1960s, with Hong Kong's rapid economic development and population growth, the demand for public transportation increased dramatically, resulting in severe road congestion. In 1964, a study was conducted on the future development of Hong Kong's transportation by Freeman, Fox, Wilbur Smith & Associates, a British transportation consulting organization. The results of the study were published in 1967 and indicated that there was a strong need for a mass transit system to address Hong Kong's traffic problems (Freeman et al., 1967). In 1970, further studies on the construction of underground railway systems was completed and the final report was issued, which made a concrete proposal for the construction of the rail system (Freeman et al., 1970). In 1975, the government-owned Hong Kong Mass Transit Railway Corporation was established to oversee the construction project based on the final report with some modifications. The "Modified Initial System" route map is shown in Figure 1-3.

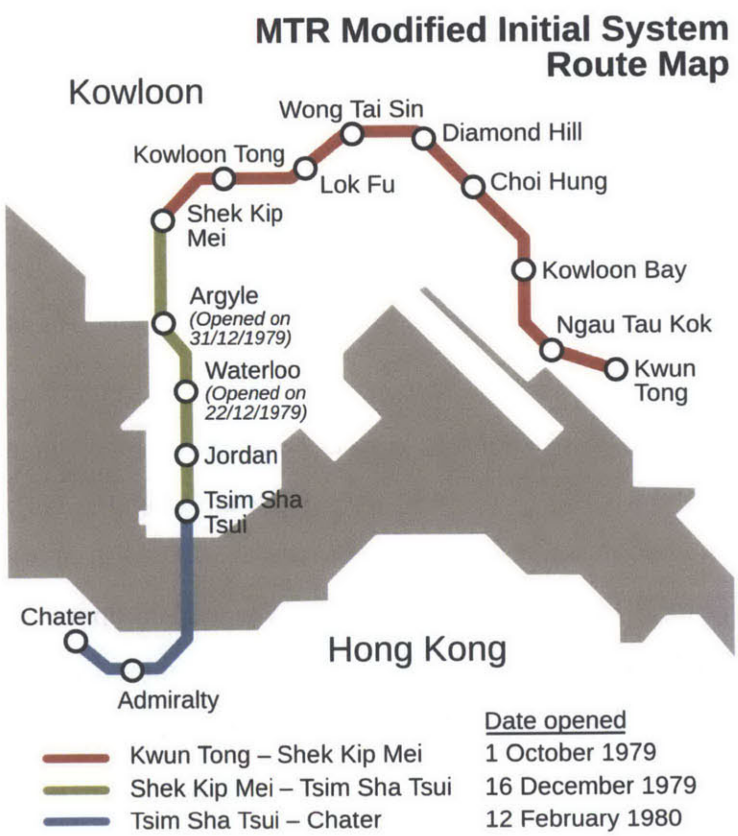


Figure 1-3: Modified Initial System Route Map

The initial 15.6-km network was immediately popular followed by several line extensions shown in Table 1.1.

Line	**Opening**	**Latest Extension**	**length (km)**
East Rail Line*	1910	2007	41.1
Kwun Tong Line	1979	2002	11.2
Tsuen Wan Line	1982	1982	16.0
Island Line	1985	1986	13.3
Tung Chung Line	1998	2005	31.1
Tseung Kwan O Line	2002	2009	11.9
West Rail Line*	2003	2009	35.4
Ma On Shan Line*	2004	2004	11.4
Disneyland Resort Line	2005	2005	3.3
Light Rail (12 Routes)	1988	2003	36.2
Airport Express	1998	2005	35.2

Table 1.1: MTR Line Extensions

* Note that East Rail Line, West Rail Line and Ma On Shan Line were operated by KCR before the merger with MTR.

MTR now operates three separate systems: (i) Heavy rail, which consists of 10 lines and 84 stations with total route length of 182 km (Figure 1-2); (ii) Light rail, which consists of 12 routes and 68 stops with total route length of 36.2 km; and (iii) Bus, which consists of 14 routes and 143 buses. The system operates 19.5 hours per day with scheduled headways ranging from 2 min to 12 min. Figure 1-4 shows the headways of MTR's rail services as a function of time of day.

While MTR operates feeder buses to and from many MTR stations in the New Territories, five franchised companies also provide bus service across Hong Kong over more than 700 routes serving more than 3.6 million passengers per day:

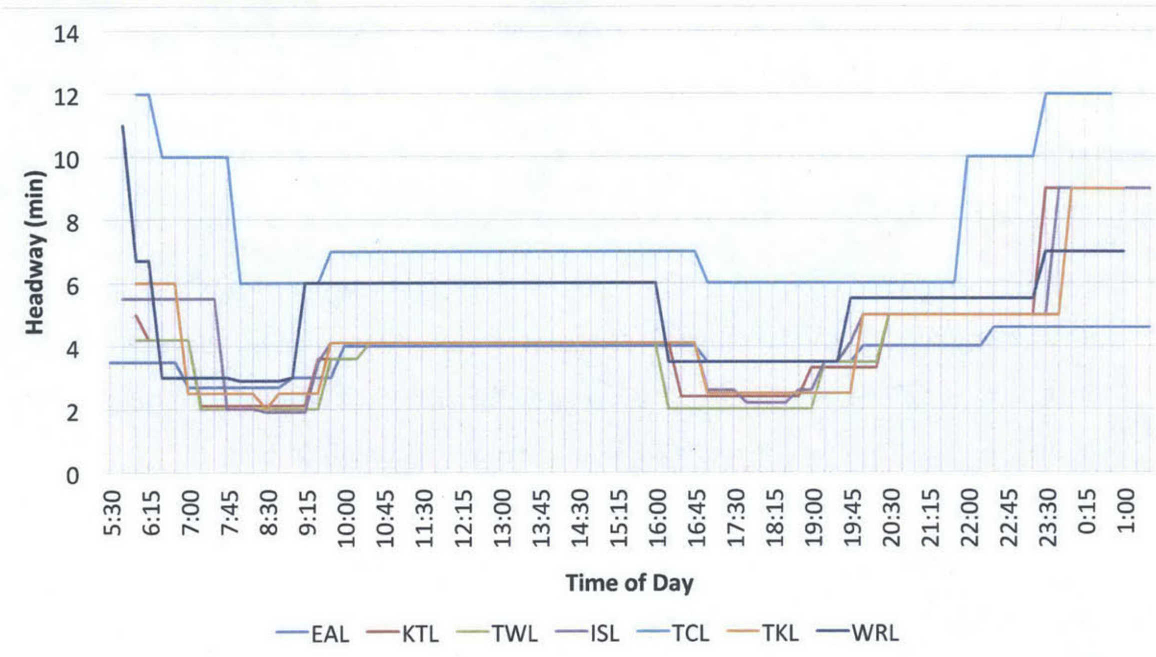


Figure 1-4: Rail Services Headways

Operator	Number of Routes	Fleet Size	Daily Ridership
City Bus Limited	108	946	621,000
New World First Bus Service Limited (NWFB)	90	715	499,000
The Kowloon Motor Bus Company Limited (KMB)	375	3,800*	2.38 million
Long Win Bus Company Limited	19	165	85,400
The New Lantao Bus Company Limited (NLB)	23	108	60,900

Table 1.2: Bus Service in Hong Kong (Transport Department of HKSAR, 2014)

* As of 31 December, 2012.

Other than the franchised bus companies, the non-franchised bus (NFB) service provided by different private bus companies operates 7059 registered buses which supplement the main carriers during peak hours and in remote areas (Transport Department of HKSAR, 2014).

1.4.1 Fare System

MTR's most widely used ticket types are (i) the single journey ticket, (ii) the stored value card called Octopus, and (iii) the tourist pass. Fares for journeys involving a harbor crossing and airport express are usually higher. For single journey tickets, children and senior citizens enjoy discounts ranging from 40 to 60%.

There are four main types of Octopus card: (i) adult, (ii) child, (iii) student, and (iv) senior citizen or eligible person with a disability. Fares for seniors and persons with disabilities are typically lower. The Tourist Pass has 6 types, valid for 1,2 or 3 days and with choices of either a single trip or round trip to/from the airport.

The Octopus card has become the most popular payment method for Hong Kong's public transport system, and is used for about 96% of all MTR rail transactions. The card can also be used in convenience stores, fast-food restaurants, and on-street parking, etc. Hence many people may own more than one card, which can pose problems for some analyses. The number of cards in circulation is about 20 million, which is nearly three times the population of Hong Kong (Octopus Cards Limited, 2014).

1.4.2 MTR Operations

In 1990 MTR implemented an Automatic Train Regulation (ATR) system for the Island Line, aiming at (i) facilitating recovery after disturbance, (ii) reducing inter-station stops and energy consumption and (iii) improving synchronization of train arrivals and departures at transfer stations (MTR Corporation, 2012a). It is a fully automated control system with six regulation modes:

- Automatic Regulation: the normal operating mode under which timetables are required to determine train departure times.

- Constant Headway Regulation: when a suitable timetable is not available, trains are dispatched a scheduled headway after the previous train's departure time.

- Short-line Regulation: when a segment of the line is not available, a short loop is created and the line is divided into two non-overlapping operating loops with constant headway.

- Cross-platform Regulation: to minimize the waiting time for transfer passengers, the arrival and departure times of trains at key transfer stations are adjusted.

- Disturbance Regulation: when delays occur, this mode is activated automatically to regulate the trains with even headways by increasing the dwell time of the train(s) ahead of the delayed train and reducing the inter-station run-time for the delayed trains.

- Manual Regulation: when neither Automatic nor Constant Headway Regulations are appropriate, ATR calculates dispatching times but does not send the control signals to trains.

The operating performance of the system is monitored through a number of metrics. It consistently exceeds the targets which are part of the MTR agreement with the government. The performance data is published on the MTR website (see Table 1.3).

Train service delivery is calculated based on the scheduled number of trips compared with the services actually delivered. Train punctuality is calculated based on a 5-min threshold at terminal stations (e.g. a train that arrives at the terminal less than 5 min prior to the scheduled time is considered on-time). The passenger journeys on time metric is estimated based on the 15-min passenger flow estimation and the train punctuality. All the passengers on any train delayed by 5 min or more are counted. The statistics show that the service is highly reliable and exceeds customer service quality of many other system (MTR Corporation, 2010).

Social Performance	2011	2012
(A) TRAIN SERVICE DELIVERY (%)		
Island, Kwun Tong, Tseung Kwan O, Tsuen Wan, Tung Chung,and Disney Resort lines and Airport Express	99.8	99.9
East Rail Line (including Ma On Shan Line)	99.9	99.9
West Rail Line	99.9	99.9
Light Rail		99.9
(B) PASSENGER JOURNEYS ON TIME (%)		
Island, Kwun Tong, Tseung Kwan O, Tsuen Wan, Tung Chung,and Disney Resort lines	99.9	99.9
Airport Express	99.9	99.9
East Rail Line (including Ma On Shan Line)	99.9	99.9
West Rail Line	99.9	99.9
(C) TRAIN PUNCTUALITY (%)		
Island, Kwun Tong, Tseung Kwan O, Tsuen Wan, Tung Chung,and Disney Resort lines	99.7	99.7
Airport Express	99.9	99.9
East Rail Line (including Ma On Shan Line)	99.9	99.8
West Rail Line	99.8	99.8
Light Rail	99.9	99.9
(D) TRAIN RELIABILITY (Revenue car-km/Incident)		
Island, Kwun Tong, Tseung Kwan O, Tsuen Wan, Tung Chung,and Disney Resort lines and Airport Express	2,459,083	1,841,882
East Rail Line (including Ma On Shan Line) and West Rail,line	3,813,015	3,292,956

Table 1.3: MTR Social Performance in 2011 and 2012 (MTR Corporation, 2012c)

1.4.3 Network Expansion

MTR is constantly making system improvements in terms of passenger communications, facilities, rolling stock, etc. Substantial service expansion is planned with 5 new lines by 2018 (see Figure 1-5), aiming at adding capacity and reaching new markets. The planned expansion includes:

1. West Island Line: an extension of the current Island Line to the western district of Hong Kong Island.

2. Guangzhou-Shenzhen-Hong Kong Express Rail Link: a 26-km express link from Hong Kong to Shenzhen that will connect with the National High-speed Railway Network in mainland China.

3. Shatin to Central Link: a "strategic railway" stretches from Tai Wan, the terminal station of Ma On Shan Line, to Admiralty on the Hong Kong Island. It mainly serves the eastern district in Kowloon and will pass through Kwun Tong Line, East Rail Line, West Rail Line, Tung Chung Line, Island Line and the new South Island Line (East) with convenient interchanges.

4. Kwun Tong Line Extension: a connection between Yau Ma Tei (on the Tsuen Wan Line), Ho Man Tin (on the Shatin to Central Link), Hung Hom (on the West Rail Line) and the Whampoa area, which is not yet served by rail.

5. South Island Line (East): a 7-km medium capacity railway with approximate 3 min headway during peak hours serving the southern district of Hong Kong Island, which is strongly supported by the Southern District Council.

Three potential future extensions are under consideration (see Figure 1-5): the *North Island Link* the *Northern Link* and the *South Island Line (West)*.

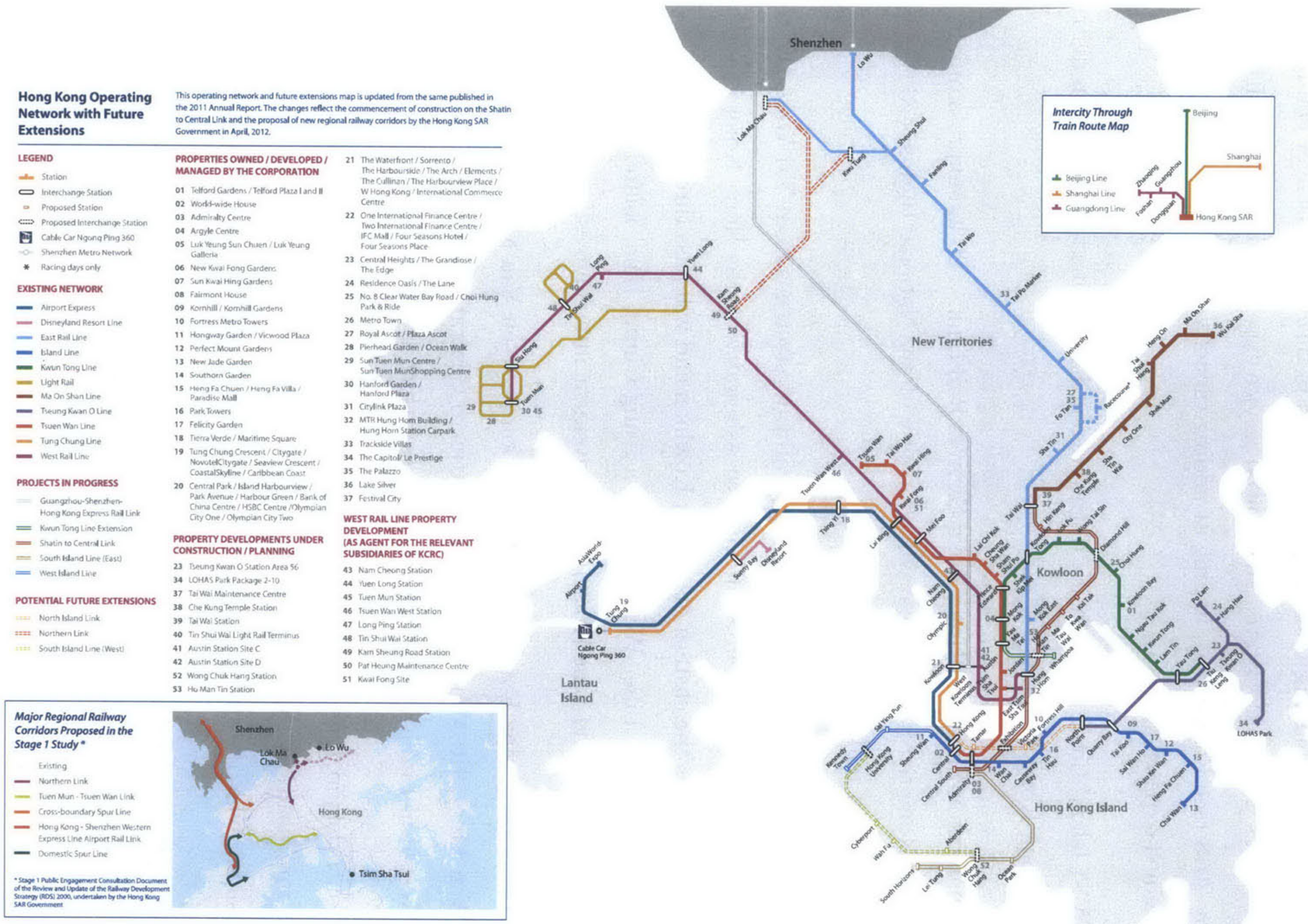


Figure 1-5: MTR Network Extension

1.5 MTR Challenges

With the rapid expansion of the economy and the population growth in Hong Kong, MTR travel demand has continued to increase by 3-4% per year in recent years (see Figure 1-6).

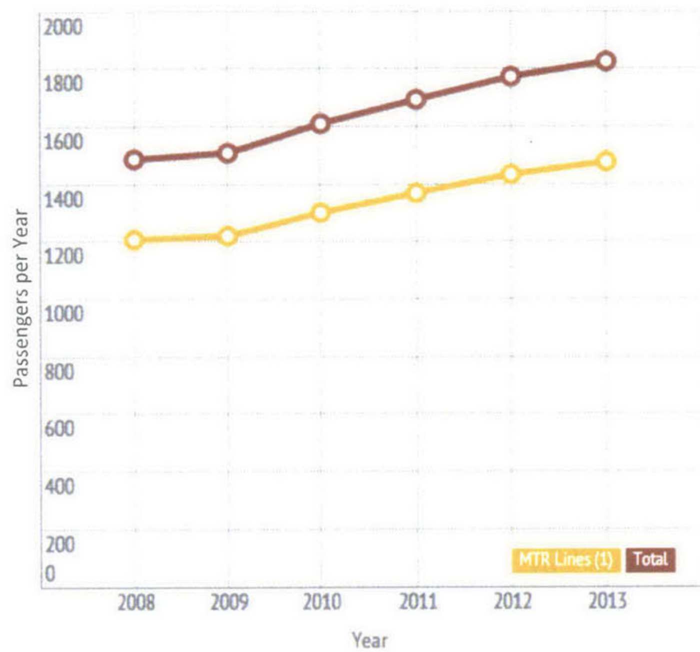


Figure 1-6: Annual MTR Patronage

The red line shows the annual patronage of the entire MTR system including the bus, Air Express, inter-city railway and light rail systems. The yellow line shows the patronage of MTR Lines including Tsuen Wan, Island, Kwun Tong, Tung Chung, Tseung Kwan O and Disneyland Resort Lines as well as East Rail, Ma On Shan and West Rail Lines. The total patronage has increased by 22.7% since 2007 (MTR Corporation, 2014).

The passenger growth has presented a number of challenges for MTR. Foremost is the crowding on platforms and trains. As a result of the severe crowding, passengers have difficulty getting on and off trains and many are left on the platforms when a train departs. Queuing for escalators, customer service counters, and at train doors can be severe during the peak of the peak period. The overcrowding also results in increased dwell times because the train doors can not be closed promptly while passengers are trying to squeeze in. On the other hand, safety concerns have increased with more platform-train interface incidents. All of those facts negatively affect the safety and reliability of the MTR system.

For crowding on trains, MTR sets targets of the crowding level for each car as shown in Table 1.4.

Line	**Passengers per car**	
	Peak	Off-Peak
ISL, TWL, KTL, TKL, TCL, WRL, EAL & MOL	250	145
AEL	100	64
DRL	180	120

Table 1.4: Car Loading Standard in 2000

A survey was conducted by asking respondents to rate their acceptance level of different crowding levels of the car. In 2012, the survey shows that with increasing car loading, the passenger acceptance level decreases (MTR Corporation, 2012b).

To deal with these challenges, an internal committee has been formed to focus on "Near Capacity Operation" (NCO). The goal of the committee is to review the current operating strategies and manpower deployment, aiming at exploring future capacity enhancements.

1.6 Thesis Organization

This thesis is organized into 6 chapters. Chapter 2 reviews previous research on passenger assignment models and related topics. Chapter 3 develops the methodology for the passenger assignment problem using the available automated data. Chapter 4 discusses the methodology for parameter estimation. Chapter 5 presents an application of the model to the MTR's network and examines the capacity utilization of the

Tsuen Wan Line. Chapter 6 summarizes the research findings and proposes areas for future research.

Chapter 2

Literature Review

This chapter is organized into two sections. Section 2.1 discusses the use of automated data to achieve a better understanding of transit system performance and passenger behavior. Section 2.2 focuses on the passenger assignment problem especially at the train/vehicle level to support both, planning of the network and operations.

2.1 Automated Data Sources

Smart cards while serve the fare collection for transit agencies, they also constitute constitute a significant data source that helps operators to obtain a better understandings of passenger behavior. Analysis of the Automatic Fare Collection (AFC) data can support understandings of the (i) travel pattern of passengers, (ii) transit service demand and (iii) system performance (Agard et al., 2006; Ortega-Tong, 2013; Pelletier et al., 2011; Bagchi and White, 2005; Zhao et al., 2007; Chan et al., 2007).

Morency et al. (2007) used data mining approaches to identify transit use variability to optimize vehicle allocation and improve operational efficiency. Bagchi and White (2005) used smart card data to analyze users' travel pattern consistency in both time and space. Furthermore, smart card data with vehicle location information (e.g., GPS data) facilitates the inference of activities and travel behavior. Chapleau et al. (2008) used smart card data to monitor the activity patterns at trip generators (such as schools) and provided high resolution analysis on both supply and consumption of transit service. Based on different travel characteristics, such as activity patterns, mode choice, temporal and spatial variability and socio-demographic characteristics. Ortega-Tong (2013) classified public transport users into homogeneous clusters. The travel profile of each group provides rich information on user behavior to inform studies about customer experience and transportation planning.

Detailed analysis of passenger behavior can be studied at the (transit) Origin-Destination level. AFC and AVL data have been used in a number of studies to infer Origin-Destination pairs at the system level.

For example, Farzin (2008) developed a methodology to integrate AFC data, AVL data, and station location information to infer the destination zone for each trip. The results were validated using a household survey. Munizaga and Palma (2012) proposed a method to estimate the OD matrix from smart card and GPS data. Time and location of alighting events were inferred for over 80% of the transactions.

Alfred Chu and Chapleau (2008) further enriched the inference process to identify transfers using spatial-temporal criterion in a bus network.

Gordon (2012) extended previous OD level methods by combining bus and metro services and analyzed the full multi-modal itineraries in London. Since the AFC system for the London Underground is a "closed" system, the data records the tap-in/out times and locations for all rail transactions. For bus transactions, only boardings are recorded. Gordon (2012) developed a rigorous process to infer the bus origin/destination and interchange(s) for each individual to build a full-journey matrix. Given this information as a seed matrix, control totals from various sources (bus ridership, entry/exit of rail stations) were then used to scale up the demand estimation to the full population. The model was embedded into a Java program which proved to be highly efficient. The processing time was less than 30 min to extract one day's data hence the method is suitable for large scale applications.

At a more detailed level, the problem of inferring details of the passenger journeys, for example, journey time components, passenger locations, and crowding level, has also drawn interest.

Sun et al. (2012) developed a regression model based on AFC data and the distances between origin and destination stations to decompose the gate-to-gate journey time. The analysis was based on the assumption that three key parameters were constant for all users: (i) walking times between gates and platforms, (ii) train speed between stations and (iii) trains' dwell times at stations. A regression estimation between the total journey times and the above quantities was estimated. The estimated parameters were significant and used to identify the approximate locations of individuals and estimate passengers' "spatio-temporal density" in Singapore's metro system. Their proposed future work focused on more complex train operation scenarios with heterogeneity among passengers.

Cellular phone networks operating in underground rail systems also provide new possibilities to model passenger movements. Aguiléra et al. (2013) conducted experiments in Paris' underground system to assess the potential of this emerging data source to infer travel times, train occupancy levels, and OD flows. They used the records of signaling events (GSM data) triggered by switched-on mobile phones when they changed locations. This data contained location information at the station level for each cell phone and were used to track passengers throughout their trips. Even though the data was sparse, the aggregation of large amounts of this data provided a way of overcoming limitations of the AFC/AVL data. The train trajectory and mobile phone trajectory events were linked by partitioning the "density map" (see Figure 2-1).

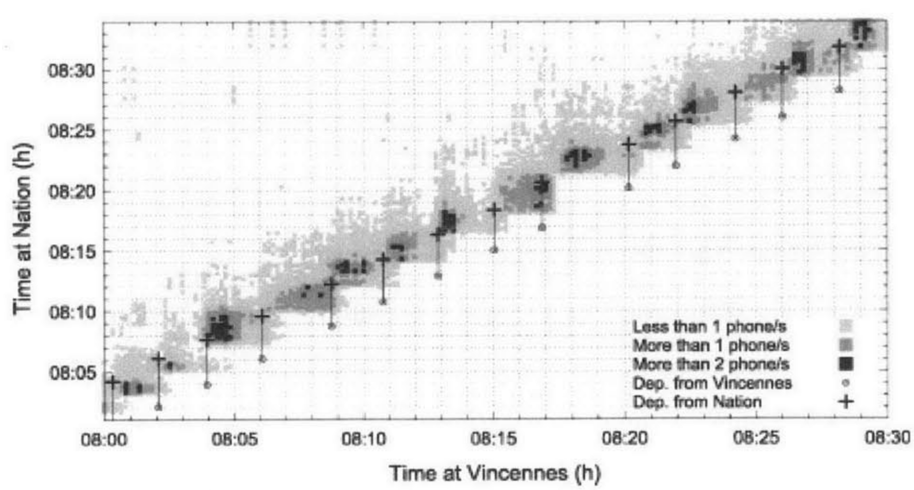


Figure 2-1: Density Map Between Vincennes and Nation for Half-Hour Data

In the map, each dot represents a cell-phone trajectory with the x-axis indicating the time stamp at the origin station and y-axis indicating the time at the destination station. The dots fell in a distinguished, rectangle shaped area that corresponds to one train itinerary, associating the cell-phone signal with the train. The comparison of the estimation results with the AFC data analysis showed a good level of consistency, indicating that the cell-phone data was a promising data source for operators and transport authorities to monitor system operations.

With the availability of the loadweigh data from the weighing systems installed in some trains, a new counting technique was developed to facilitate the study of passenger loads through the calibration of parameters. Frumin (2010) regressed the loadweigh data on manual passenger counts and estimated the average passenger weight and vehicle tare weight (which is the weight when it is empty) to infer passenger load on trains. Nielsen et al. (2013) proposed an "inverse model" and used the weight as explanatory variable and number of passengers as dependent variable. The analysis of the passenger distribution in the network based on this research could be used as a part of a continuous quality control regime for operators to monitor the capacity utilization of the network (Nielsen et al., 2013).

2.2 Passenger Assignment

Another approach to examine the system operations through the train occupancy level, or the train load, is through a passenger assignment model. The model aims at assigning passengers to travel routes (or transit vehicles) to predict (or estimate) how the passengers utilize the network capacity. With more detailed data as input, the trainload estimation could shed more light on planning and operations. At the planning level, the passenger assignment model can serve as a basis for analyzing service adjustments or network changes by predicting future outcomes. At the operational level, the model estimates the capacity utilization of the network based on archived data and provides precise service performance indicators for the transit service.

2.2.1 Planning-Level Studies

Two main approaches are used for the passenger assignment problem: frequency-based and schedule-based. The frequency-based approach analyzes the transit system by line and computes the traffic flow based on the service frequency (Nguyen and Pallottino, 1988; Spiess and Florian, 1989). Approximations are made to estimate the passenger waiting times and vehicle load based on service frequency (instead of the detailed service plan). The schedule-based model explicitly considers individual trips and their detailed scheduled departure/arrival times to assign passengers to the vehicles. The models can be used to track the effects of schedule changes (Nuzzolo et al., 2012). Most of the work discussed in this section uses the second approach.

Nguyen et al. (2001) developed a graph-theoretic framework for the passenger assignment problem and considered departure times and route choices simultaneously as a traffic equilibrium problem. The dis-utility of paths were associated with the not only travel time but also penalty for late or early departures/arrivals. Timetables and OD demands were the main inputs to the problem and an equilibrium of passenger flows was obtained using a convergent algorithm for the estimation of the shares of route segments.

Poon et al. (2004) proposed an optimization formulation for the equilibrium assignment problem and explicitly considered the vehicle capacity at each boarding station. Passengers were assumed to have full information about future network conditions and select paths to minimize the total cost of the trip (a function of the in-vehicle time, waiting time, walking time, and transfer penalty). The user equilibrium was achieved by a simulation-based, iterative approach using the method of successive averages. The paths were generated using time-dependent shortest paths as in Tong and Richardson (1984). In each simulation run, the queuing delays were updated based on the passenger profiles in the network and minimum paths were calculated dynamically in each simulation run. The capacity constraints were explicitly considered for each vehicle by assuming first come first serve (FCFS) queuing discipline at the boarding stations. The method incorporated route choice while other choice dimensions were not considered, such as departure times and entry, transfer and exit stations. The authors suggested that the model can be used as a tool for the evaluation of the performance of a transit system with pre-determined schedules and of the effects of service changes.

Hamdouch and Lawphongpanich (2008) proposed a user equilibrium transit assignment model by solving a dynamic program through an iterative process. Service, demand and access/egress were presented in a "diachronic" graph. As in Ahuja et al. (1993) and Hamdouch et al. (2004), a time-expanded network was used to represent the temporal information and the network route choices. The model assumed that passengers use travel strategies by specifying, at each station and time point, an ordered list of transit lines they preferred. This information was incorporated in the travel costs of the paths, which consisted of in-vehicle time, fares and other costs associated with the strategy, such as crowding, opportunity costs associated with early departures and late arrivals. Passengers were allowed to bicycle or drive to transit stations and transfer at a nearby station by walking. The user equilibrium was formulated as a variational inequality problem and solved by the method of successive averages.

Kusakabe et al. (2010) introduced choices between express trains, rapid trains, local trains and multiple transfer stations in a study related to the Japanese Railways. The approach was to identify all the possible itineraries based on the timetables of different types of trains. Kusakabe et al. (2010) solved the problem by developing a time-space network to represent the train trajectories and enumerating all the possible paths for each individual. Based on AFC data, they assigned all passengers to the "shortest path" (the path with minimum access time at entry station, minimum lost time at arrival station and least number of transfers). Passenger usage patterns were revealed, which provided useful information for operators to achieve better demand management and improve the scheduling.

2.2.2 Operation-Level Studies

Most of the studies on passenger assignment discussed in the previous section focused on the planning level where different service plans can be tested and evaluated by predicting future outcomes. In this section, models were reviewed which captures the system performance based on actual, archived data.

Buneman (1984) used reverse-time simulation to assign passengers to the last train that arrived at their exit station and "loaded" the transfer passengers onto the last departing train. The analysis of detailed data from the Bay Area Rapid Transit (BART), produced operational performance measures, such as delays, and served as a daily tool for the operators.

Paul (2010) developed a method to assign passengers to trains using actual train tracking and Oyster data in the London Underground (LU). Instead of assuming a constant walking time as Sun et al. (2012), the method relied on the distribution of access and egress times which were derived from two sources:

- London Underground surveys, in which the journey time components were measured by surveyors following random passengers and recording their walking times, waiting times, in-vehicle times, etc.

- The subset of passengers (about 10%), from Oyster card transactions, who had only one possible train itinerary based on their tap-in and tap-out times. For this subset of passengers, their egress times was derived as the differences between their tap-out times and the train arrival times.

The ratio between the expected value of access and egress time distributions was assumed to be the same as the ratio of the average access time and egress time in the manual survey. Under this assumption, the distribution of egress time was first estimated based on the 10% passengers with a single itinerary and then "scaled up" using the ratio based on the manual survey. After examining all the possible train itineraries, a "same percentile" assumption was made to select the most likely train itinerary and corresponding route. That is, given egress time calculated for each itinerary, the access time and interchange time were assumed to be at the same percentile of the cumulative distribution as the egress time is in the distribution at the exit station. If the time intervals related to access and transfer times in an itinerary were shorter than these percentiles, this itinerary would be eliminated since no waiting times were included in it. However, during each step of the elimination, if all the itineraries were deleted, the method would keep all the itineraries and continue to the next step. For each individual, the selection process followed 6 steps (see Figure 2-2):

1. Generate the set of feasible itineraries for the passenger.

2. If all the itineraries are the same route, go to the next step. If more than one routes are used, choose the route with fewest itineraries.

3. If the selected route contains only one feasible itinerary, the itinerary is selected and the process terminates.

4. If multiple itineraries are available, apply the "same percentile" rule on access time and eliminate the ones with time intervals shorter than the access time in the same percentile of the distribution as the egress time. If one itinerary is left, select the itinerary and terminate the process. If no itineraries are left, revert to the original set, else continue.

5. For the remaining itineraries, for the ones with interchanges, apply the "same percentile" rule on interchange time and eliminate the ones with time intervals shorter than the interchange time in the same percentile of the distribution as the egress time. If one itinerary is left, select the itinerary and terminate the process. If no itineraries remain, revert to the original set, else continue.

6. For the remaining itineraries, calculate their egress times as the interval between the tap-out time and train arrival times and choose the one with most probable egress time based on the egress time distribution.

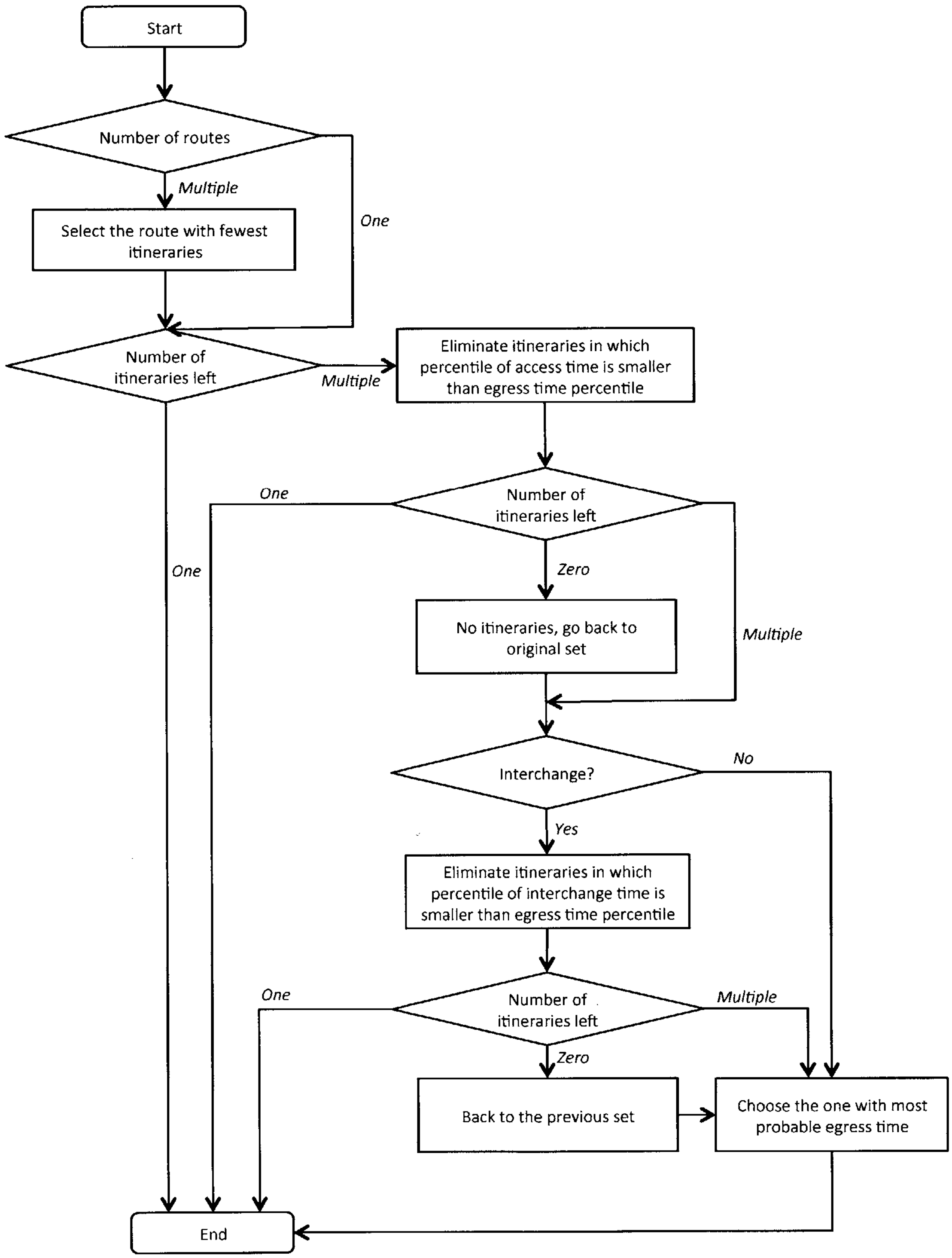


Figure 2-2: Itinerary Selection Process of Paul (2010)

Nonetheless, this method has a number of limitations:

- The distribution of the journey time components may be biased toward lower access/egress times because of the lack of representativeness of the sample. The passengers with a single itinerary are likely to be the ones with faster walking speeds which enable them to catch the first train arriving after they tap-in, and tap-out before the second train arrives at the destination station. Passengers with longer access times and egress times generally have more feasible itineraries and will not be in the sample.

- Due to data limitations, the assumptions used in this TfL study, such as the "same percentile" assumption could not be fully tested, especially when the access and egress times are influenced by external factors other than individual characteristics, such as station configuration, crowding level, etc. In the selection process, due to this assumption, all itineraries may be eliminated and the program has to go back to the original itinerary set.

- The method deterministically assigns passengers to trains, which neglects many other possibilities but with relatively small probabilities. It is hard to simulate outliers in the system.

- The manual survey data used in this approach is very hard to obtain and expensive. It is not applicable to systems without similar data availability.

Using a similar methodology for the MTR network is even more challenging because of a number of unique characteristics, such as the commercial activities in paid areas (after entering through the fare gates). In this case, the journey times inferred by tap-in and tap-out times can include the time spent on shopping activities. This time component cannot be observed directly from the data.

Building on Paul (2010)'s work, a probabilistic methodology is developed that is more generally applicable and with more detailed analysis on passenger behavior at stations. The methodology also uses automated data to estimate egress speeds without relying on manual data.

Chapter 3

Methodology

A "closed" Automatic Fare Collection (AFC) system is one which requires fare transactions at both entry and exit stations necessary to support distance-based fare structures. Such AFC systems provide location and time information data at both the start and end of each trip. However, to infer details of the journey (e.g. the journey time components, etc.) and capture the movement of each passenger, the train(s) used in the journey should be inferred. At the aggregate level, this information can be used to estimate the train-passenger-load, which provides valuable information on the capacity utilization of the network.

The Passenger-to-Train Assignment Model (PTAM) presented in this chapter aims at assigning passengers to train itineraries in a closed system. Section 3.1 presents an overview of the PTAM, describes the problem in detail and develops the methodological framework. Section 3.2 presents the model formulation and develops the first component, the passenger assignment. Section 3.3 discusses the approach to the second component of the framework, the trainload model. Section 3.4 summarizes the main contributions of this chapter.

3.1 Overview of the PTAM

3.1.1 Problem Description

In a closed system such as MTR, the AFC data includes the origin and destination station, the entry time and exit time of each trip. The total journey time can be calculated as the difference between the entry time and the exit time. For a trip without transfers, the total journey time (from tap-in to tap-out) consists of four components: (in-station) access time, waiting time, in-train time, and (in-station) egress time (see Figure 3-1).

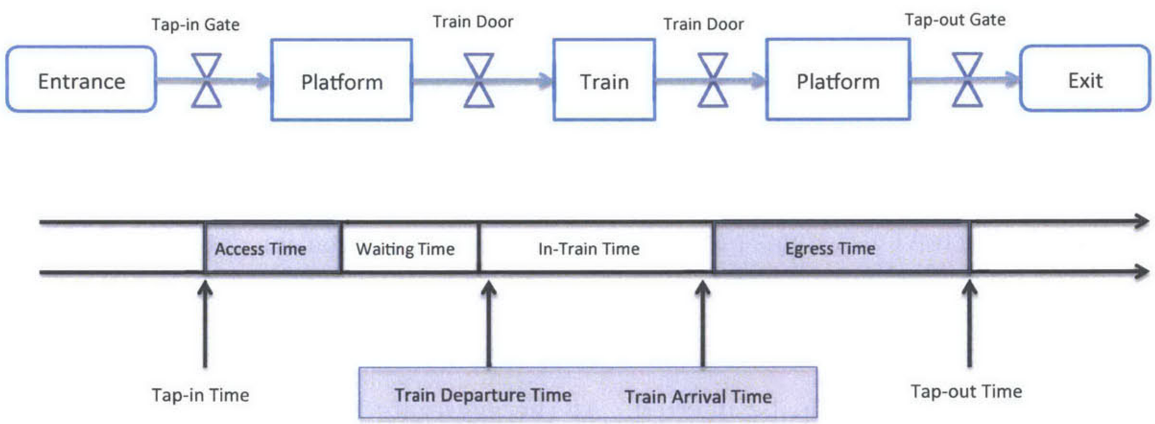


Figure 3-1: Passenger Movement in System

The access time is defined as the time it takes to walk from the tap-in gate to the platform; the waiting time is the time that a passenger waits on the platform; and the egress time is the time to walk to the tap-out gate after alighting from the train (see Figure 3-1).

Each passenger, based on the arrival time at the platform, may have several trains that he/she may have used. These feasible trains (itineraries) can be identified by combining the AFC transaction and the train movement data. However, to track precisely the alternatives and the details of the trip, many questions remain to be answered:

- how long is the access time and waiting time;
- which train's departure/arrival time is the boarding or alighting time for this passenger;
- how long is the egress time.

Figure 3-2 illustrates the possible itineraries for a hypothetical passenger who enters the system at t^{in} and exits at t^{out}.

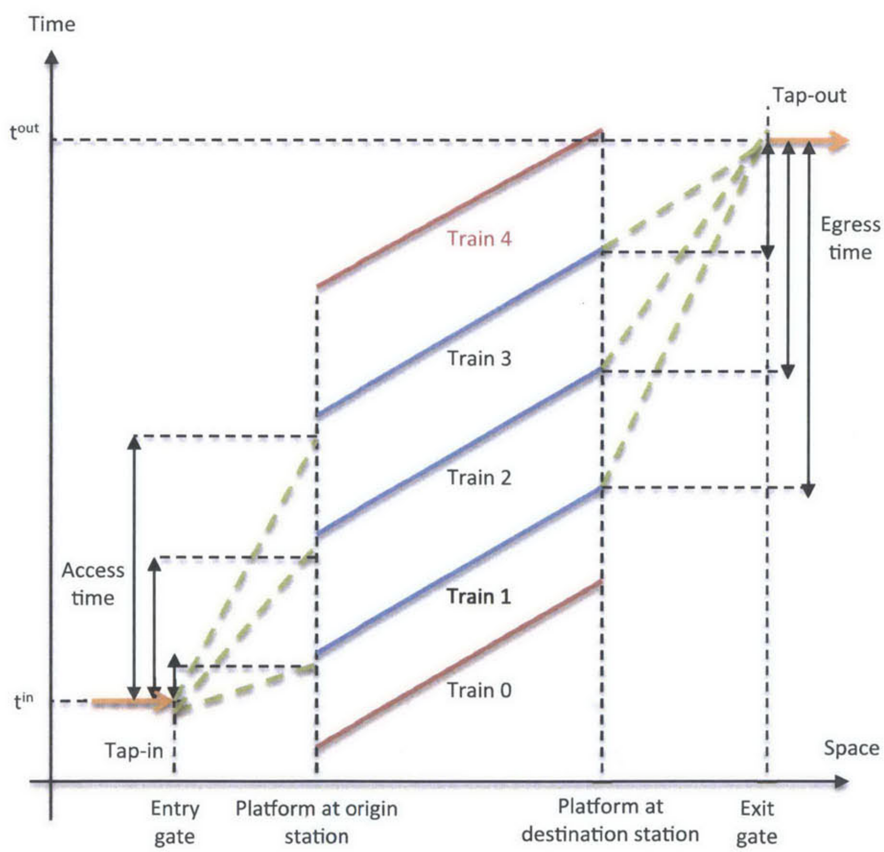


Figure 3-2: Time-Space Diagram for A Passenger and Trains

The passenger taps-in through the entry gate, walks to the platform, waits for a train, boards it, alights and finally taps-out at the exit gate. Some passengers, during their waiting at the origin station platform, may try to make their exit time as early as possible. In that case, if a train is not at the station, they may walk on the platform at the origin station in order to position themselves closer to their exit gate when they alight from the train at the destination platform.

Depending on access and egress times, the passenger may have boarded a number of trains. Under the conservative assumption that the minimum access and egress time are zero, the passenger in Figure 3-2 has three feasible trains (1,2,3). Train 0 is not feasible because the departure time is too early (before the tap-in time), while Train 4 is not feasible because it arrived at the destination after the tap-out time. Under no circumstances, a passenger is able to board a train before he/she taps-in or taps-out before the train arrives at the destination.

In general, itineraries fulfilling the following criterion are defined as feasible:

1. The train departs from the origin station after the passenger taps-in the system:

$$t^{in} + \tau_{access} \leq DT_j \tag{3.1}$$

2. The train arrives at the destination station before the passenger taps-out:

$$AT_j \leq t^{out} - \tau_{egress} \tag{3.2}$$

Where,

t^{in}: passenger tap-in time.

τ_{access}: minimum access time, (set conservatively equal to zero).

DT_j: departure time of train j at the origin station.

AT_j: arrival time of train j at the destination station.

t^{out}: passenger tap-out time.

τ_{egress}: minimum egress time, (set conservatively equal to zero).

Different assumptions can be made about the minimum access and egress times.

For large stations, the minimum access/egress time should be larger than for small stations. With longer minimum access/egress time, fewer itineraries will meet the above criterion. In this thesis, to be conservative, the minimum access/egress time is set to 0, which could overestimate the number of the feasible itineraries for a passenger.

Figure 3-3 illustrates all possible instances as a tree diagram for one passenger given the set of feasible trains (size M).

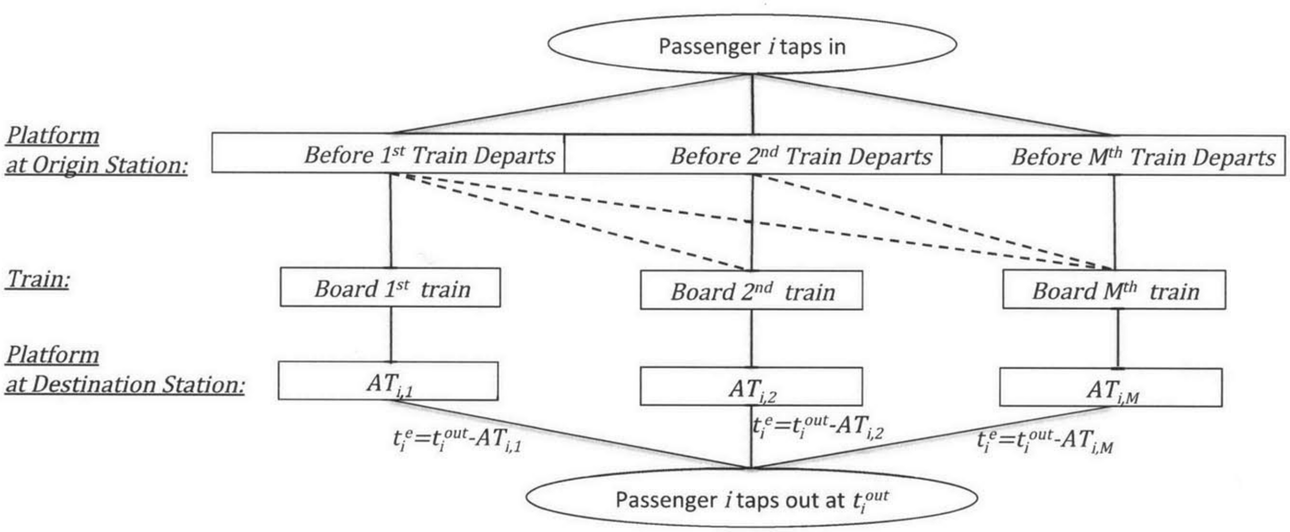


Figure 3-3: General Passenger-to-Train Assignment Model Structure

Where,

i : passenger index,

t_i^e : the egress time for passenger i,

t_i^{out} : the tap-out time for passenger i,

$AT_{i,j}$: the arrival time of j^{th} train at the destination station of passenger i.

After passenger i taps in, he/she walks to the platform. The passenger has M feasible trains they may board. In Figure 3-3, the branches with a dashed line represent the cases of denied boarding. For example, even if the passenger arrives before the first train to depart, especially during the peak-hours, he/she can still be left behind and have to board the second (or third) train due to the capacity constraints when there is no room for more passengers on the train.

A special case of this general framework is when the capacity constraints are not binding. This is likely to be the case for example during off-peak hours on many systems. The model structure without binding capacity constraints is shown in Figure 3-4. In this case, if the arrival time at the platform for passenger i is before the departure time of train j but after train $j-1$, the passenger will board train j with certainty.

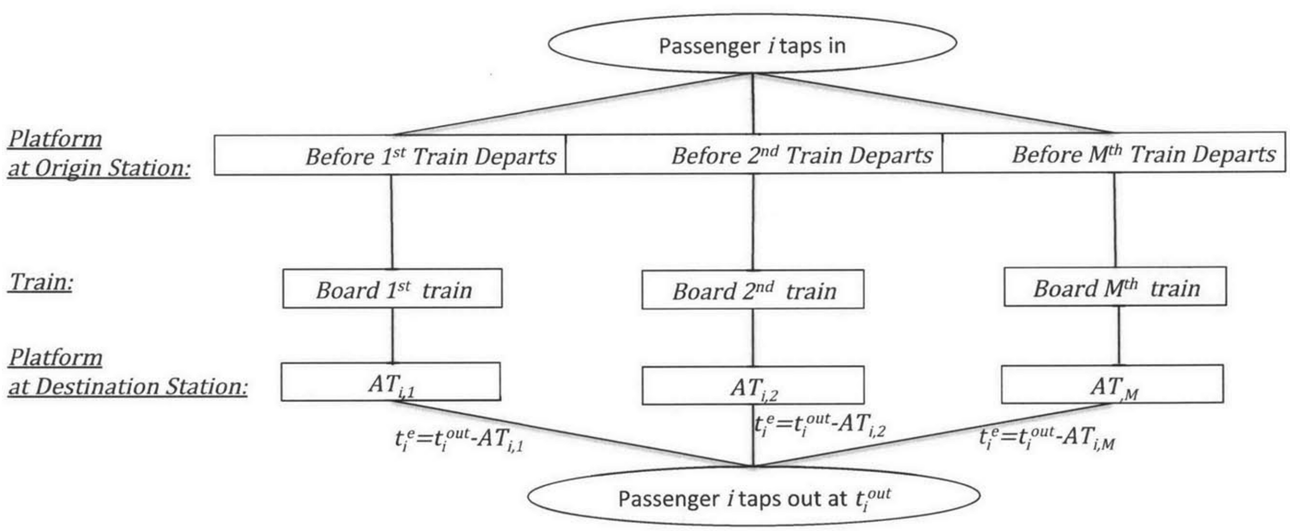


Figure 3-4: Passenger-to-Train Assignment Model Structure without Capacity Constraints

For a trip with transfer(s), the model structure needs to be modified. First, the route choice should be incorporated in the first step to develop the feasible itinerary set for each route. Second, for each itinerary, additional journey time components will enter the structures, including transfer times and in-vehicle times for all segments of the route. More layers are added into the tree diagram based on the number of transfers.

This thesis focuses on trips without transfers and the off-peak period cases without capacity constraints. Future work will expand the proposed framework to deal comprehensively with those issues.

Under the assumption of no binding capacity constraints and given the tap-in/out times, the boarding train for a specific passenger largely depends on the egress and access times for each itinerary. For example, if we assume that most people's walking speed is around 1 m/s and the walking distance from the fare gate to the platform at the origin and destination stations are 100 meters, an itinerary with 100 seconds of access and 100 seconds egress time is more likely to be the actual one than an itinerary with 190 seconds of access time and 10 seconds of egress time. Given the distribution of passengers' walking speed at stations, the probability of choosing each itinerary can be derived based on the likelihood of different access and egress times. In this research, building upon the work of Paul (2010), instead of deterministically assigning a passenger to an itinerary, the probabilities for each passenger to have boarded different trains is estimated given the distribution of passengers' walking speed.

3.1.2 Model Framework

The PTAM consists of two parts: the *passenger model* and the *trainload model* (see Figure 3-5). The passenger model uses the ATR and AFC data to generate a feasible itinerary set for each individual. The distribution of access/egress speed is used to estimate the probabilities of each itinerary being selected. The probabilities are used as input to the trainload model along with the ATR data to estimate the trainload for each train based on the archived records. Given capacity constraints, before assigning a passenger to a train, the load should be examined to check capacity feasibility. If the train has no capacity for additional passengers, this information will be returned to the passenger model to re-estimate the probabilities of boarding other trains. A detailed description of each step is provided in the following sections. Figure 3-5 provides an initial treatment of capacity. However, further research is required to incorporate capacity constraints effectively.

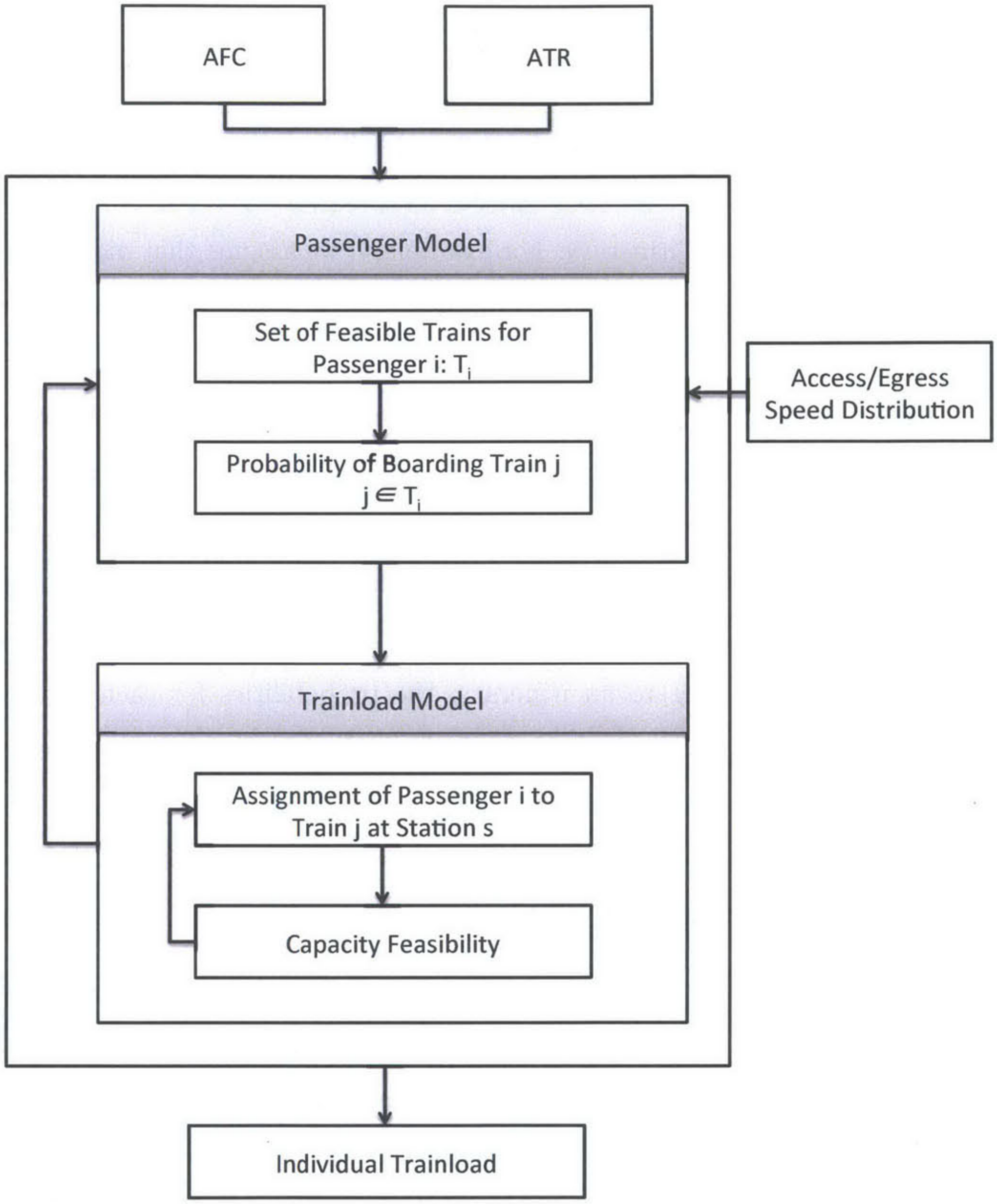


Figure 3-5: Model Framework

As mentioned in the previous section, in this research, the model is developed based on two restrictions as a first step towards a more general model: capacity constraints and transfers are both excluded. We start from the typical situation in the off-peak period, when trains are not crowded and so no capacity constraints at the station level and the train level are needed. We also focus on trips without transfers, which means only trips within a specific line are considered. Assuming a route choice model is available, the proposed methodology can incorporate the route choices as the first step before assigning passengers to trains. Relaxing these two assumptions is an important future research direction.

3.2 The Passenger Model

The passenger model is the fundamental element of the methodology and estimates the probability of passenger i boarding the j^{th} train in its feasible itinerary set based on the tap-in/out times and the feasible itineraries' arrival/departure times. The probabilities will vary among individuals. Figure 3-6 provides an example of the model results for a passenger with three feasible itineraries.

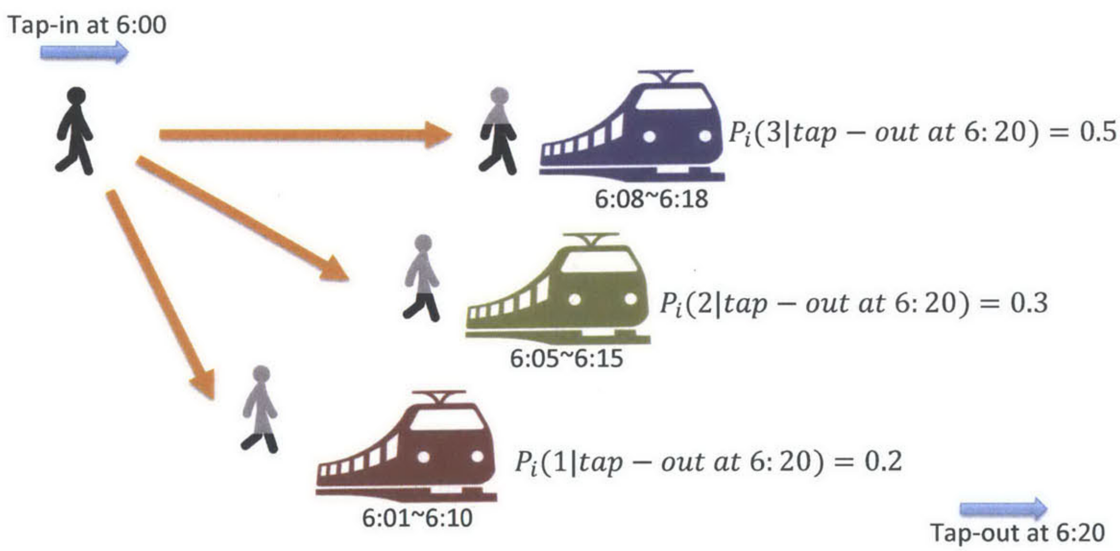


Figure 3-6: Passenger Model

The passenger tapped-in at 6:00 and tapped-out at 6:20 and had three feasible itineraries. The first departed the origin station at 6:01 and arrived at the destination station at 6:10. The second departed at 6:05 and arrived at 6:15. The last feasible itinerary departed at 6:08 and arrived at 6:18. The passenger model estimates the probabilities for this passenger to have boarded these itineraries as 0.2, 0.3 and 0.5

respectively.

3.2.1 Notation

The following notation is used:

i: passenger index.

t_i^{in}: tap-in time of passenger i.

t_i^{out}: tap-out time of passenger i.

JT_i: journey time of passenger i, where $JT_i = t_i^{out} - t_i^{in}$.

t_i^a: access time of passenger i.

t_i^e: egress time of passenger i.

M_i: the number of feasible itineraries for passenger i.

$DT_{i,j}$: the "relative" departure time at the origin station for the j^{th} train in the feasible itinerary set after setting the tap-in time of passenger i to time zero. $j \leq M_i$.

$AT_{i,j}$: the "relative" arrival time at the destination station for the j^{th} train in the feasible itinerary set after setting the tap-in time of passenger i to time zero. $j \leq M_i$.

$f_a(t)$: access time distribution.

$f_e(t)$: egress time distribution.

3.2.2 Train Boarding Probability

The probability of a passenger to have boarded train j given that he/she tapped-out at t_i^{out} is a conditional probability computed using Bayes' theorem. It equals the probability of boarding train j and tapping-out at t_i^{out} divided by the probability of tapping-out at t_i^{out}:

$$P_i(board\, j^{th}\, train|t_i^{out}) = \frac{P_i(board\, j^{th}\, train, t_i^{out})}{P_i(t_i^{out})} \tag{3.3}$$

Using the law of total probability, the denominator of expression 3.3, the probability for passenger to tap-out at t_i^{out}, is the sum of the probabilities of boarding any train in the feasible itinerary set:

$$P_i(t_i^{out}) = \sum_{j'=1}^{M_i} P_i(board\, j'^{th}\, train, t_i^{out}) \tag{3.4}$$

By substituting equation 3.4 into equation 3.3 we get:

$$P_i(board\, j^{th}\, train | t_i^{out}) = \frac{P_i(board\, j^{th}\, train, t_i^{out})}{\sum_{j'=1}^{M_i} P_i(board\, j'^{th}\, train, t_i^{out})} \tag{3.5}$$

Given the set of feasible itineraries, the access time for passenger i should be shorter than the difference between the departure time of train M_i (last train in the feasible set), which is DT_{i,M_i}, and the tap-in time. Hence, the probability of passenger i arriving at the platform before train 1 departs given the fact that the access time is shorter than DT_{i,M_i} is a conditional probability:

$$P(t_i^a < DT_{i,1} | t_i^a < DT_{i,M_i}) = \frac{\int_0^{DT_{i,1}} f_a(t)dt}{\int_0^{DT_{i,M_i}} f_a(t)dt} \tag{3.6}$$

If the access time is longer than $DT_{i,1}$ and shorter than $AT_{i,2}$, the passenger will arrive during the interval between the departure of train 1 and train 2, and so forth. In general, the probability of passenger i arriving at the platform between trains $j-1$ and j departures given the fact that the access time is shorter than DT_{i,M_i} is:

$$P(DT_{i,j-1} \leq t_i^a < DT_{i,j} | t_i^a < DT_{i,M_i}) = \frac{\int_{DT_{i,j-1}}^{DT_{i,j}} f_a(t)dt}{\int_0^{DT_{i,M_i}} f_a(t)dt} \quad \text{for } 2 \leq j \leq M_i \tag{3.7}$$

Given the assumption of no capacity constraints, a passenger can always board the first train after arriving on the platform. Hence the probability to have boarded train j depends on the probability of arriving at the platform during the specific time interval between train $j-1$ and train j departing:

$$P_i(j) = P(DT_{i,j-1} \leq t_i^a < DT_{i,j}) \quad \text{for } 1 \leq j \leq M_i \tag{3.8}$$

Where we define $DT_{i,0} = 0$.

By substituting equations 3.6 and 3.7 into equation 3.8 we get:

$$P_i(j) = \frac{\int_{DT_{i,j-1}}^{DT_{i,j}} f_a(t)dt}{\int_0^{DT_{i,M_i}} f_a(t)dt} \quad \text{for } 1 \leq j \leq M_i \tag{3.9}$$

The conditional distribution for the egress time can be derived based on the knowledge on the feasible itinerary set. The possible values of realized egress times are limited by the number of feasible itineraries, hence the conditional probability density function of possible egress times is not continuous but discrete:

$$P(t_i^e = JT_i - AT_{i,j}) = \frac{f_e(JT_i - AT_{i,j})}{\sum_{j'=1}^{M_i} f_e(JT_i - AT_{i,j'})} \quad \text{for } 1 \leq j \leq M_i \tag{3.10}$$

The probability that passenger i boarded the j^{th} train and tapped-out at t_i^{out} (had a journey time equal to JT_i) involves two independent events: boarding train j and having the egress time equal to $JT_i - AT_{i,j}$. Hence this probability is the product of the probabilities of boarding train j and having egress time equal to $JT_i - AT_{i,j}$:

$$P_i(board\, j^{th}\, train, t_i^{out}) = P_i(j)P(t_i^e = JT_i - AT_{i,j}) \tag{3.11}$$

By substituting equations 3.9 and 3.10 into equation 3.11 we get:

$$\begin{aligned} & P_i(board\, j^{th}\, train, tap-out\, at\, t_i^{out}) \qquad \text{for } 1 \leq j \leq M_i \\ = \; & \frac{\int_{DT_{i,j-1}}^{DT_{i,j}} f_a(t)dt}{\int_0^{DT_{i,M_i}} f_a(t)dt} \frac{f_e(JT_i - AT_{i,j})}{\sum_{j'=1}^{M_i} f_e(JT_i - AT_{i,j'})} \end{aligned} \tag{3.12}$$

Finally, the probability that passenger i boarded train j given the fact that he/she tapped-out at t_i^{out} is derived by substituting equation 3.13 into equation 3.5:

$$\begin{aligned} & P_i(board\, j^{th}\, train|tap-out\, at\, t_i^{out}) \qquad \text{for } 1 \leq j \leq M_i \\ = \; & \frac{\int_{DT_{i,j-1}}^{DT_{i,j}} f_a(t)dt f_e(JT_i - AT_{i,j})}{\sum_{j'=1}^{M_i} [\int_{DT_{i,j'-1}}^{DT_{i,j'}} f_a(t)dt f_e(JT_i - AT_{i,j'})]} \end{aligned} \tag{3.13}$$

3.3 The Trainload Model

The trainload model aims at measuring the system utilization spatially and temporally and providing information about how close the system is operating to its limit. To estimate the trainload, the probabilities for all the passengers who can possibly board this train will be examined and loaded/unloaded to/from the train on corresponding line segments.

For example, in Figure 3-7, the highlighted passenger who traveled from the first to the third station has 0.5 probability of boarding this train. In this case, he/she

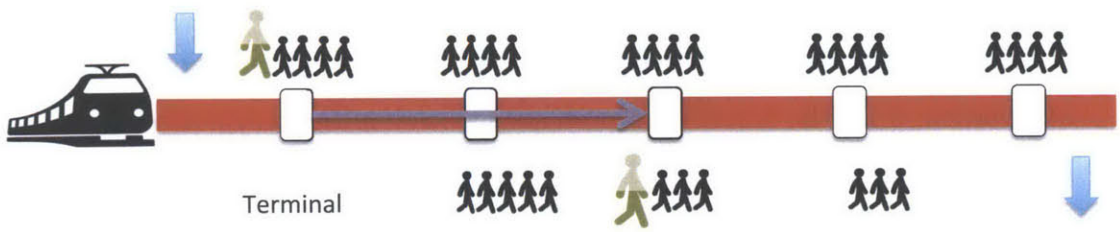


Figure 3-7: Trainload Model

Starting from the origin terminal station, the trainload for train k after departing is the sum of the probabilities for passengers who traveled from the terminal station, which is denoted as station 1, to have boarded this train:

$$E_1(k) = \sum_{for\,all\,i\,where\,O_i=1} P_i(board\,train\,k|t_i^{out}) \tag{3.14}$$

Where,

$E_1(k)$: the trainload for train k after departing terminal station.

O_i: the origin station index for passenger i (e.g., if passenger i traveled from the terminal station, O_i=1).

D_i: the destination station index for passenger i and $D_i > O_i$.

The trainload for train k from station m to $m+1$ ($m \geq 2$) can be derived based on the load on the previous segment of the line and the probabilities of choosing this itinerary for two groups of passengers: (i) passengers boarding at this station and (ii) passengers alighting at this station.

$$E_m(k) = E_m(k-1) - \sum_{for\, all\, i\, where\, D_i=m} P_i(board\, train\, k|t_i^{out}) + \sum_{for\, all\, i\, where\, O_i=m} P_i(board\, train\, k|t_i^{out}) \quad (3.15)$$

Where,

m: the station index.

$E_m(k)$: the trainload for train k after departing station m.

O_i: the origin station index for passenger i (e.g., 1 represents the terminal station).

D_i: the destination station index for passenger i and $D_i > O_i$.

In equation 3.15, the first term represents the load on the previous segment, the second term represents the estimated total number of passengers alighting at station m, and the third term represents the estimated total number of passengers boarding at station m. Therefore, the trainload can be calculated from the origin terminal station to the destination terminal station using equation 3.15.

Since the focus of this thesis is on trips within the same line, the transfer passenger flow at transfer stations is not included in this expected trainload calculation. With an appropriate route choice model, transfer passengers can be assigned to different routes. With the knowledge of their routes and transfer stations, it is possible to use the passenger model to calculate their probabilities of taking different itineraries at their transfer station to accommodate the transfer demand.

Similarly, the capacity constraints must be considered if we extend this research to peak hours. Instead of processing the passenger model before the trainload model, an iterative process can be used to consider the trainload and the assignment problem simultaneously. Passengers with one feasible itinerary are loaded on to the trains first (see Figure 3-8).

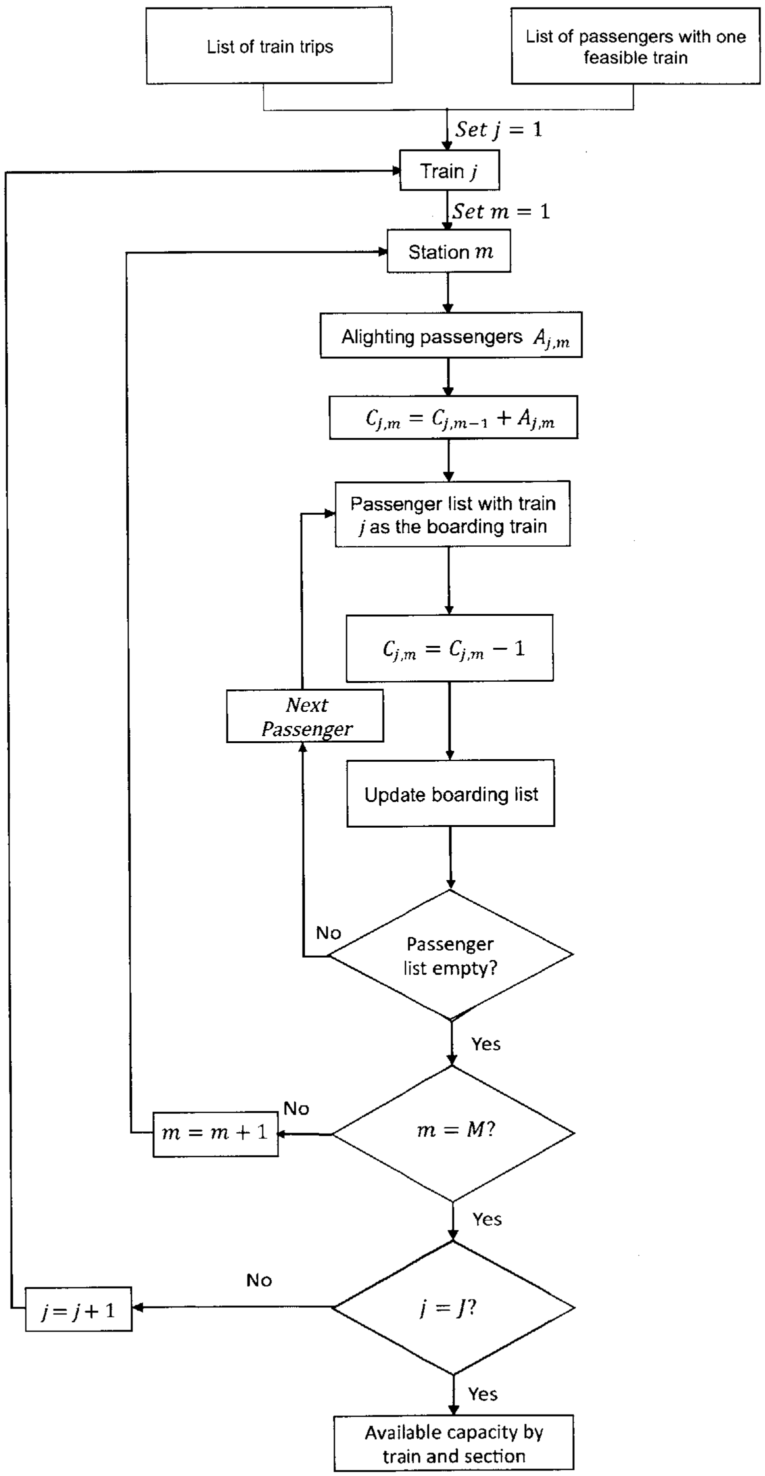


Figure 3-8: PTAM with Capacity Constraints: Load Passengers with One Feasible Itinerary

Where,

j: train index.

J: total number of train itineraries.

m: station index.

M: total number of stations on the line.

$A_{m,j}$: alighting number of passengers on train j at station m.

$C_{j,s}$: available capacity for train j at station m.

The list of train trips for the day and the list of passengers with one feasible itinerary (and their boarding trains) are used as input to this process. Since it is a simulation-based process, to achieve the final convergence, many replications are needed. The available capacity is calculated from the first train ($j = 1$) and from the terminal station ($m = 1$). For each train and each station, passengers are allowed to alight first and the available capacity is updated. At each station, the list of passengers with train j as their only feasible itinerary is generated and all those passengers are loaded. After all the passengers with one feasible itinerary have been loaded at every station on every train, this process terminates with the available capacity for each train and station as out put. This outpur is now input to the next process which loads the remaining passengers (see Figure 3-9).

The list of train trips and passengers with their initial feasible itineraries and corresponding probabilities (estimated without capacity constraints) are used as input to this process. By drawing a random variable based on the probabilities of boarding different trains, a passenger is assigned to a train (temporally). This information is input to the trainload model. Based on the same procedure, a passenger is loaded/unloaded to/from a train. But if the capacity constraint is binding before a passenger is loaded, this train itinerary will be deleted from this passenger' feasible set and the passenger model is used to re-calculate the probabilities based on the new feasible set. Another random variable is then drawn to determine the boarding train of this passenger. After all the passengers being examined and the trains being loaded and unloaded at all stations, a completed trainload profile is generated. With this approach, two issues need to be further discussed.

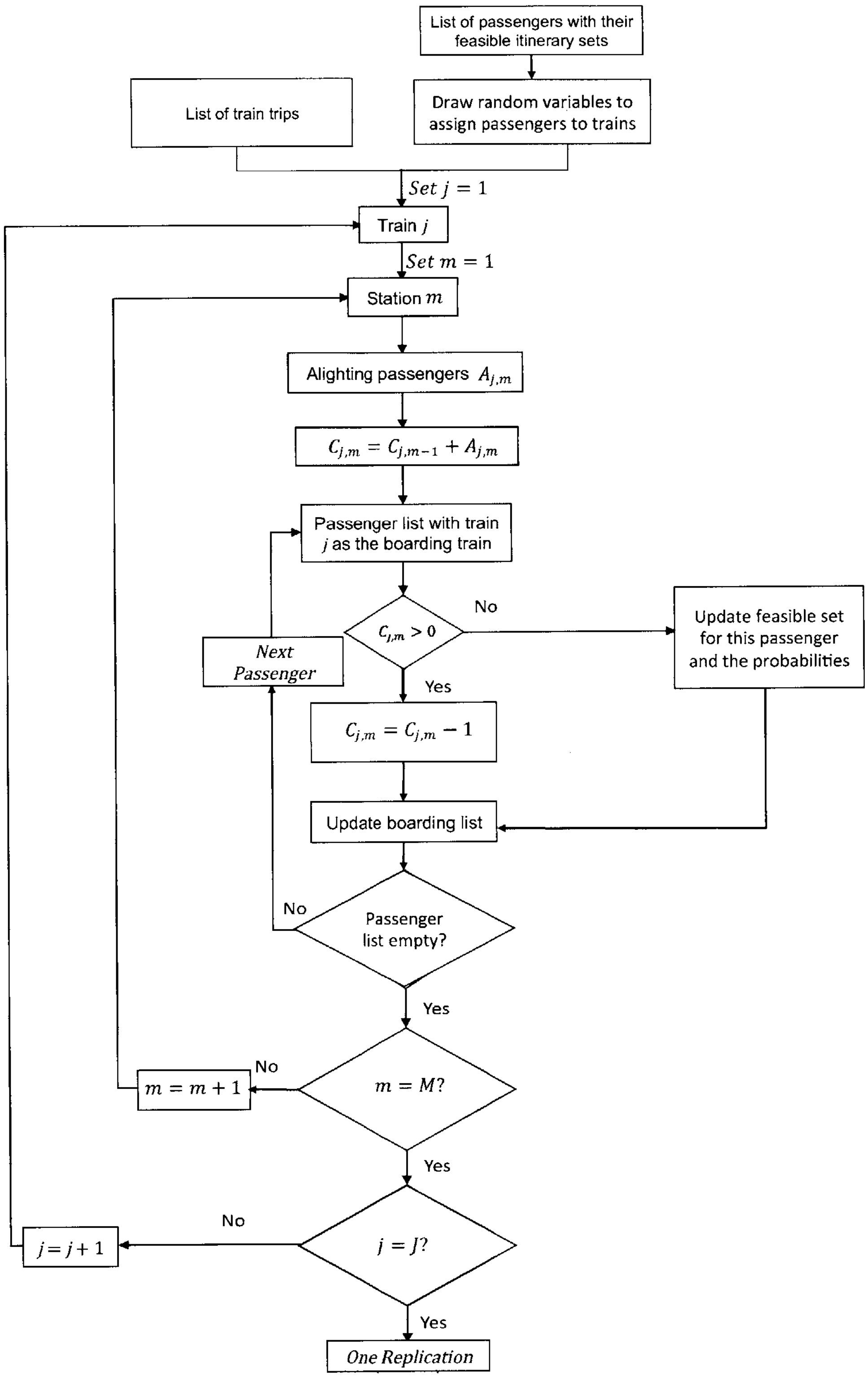


Figure 3-9: PTAM with Capacity Constraints

First, the order of the passengers in the list is critical, since it determines who is left behind if the train is full. One alternative is to order all the passengers by their tap-in times, which assumes a "first-tap-in-first-board" rule. The tap-in gate information can also be considered as another sorting criterion to let passengers with shorter walking distances board first. Another alternative is to randomly order the passengers.

Second, when passengers are denied boarding, there is an easier way to update the probabilities of boarding trains under the new feasible itinerary set. The passenger model can be used to recalculate the probabilities but it is easier to update the probabilities directly based on the results from the original feasible set:

$$P_i'(j|t_i^{out}) = \frac{P_i(j|t_i^{out})}{\sum_{j' \subset New\ Set}[P_i(j'|t_i^{out})]} \tag{3.16}$$

Where,

$P_i(j|t_i^{out})$: the probability of boarding train j under the original feasible set.

$P_i'(j|t_i^{out})$: the probability of boarding train j under the new feasible set.

The main difference between the two methods is whether deleting the itinerary with no available capacity will significantly affect the probabilities of boarding the second train. For example, in the first method, where the passenger model recalculates the probabilities, the probability of boarding the 2^{nd} train will increase dramatically and the probabilities of boarding the 3^{rd} (or later) trains will be little changed. In the second method, probabilities of boarding all the trains in the new feasible itinerary set will proportionally increase while the ratio between them stay the same. The results from recalculating the passenger model can be closer to reality because passengers left behind by the first train are more likely to board the second one to arrive. Based on this fact, another extreme is that, given a passenger is denied boarding, the probability of him/her to board the second train is set to be one. In this case, this passenger will enter the first process as in Figure 3-8 as a passenger with one feasible itinerary.

This represents as initial approach to incorporate capacity constraints. However, further research is needed to both test the approach and capture the impact of capacity accurately.

3.4 Summary

This chapter developed a methodology to solve the passenger-to-train assignment problem at the vehicle level. The probabilities of passengers to have boarded different trains were estimated for each individual. At the aggregate level, this information was used to estimate the trainload using the Trainload Model and provided valuable insight into the capacity utilization of the network. The estimation of input parameters will be discusses in Chapter 4 and the model is then applied to the MTR network, as discussed in Chapter 5.

Chapter 4

Parameter Estimation

The distributions of the access and egress times are key inputs to the Passenger-to-Train Assignment Model (PTAM). This chapter discusses the methodology to estimate the key parameters (mean and variance) for those distributions. The walking speeds of passengers in stations are estimated and the walking distances are measured from the station plan. With knowledge of both the speeds and the distances, the access/egress time distribution can be derived.

Section 4.1 develops the walking speed model and illustrates the underlying assumptions. Section 4.2 provides the walking distance estimation method based on the station configuration. Section 4.3 describes the maximum likelihood estimation method using the truncated data sample. Section 4.3.1 provides an estimation example using synthetic data and validates the result. Section 4.4 draws conclusions and proposes future work.

4.1 Walking Speed Model

The access and egress time distributions are a direct input to the PTAM. Therefore, the distribution of the walking speed in general, as the first step in modeling passenger behavior at stations, is important.

Passengers' walking speeds at different stations is a function of:

- Individual characteristics, such as age and gender. Familiarity with the system and the stations is also a factor.

- Station configuration and characterization, such as ramps, stairs, and escalators.
- The degree of crowding–especially during peak hours, as crowding increases the interactions between passengers and reduces their walking speeds.
- Trip purpose, commuters, for example, will generally be faster than tourists.

The walking speed is modeled as a random variable following a specific distribution (for example normal or log-normal). The mean (and variance) of this distribution can be expressed as a function of many factors.

$$\mu_i = \alpha_0 + \alpha X_i \tag{4.1}$$

Where,

μ_i : the mean of the distribution.

α : vector of parameters.

X: set of explanatory variables.

Example of explanatory variables include:

$$X_{1,i} = \begin{cases} 1 & \text{for senior card holders} \\ 0 & \text{o.w.} \end{cases}$$

$$X_{2,i} = \begin{cases} 1 & \text{for frequent travelers (e.g., more than 10 trips per week)} \\ 0 & \text{o.w.} \end{cases}$$

$X_{3,i}$: measure of station complexity.

$$X_{4,i} = \begin{cases} 1 & \text{for trips during peak hours} \\ 0 & \text{o.w.} \end{cases}$$

In the work of Kim et al. (2006), a detailed mobility model for pedestrians was constructed based on a 13-months tracing data to estimate the physical location of users. Both pause time, walking speed and movement direction were examined. They reported that the walking speed followed a log-normal distribution. The reported average walking speed was 1.26 m/s. Several studies on pedestrian movements also found that a normal or log-normal distribution is a good probability distribution to represent walking speeds. Especially, when the walking speed is asymmetric, a log-normal distribution is better (Ottomanelli et al., 2012; Zhang et al., 2009; Daamen and Hoogendoorn, 2006). The two parameters of the log-normal distribution–μ_i and σ will be estimated based on the observed walking speeds of individuals at both the origin and destination stations.

It is expected that access and egress speeds are correlated. Paul (2010) dealt with this problem by assuming that for the same individual, the access time has the same percentile as the egress time distribution. To relax this assumption, the access and egress speeds can be modeled separately but with a degree of correlation as shown below:

$$(v_i^e, v_i^a) \sim f_{(V_i^e, V_i^a)}(\mu_i^e, \sigma_i^e, \mu_i^a, \sigma_i^a, \rho) \tag{4.2}$$

Where,

v_i^e : the egress speed of individual i.

v_i^a : the access speed of individual i.

ρ: the correlation between egress speed and access speed.

$f_{V_i^e, V_i^a}$: the joint distribution of access/egress speed for passenger i.

$\mu_i^e, \sigma_i^e, \mu_i^a, \sigma_i^a$: parameters for the distribution.

4.2 Walking Paths at Stations

The walking distance is a key element to transform the walking time observations into speeds and hence to derive the distributions of access and egress times for input to the PTAM. From the AFC data, the tap-in/out gates for each individual are known, which can be used to identify the exact entry/exit points given the station layouts.

However, even though the tap-gates are recorded, the exact locations of the platforms each passenger alighted on, or boarded at, and the path he/she chose are not observed. The boarding locations along the platform should be inferred to estimate the walking distances, since the platforms are long and the walking distances on the platform level can account for a large portion of the walking paths. In terms of in-station walking distances, it is assumed that passengers are divided into two groups. The first group optimize their location to minimize the distances to/from the gates. The second group of passengers randomly choose their locations to alight from (or board at) on the platforms. In this case, some passengers will have long walking distances.

To capture this behavior, we introduce a parameter representing the proportion (or the probability) of passengers who optimize their locations on the platform. Then the walking distance distribution for a random passenger can be expressed as:

$$f_{D_i}(d) = p f_{D_i^l}(d) + (1-p) f_{D_i^u} \tag{4.3}$$

Where,

$f_{D_i}(d)$: the walking distance distribution for a random passenger i.

$f_{D_i^l}(d)$: the walking distance distribution for passenger i given that he/she optimizes their platform locations.

$f_{D_i^u}(d)$: the walking distance distribution for passenger i given that he/she is located randomly on the platform.

p: the proportion (or the probability) of passengers who optimize their locations.

The parameter p can be estimated as an additional parameter in the model. However, in this thesis, the two cases are tested separately, stipulating $p = 1$ and $p = 0$ to obtain estimates of walking distances for the two groups respectively instead of estimating the value of p.

4.2.1 Distance for "Optimizing" Passengers

For this group, the lower bound on walking distance can be obtained by assuming that all passengers will alight at the section of platform that is closest to their tap-out gates and the nearest section to board the train after entering through the tap-in gates at the platform level. In calculating the egress distance, for example, a passenger who is familiar with the station, while waiting at the origin station, can always move to the train door through which he/she can alight at the part of the destination platform with the shortest egress distance.

Each platform is divided into sections and each gate group is assigned to the closest section of the platform. Figure 4-1 shows a simplified station layout with the orange area representing the concourse (fare gate) level and the blue area representing the platform level.

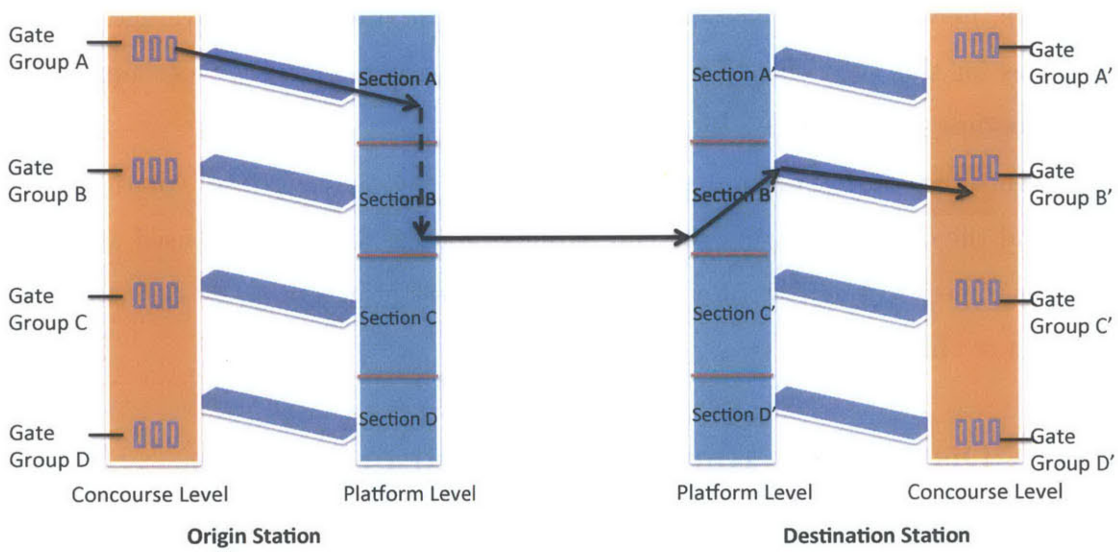


Figure 4-1: Simplified Station Layout

The fare gates are categorized into groups A, B, C and D based on their locations. The platform is divided into four sections based on the closest fare gate group, with boundaries drawn at the mid-point of the distance between adjacent escalators' entries.

For this type of passenger, for example a passenger who tapped-in through fare gate group A and tapped-out though fare gate group B, the path "A-A-B-B'-B'" would be taken, which represents the case that the passenger walked from fare gate group A to section A, moved from part A to part B on the origin platform during his/her waiting time, alighted at section B on the destination platform, and walked out through the fare gate group B. At both entry and exit stations, the walking distances are minimized. Note that the distance on the origin platform from section A to section B is not counted in the access distance because the passenger has arrived at the platform and the access time that determines his/her boarding train is not affected by this extra walking. However, if there was not enough time for this passenger to move along the origin platform (such as when the passenger arrived at the platform and the train was about to leave), this passenger could also follow the path "A-A-A'-B'". In this case, the egress distance will be longer than for the previous path.

We assume that under most circumstances, an "optimizing" passenger can always minimize the walking distances at both entry and exit stations. The average walking distances for this type of passengers are estimated from the fare gate groups to the corresponding sections.

Given inferred origin and destination points at the platform level (platform section) and the concourse level (fare gate group), shortest distances are used assuming that passengers will not "wander around" inside the station but go straight from the platform to the fare gate.

4.2.2 Distance for Randomly Located Passengers

For this group, we assume that a passenger's alighting/boarding location is randomly located along the platform no matter which gates he/she used. Under this assumption, passengers may alight from one end of the platform, walk to the other end of the platform and tap-out through a gate that is far from the alighting location. In Figure 4-1, passengers can take a longer path such as "A-A-A'-B'", or "A-C-C'-B'". We should keep in mind that, even passengers who are not familiar with the stations, can still choose the optimal path as for the first group by chance. However, the average walking distance for this group should be longer than the "optimizing" group. Both the average access and egress distances are calculated as the mean distance from any point on the destination platform to the recorded gate.

4.3 Estimation Methodology

Measurements of the walking speed of passengers can be obtained through direct observation by having surveyors follow passengers when they enter the system. MTR for example, has such surveys data for 10 key stations. Figure 4-2 shows the survey data for Causeway Bay (CAB) station during the morning period with different passenger groups being surveyed.

		Walkway			Stair (Up)		
		Size	Range	Mean(SD)	Size	Range	Mean(SD)
CAB (AM)	Male						
	Female						
	Elderly	11	0.81-1.59	1.22(0.27)	17	0.39-0.66	0.54(0.08)
	Children	21	0.92-3.37	1.36(0.49)	8	0.47-1.04	0.63(0.21)
	Disabled	0	-	-	0	-	-
	Tourist	0	-	-	6	0.46-0.95	0.76(0.3)

Figure 4-2: MTR Survey Data on Walking Speeds

However, there are several concerns about using such data. The most important concern is the typically small sample size, which undermines estimation accuracy. Manual data collection is an expensive and time consuming process, explaining the small sample sizes.

The alternative, which is used here, is to use the automated data for estimation and use survey data (if available) for validation. Based on AFC and ATR data, there are a large number of passengers who have only one feasible itinerary. For these passengers, their unique itinerary is certainly the one they took. Therefore, for this subset of trips, the actual egress time for passenger i can be calculated as the difference between the arrival time of the train and the passenger's tap-out time:

$$t_i^e = t_i^{out} - AT_{i,1} \tag{4.4}$$

Where,

t_i^e: egress time of passenger i,

t_i^{out}: tap-out time,

$AT_{i,1}$ is the arrival time of the first (only) feasible train at the destination for passenger i.

Using five days' data from the MTR network, over one million trips within Tsuen Wan Line have a single feasible itinerary. The histogram of the egress times is shown in Figure 4-3.

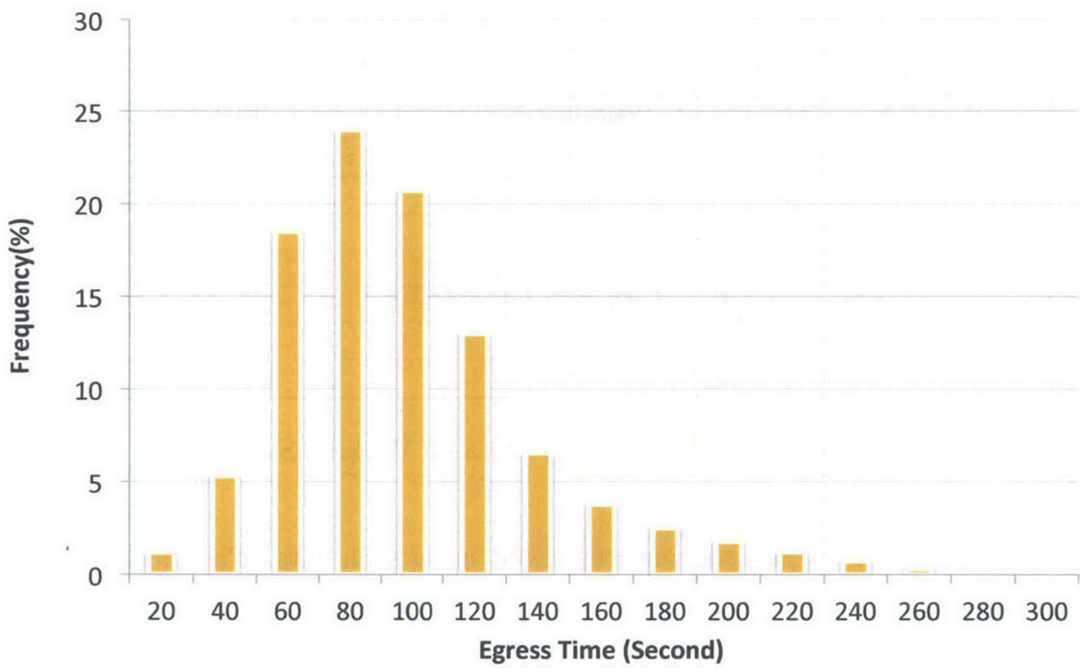


Figure 4-3: Egress Time Distribution for Trips to Central with One Feasible Itinerary

However, this sample is truncated since it only contains observations of passengers who completed their tap-out before the arrival of the next train. In general, there are certain conditions for passengers to have a single itinerary. First, the passenger should arrive at the platform before the first train departure following his/her tap-in. The time between the train departure and the tap-in time represents the upper bound on his/her access time. Similarly, the egress time at the destination for the second itinerary represents another upper bound. If this passenger walked slowly so that the tap-out time was later than the arrival of the second train at the destination station, there will be at least two feasible itineraries.

In summary, the sample of passengers with one feasible itinerary is truncated and is drawn from a conditional distribution with a minimum speed for each individual based on his/her tap-in/out times and the departure/arrival time of the corresponding train. If we assume that the access and egress speeds are perfectly correlated, the probability density function of the speed distribution in the truncated sample will be:

$$f_{V|V_{min,i}}(v|v_{min,i}) = \frac{f_V(v)}{1 - F_V(v_{min,i})} \tag{4.5}$$

$$v_{min,i} = max\left\{\frac{d_i^a}{DT_{i,1}}, \frac{d_i^e}{AT_{i,2} - AT_{i,1}}\right\} \tag{4.6}$$

Where,

i: the passenger index.

$f_{V|V_{min,i}}(v|v_{min,i})$: the conditional probability density function of walking speed for passenger i.

$f_V(v)$: the probability density function of the walking speed distribution for the whole population.

$F_V(v)$: the cumulative density function of the walking speed distribution for the whole population.

$v_{min,i}$: the minimum speed for this passenger.

d_i^a: the walking distance for passenger i at the origin station, or access distance.

d_i^e: the walking distance for passenger i at the destination station, or egress distance.

$DT_{i,1}$: the departure time of the 1^{st} train at the origin station for passenger i after the tap-in time.

t_i^{in}: the tap-in time for passenger i.

$AT_{i,1}$: the arrival time of the 1^{st} train at the destination station after the tap-in time.

Based on the above data, maximum likelihood estimation can be used to estimate the model parameters. The log-likelihood function is given by:

$$L^* = \sum_i log\left(\frac{f_V(v_i)}{1 - F_V(v_{min,i})}\right) \tag{4.7}$$

4.3.1 Example

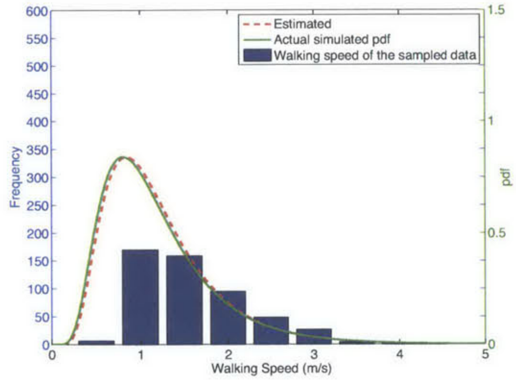
In this section, synthetic data is generated based on the actual AFC tap-in times and the ATR data to test this method. A log-normal distribution for the whole population is assumed and observations are generated for individuals to represent their access and egress speeds. The arrival time at the origin platform, boarding train, and egress time are determined for each individual as well as his/her tap-out time. The subset of people with a single itinerary are then selected and used as the sample in the maximum likelihood estimation. The simulation results are shown in Table 4.1.

No.	**Sample Size**	**Actual Speed**				**Estimated Speed**			
		μ	σ	Mean	Std	μ	σ	Mean	Std
a	532	0.050	0.514	1.200	0.661	0.107	0.478	1.247	0.631
b	535	0.150	0.254	1.200	0.310	0.150	0.253	1.199	0.309
c	1274	0.640	0.326	2.000	0.670	0.635	0.322	1.987	0.656
d	1371	0.680	0.162	2.000	0.326	0.681	0.161	2.001	0.324

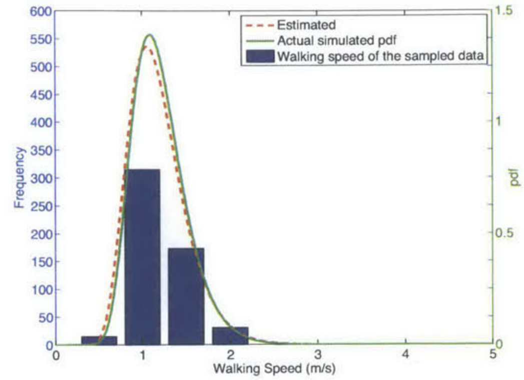
Table 4.1: Actual and Estimated Parameters

The comparison between the estimated and the actual distributions is shown in Figure 4-4 for different walking speed mean and standard deviation. The green line represents the true log-normal distribution and the red dashed line the estimated distribution. The blue bar shows the distribution of the egress times for the selected sample (passengers with single feasible itinerary). The number of passengers with a single itinerary almost doubles when the mean speed increases from 1.2 m/s to 2.0 m/s.

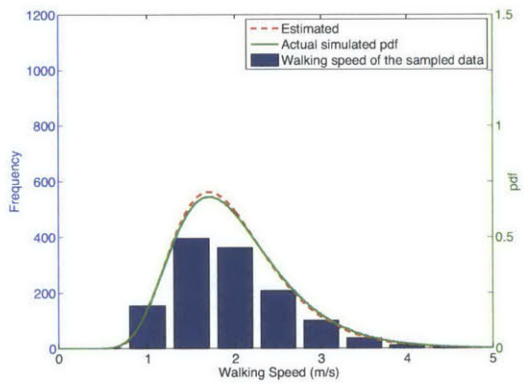
As expected, passengers who walk faster are more likely to catch the first train and tap-out before the second train arrives at the destination. Since the blue bars



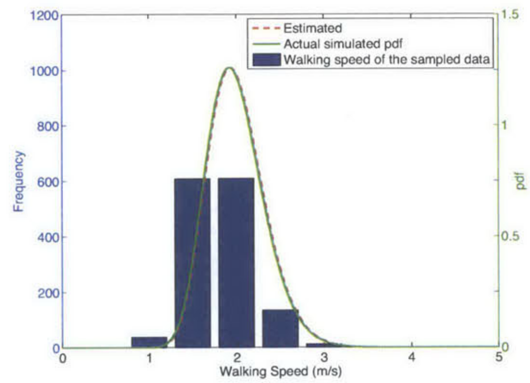
(a) Mean: 1.2 Standard Deviation: 0.661



(b) Mean: 1.2 Standard Deviation: 0.310



(c) Mean: 2.0 Standard Deviation: 0.670



(d) Mean: 2.0 Standard Deviation: 0.326

Figure 4-4: Maximum Likelihood Estimation

represent the distribution of egress times in the truncated sample, fewer passengers are observed in the left tail of the distribution. Comparing the estimated with the true parameters, the overall estimation performance is very good.

4.4 Summary

The chapter presented a methodology to model and estimate the walking speed distribution parameters for the PTAM. For the walking distance estimation, upper and lower bounds are obtained for each individual based on his/her tap-in/out gates. For the walking speed estimation, a log-normal distribution with two parameters–mean and variance–was estimated using the maximum likelihood. An example with synthetic data was used to illustrate the feasibility of the approach. The results show that the maximum likelihood method provided accurate estimation of the true distribution of walking speed for the whole population.

Chapter 5

Application

This chapter presents the application results of the Passenger-to-Train Assignment Model (PTAM) tailored to the MTR network. Specifically, Automatic Fare Collection (AFC) and Automatic Train Regulation (ATR) from the Tsuen Wan Line are used to prepare the input to the model.

Section 5.1 provides an overview of the Tsuen Wan Line. Section 5.2 discusses the processing of the MTR data. Section 5.4 presents the parameter estimation results of the walking speed distribution for the MTR system and compares it with survey data. Section 5.5 presents one of the PTAM's applications, the passenger movement based on the PTAM's output at the individual level, while section 5.6 shows the trainload estimation at the aggregate level. Section 5.3 shows the distribution of feasible itineraries based on the selection criterion described in Chapter 3. Section 5.7 shows the estimation of the number of passengers at stations to assess the crowding level. Section 5.8 summarizes the key findings and offers recommendations.

5.1 Overview of Tsuen Wan Line

Tsuen Wan Line (TWL) is one of the busiest lines in the MTR network serving over 900,000 daily passengers. It starts from the northwestern section of Hong Kong Island and runs through central Kowloon to the southwestern New Territories (see Figure 5-1), serving the central CBD and the Nathan Road corridor in Kowloon. It is the most important cross harbor link. The TWL consists of 16 stations with about 30-minute running time from the terminal to another.

Central, Admiralty, Tsim Sha Tsui, Mong Kok and Lai King (circled in Figure 5-1) are very busy transfer stations with heavy transfer volumes (over 160,000 daily patronage except Tsim Sha Tsui, whose transfer volume is 42,000). Central, Tsim Sha Tsui, and Mong Kok are among the top ten busiest stations in the whole network, each serving over 120,000 passengers per weekday.

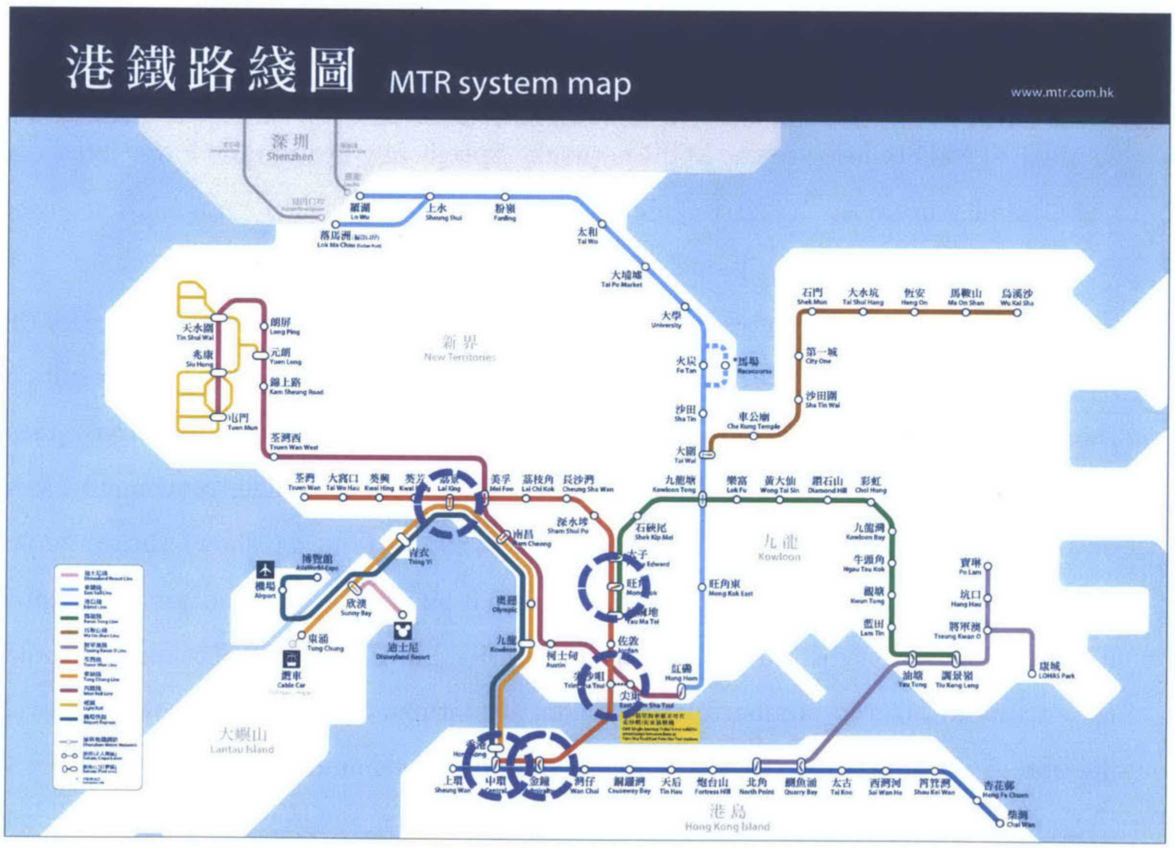


Figure 5-1: Tsuen Wan Line (MTR, 2014)

The travel demand for all the OD pairs within TWL is plotted in Figures 5-2 and 5-3 for both directions.

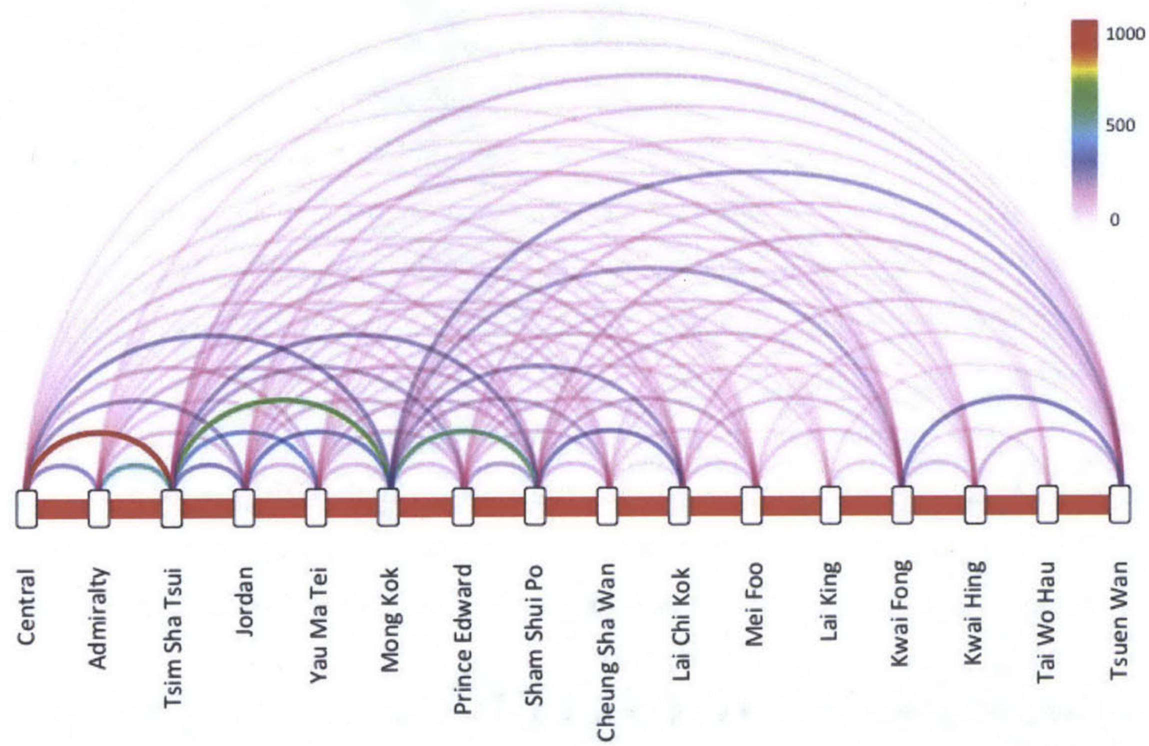


Figure 5-2: Hourly OD Volume from Central to Tsuen Wan

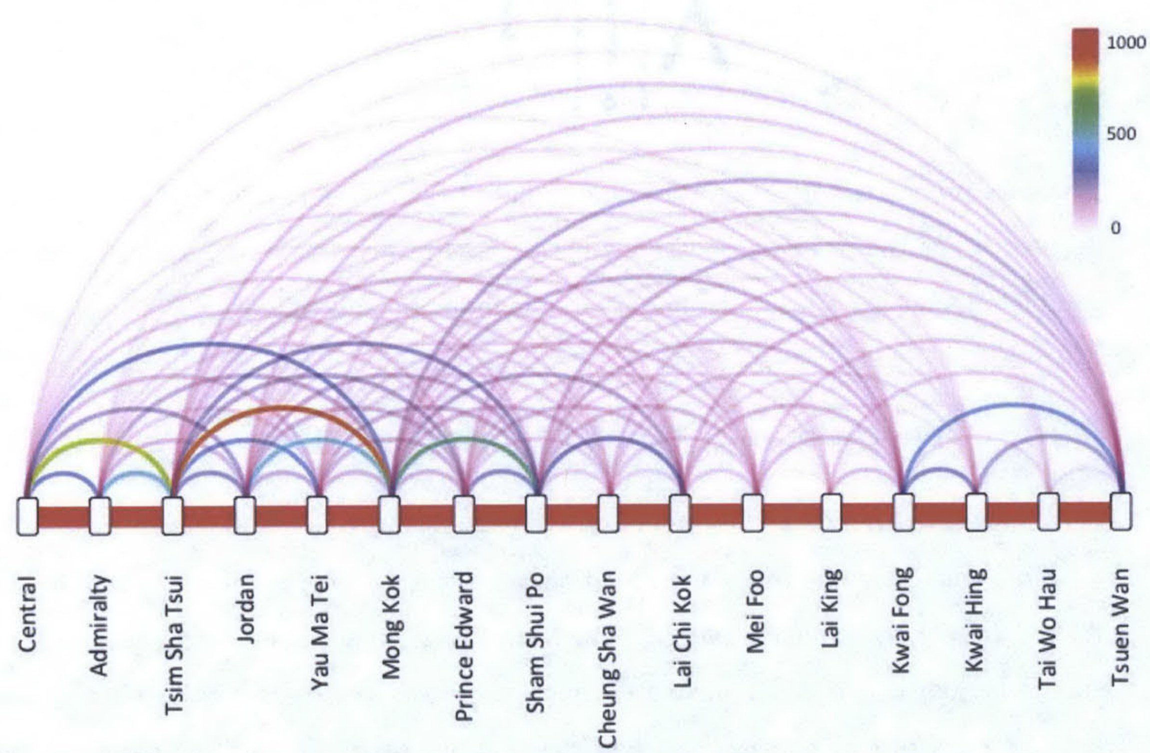


Figure 5-3: Hourly OD Volume from Tsuen Wan to Central

All OD pairs are linked by color coded arcs to represent the hourly volume based on AFC data. The two directions share the same pattern with three heavily used OD pairs: Central to Tsim Sha Tsui, Tsim Sha Tsui to Mong Kok, and Mong Kok to Sham Shui Po. Central serves the CBD area on Hong Kong Island and is the largest financial center in Hong Kong. From Tsim Sha Tsui to Mong Kok, TWL runs along Nathan Road's busiest segment, while Sham Shui Po is a densely populated residential area.

For this application, all the trips within TWL traveling in the direction from Central to Tsuen Wan between 13:00 and 16:00 on 2012/09/07 are extracted from the AFC data. Trips with transfers are not considered. In the afternoon, when the network is not as congested, we assume that the capacity constraints for passengers to board the first train after their arrival at the origin platform are not binding so there are no denied boardings. During the time period of analysis, 43,881 trips are extracted with 50 train itineraries. During the off-peak period, most of the headways range from 3 to 5 minutes.

5.2 Data Preprocessing

The data preprocessing depends on the format of the raw data obtained from transit agencies. For the MTR application, this process involves two steps: generation of complete passenger trips and generation of complete train itineraries.

5.2.1 Generation of Complete Passenger Trips

A sample of MTR's AFC data is presented in Table 5.1.

Since the tap-in and tap-out transactions are separate records, the records from the AFC data with the same *csc_phy_id*, same *train_entry_stn* and consecutive *txn_audit_no* should be joined in order to form a complete trip. The *txn_type_co* indicates whether it is an entry or exit transaction. For each complete trip, an entry transaction and an exit transaction are included.

Data Field	Record	Explanation
csc_phy_id	*********	Octopus Card ID
business_dt	9/7/12	Transaction Date
txn_dt	15:37:03	Transaction Time
txn_type_co	ENT	ENT for entry records and USE for exit records with fare deduction
txn_subtype_co	ADL	Transaction subtype code, such as ADL for adult, CHD for child, SEN for senior citizen, STD for student, DIS for disabled, etc.
train_entry_stn	1	Entry station number
txn_loc	1	Exit station number for an USE record
txn_audit_no	3452	Transaction audit number,all the transactions under this card ID have a unique sequence number
hw_type_co	2	Hardware type code for gate device
mach_no	G06	Machine number of this device
train_direct_ind	2	Direction indicator with value of 1 or 2
txn_value	8.6	HK $ value of this transaction such as fare deducted for this trip
modal_disc_value	0	HK $ value as discounted value
csc_rv_value	8.5	Remaining amount in HK$

Table 5.1: AFC Transaction Record

5.2.2 Generate Complete Train Itineraries

A sample of the ATR data is presented in Table 5.2.

In the ATR data all the departure and arrival events of a train at each station are in separate records. To form a complete train trip from one terminal to another, the records for arrival at the origin terminal are extracted and then the records at subsequent stations (both departures and arrivals) are searched for each station in sequence. Records with the same *line_id*, *i_train_nbr*, *train_nbr*, and the *time_stamp* within 10 minutes of the previous event are linked consecutively. One arrival record is followed by a departure record and the next arrival record and so on.

Data Field	Record	Explanation
time_stamp	2012-07-01 00:00:19	Time Stamp
line_id	1	Line ID
i_train_nbr	18	Train Trip Number
dest_code	H	Destination Code
train_nbr	26	Train Number
id_type	A	ID Type, "A" for Arrival, "D" for Departure
station_id	12	Station Code
platform_id	10	Platform ID with value 10 or 20
act_time	2012-07-01 00:00:42	Actual Time
ach_time	2012-07-01 00:01:26	Scheduled Time
lead_cab	180	Lead Car Number
trail_cab	251	Trail Car Number

Table 5.2: ATR Data Record

5.3 Distribution of Feasible Itineraries

2392 transactions are extracted from the period 13:00 to 16:00 for the busiest OD pair (Central to Tsim Sha Tsui). 113 trips have no feasible train itinerary, most of which are with very short journey times. This problem might be partially due to clock synchronization errors. If the clock of the AFC data is a few seconds off compared to the ATR data, some passengers will be identified as having no feasible itinerary (e.g., if the AFC clock is a few seconds faster than the ATR clock, the recorded tap-out time can be earlier than the arrival time of the passenger's boarding train, and hence no itinerary fulfills the criterion).

For the rest of the passengers, the distribution of the number of feasible itineraries is shown in Figure 5-4:

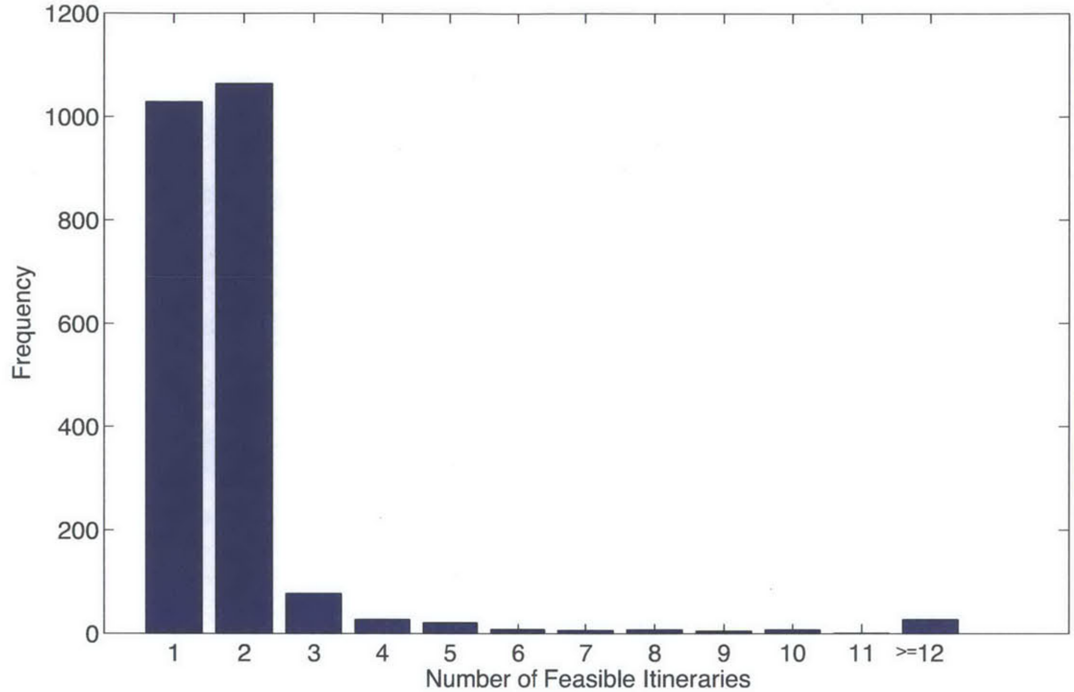


Figure 5-4: Number of Feasible Itineraries

Over 90% of the passengers have either one or two feasible itineraries which indicates that their journey times are relatively short (less itineraries will fit in the time window when passengers are in the system). The reduced crowding allows passengers to arrive at the platform quickly (assuming they engage in no other activities, such as using the ATM in the paid area). A number of passengers have over 12 feasible itineraries. Those are possibly passengers who conducted other activities in the paid area, and can be treated as outliers (Halvorsen and Wood, 2014).

5.4 Parameter Estimation

Figure 5-5 presents the framework for the estimation methodology.

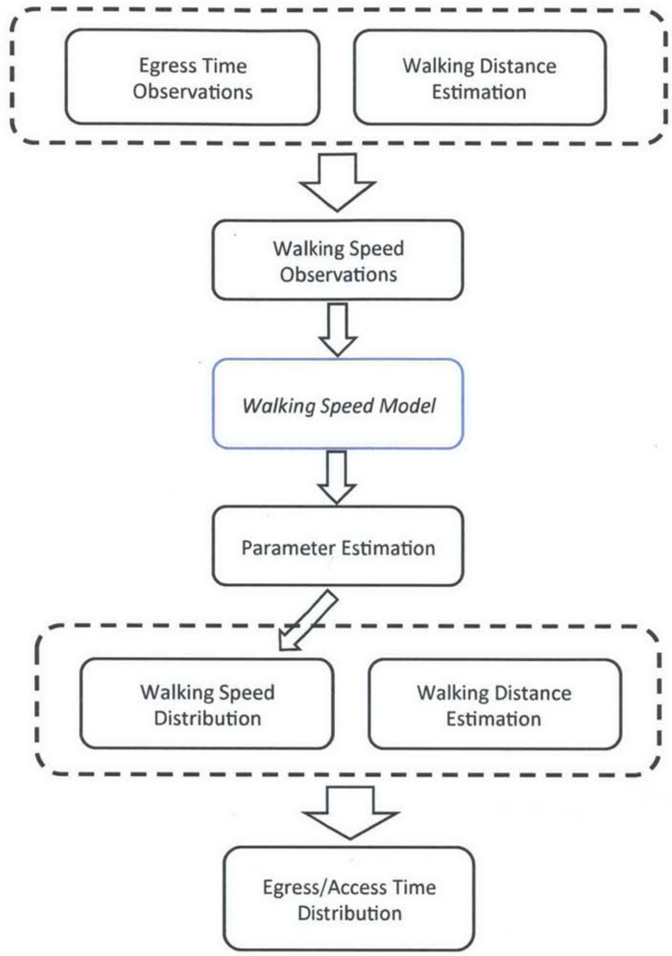


Figure 5-5: Parameter Estimation Methodology

The input data for the estimation include observations of egress times for the subset of passengers with a single feasible itinerary based on Automatic Fare Collection (AFC) and Automatic Train Regulation (ATR) data. For those individuals (with a single feasible train), their egress times are known (based on the arrival times of their trains at the stations and their tap-out times). However, those passengers form a truncated sample and in principle they may represent passengers who are faster than the general population. They caught the first coming train to arrive after they tapped-in and tapped-out before the second train arrived at the destination station. With an estimation of the walking distance for each individual, his/her walking speed can be derived to estimate the key parameters of the walking speed distribution. Based on the walking speed distribution and the estimation of the walking distances, the egress/access time distribution can be derived and input into the PTAM.

The parameters of the walking speed distribution are estimated using the transactions for the busiest OD pair on the Tsuen Wan Line–Central to Tsim Sha Tsui. In this application, a simplified model of the walking speed is estimated for the specific OD pair. The mean and variance of the walking speed distribution are estimated from the available data without specifically considering the effects of different factors such as station characteristics and individual attributes as in Equation 4.1. With more detailed analysis in the future, these parameters can be estimated as a function of these factors.

5.4.1 Egress Time

Among the 2392 transactions from Central to Tsim Sha Tsui during the analyzed time period, 42% of the trips have a single feasible itinerary. For these people, their sole itinerary is certainly the one they took. The egress times can be calculated for them as the differences between the arrival times of the train and the tap-out time. The histogram of these egress times are shown in Figure 5-6.

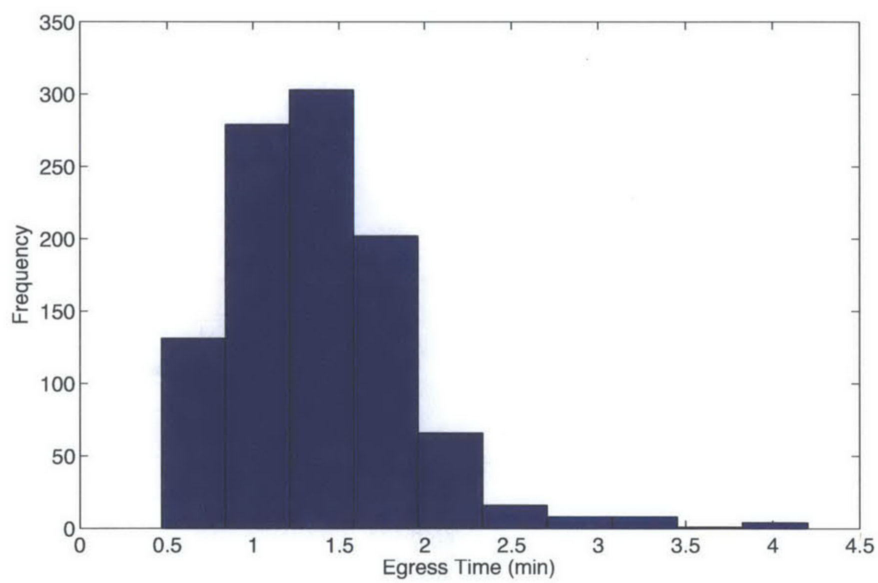


Figure 5-6: Egress Time Distribution for Trips with One Feasible Itinerary

5.4.2 Walking Distance

The location of each group of fare gates (usually 5 to 10 gate-machines are installed close together, forming a "group") can be identified using the station layout, which shows the architecture of the station (see Figures 5-7 and 5-8).

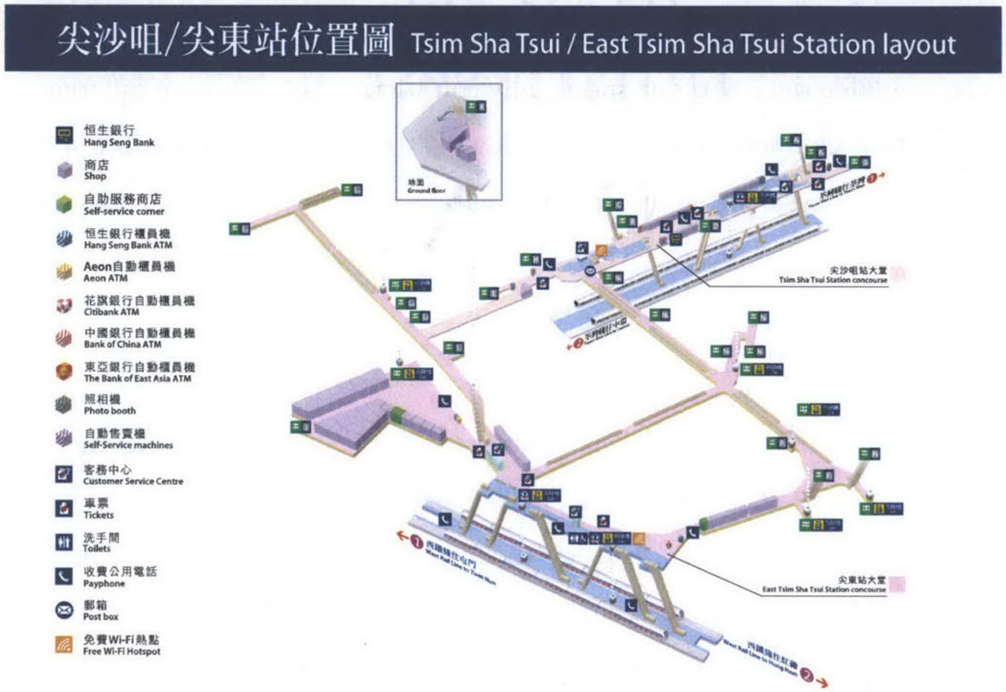


Figure 5-7: Station Layout of Tsim Sha Tsui

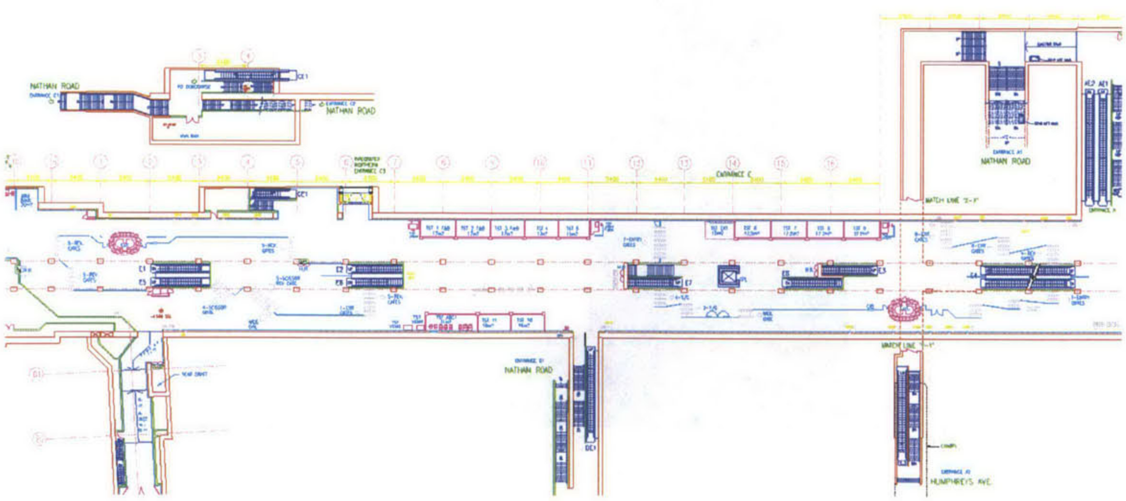


Figure 5-8: Station Design of Tsim Sha Tsui (AutoCAD)

In Figure 5-7, the blue area represents the paid area. Several groups of fare gates are located at the edge of these areas. In Figure 5-8, the actual distances to and from the fare gates can be measured accurately.

Figure 5-9 shows a simplified station layout at both origin and destination stations. The fare gates at the origin station are grouped into four groups A, B, C and D (corresponding to different sections of the platform). More specifically, passengers who tap-in at fare gate group A are more likely to arrive at the head of the platform because it is closest to this fare gate group. Similarly, groups B, C and D have a corresponding section of the platform. A similar grouping is used at the destination station.

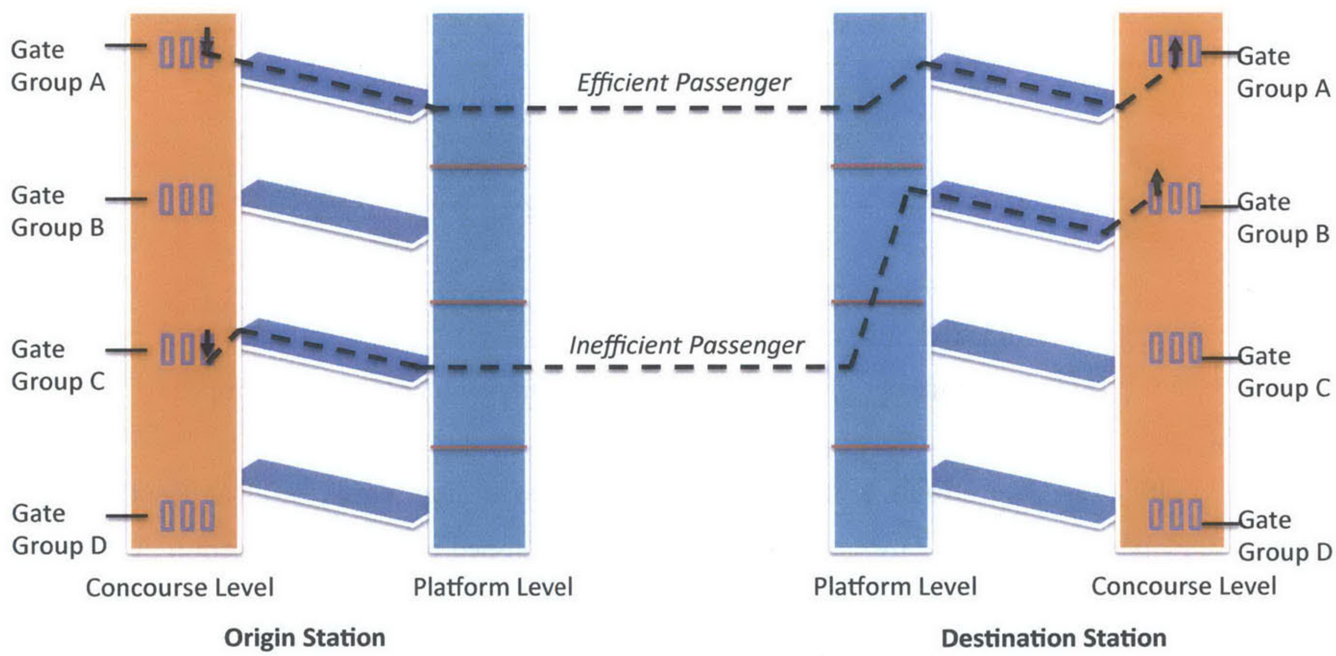


Figure 5-9: Simplified Station Layout

"Efficient" passengers choose the closest section of the platform that minimizes their egress times (i.e., they alight at the destination platform in the section closest to their exit fare gate), for example, taps-in from group A, arrives at the end of the train, alights at the up end of the destination platform and chooses the closest fare gate–group A–to tap-out. For a passenger who taps-in from group A and taps-out at group B, he/she is more likely to walk to the closest section at origin platform first, walk to the mid-up of the platform during the waiting, or walk towards the mid-up of the train during the in-vehicle time, and alight at the closest section of the platform to his/her tap-out gates. "Inefficient" passengers may randomly arrive at a section of the platform from their entry gate group and wait there for the train arrival. At the destination platform, they may have to walk to the other end to reach their tap-out gate (see Figure 5-9 for efficient and inefficient paths).

Table 5.3 shows the fraction of passengers who tap-in/out from different groups of fare gates for the OD pair from Central to Tsim Sha Tsui during the 3 off-peak hours (13:00 to 16:00) with one feasible itinerary. The fare gate groups are associated with the closest section of the platform (see Figure 5-9).

Exit \Entry Group	A	B	C	D
A	30.4%	9.4%	2.0%	4.6%
B	0.7%	0.2%	0.0%	0.1%
C	7.2%	0.9%	0.2%	0.4%
D	38.7%	3.0%	1.4%	0.9%

Table 5.3: Number of Passengers from/to Different Fare Gate Groups

In Table 5.3, group A represents the most heavily used entry gates at Central and passengers from fare gate group A not only tapped-out from fare group A at the destination station but also went to fare gate group D, in which case the walking distances are much longer. Groups A and D are the most popular exit fare gate groups while most passengers are from entry group A.

It appears that although passengers do not choose the gates completely randomly neither do they always use the closest ones. For the population, the distribution of their access and egress distances should be a mix of the two scenarios based on different assumptions about the fraction p of passengers optimizing their walking paths. By assuming that all passengers arrive randomly at the platform ($p = 0$), an upper bound on the speed distribution is obtained, while a lower bound is obtained by assuming that all passengers optimize their walking paths ($p = 1$).

For simplification, instead of assuming the walking distance as a random variable in the following sections, the average walking distances for different groups of passengers are used. This assumption is made for demonstration purposes only.

5.4.3 Estimation Results

To address the truncation problem, passengers are assumed to be drawn from a conditional distribution with a minimum speed determined by the tap-in/out times and the trains' departure/arrival times. The estimation results from the maximum likelihood method are shown in Table 5.4.

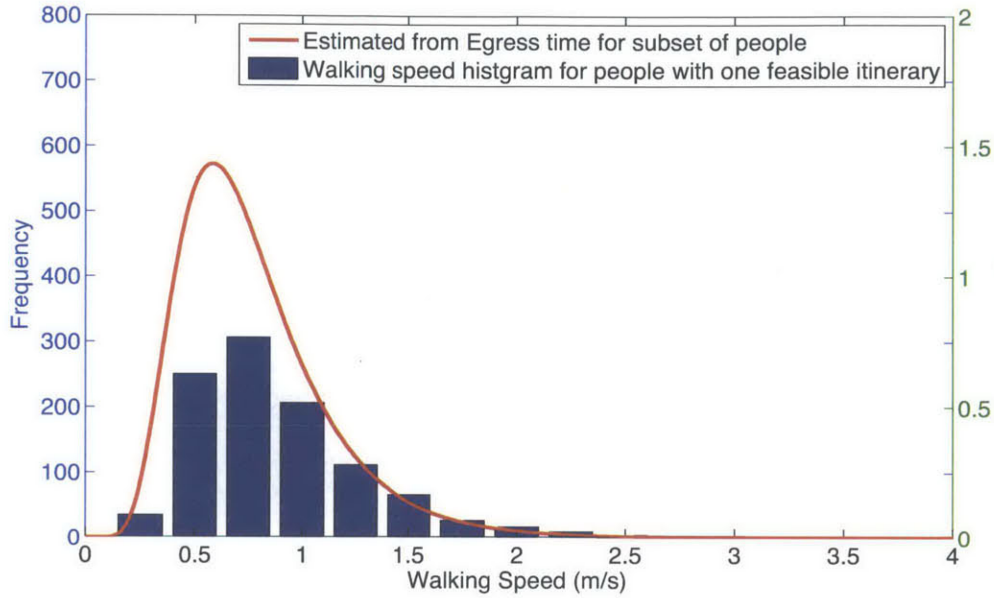
Scenario	μ	σ	**Mean Speed (m/s)**	**Std Speed (m/s)**
Upper Bound	0.1417 (0.0943-0.1891)	0.4883 (0.4604-0.5161)	1.2981	0.674
Lower Bound	-0.3521 (-0.3918- -0.3125)	0.4362 (0.4362-0.4580)	0.7734	0.354

Table 5.4: Estimation of Walking Speed Distribution (95^{th} Confidence Interval in Parentheses)

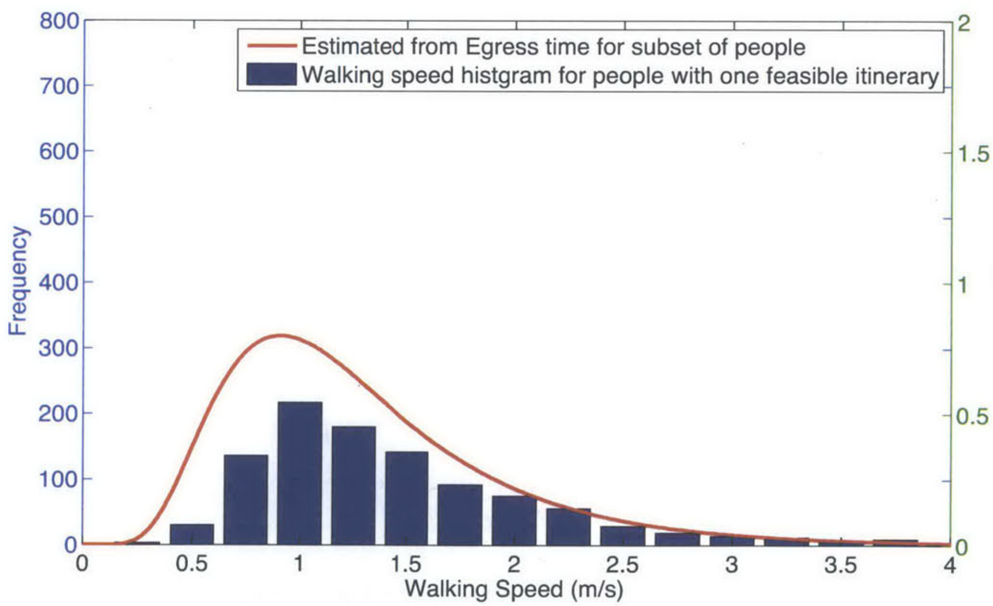
The first row represents the results assuming that passengers will randomly choose the tap-out gates (upper bound). The second row represents the results using the lower bound estimation by assuming that all passengers will optimize their walking paths (lower bound).

μ is the mean and σ the standard deviation of the exponents for the log-normal distribution. The corresponding mean and standard deviation for speeds are shown in the last two columns.

The estimated distributions are plotted in Figure 5-10, where the red line represents the estimated distribution and the blue bar shows the walking speed histogram for the selected sample based on different assumptions about the distances (upper or lower bound).



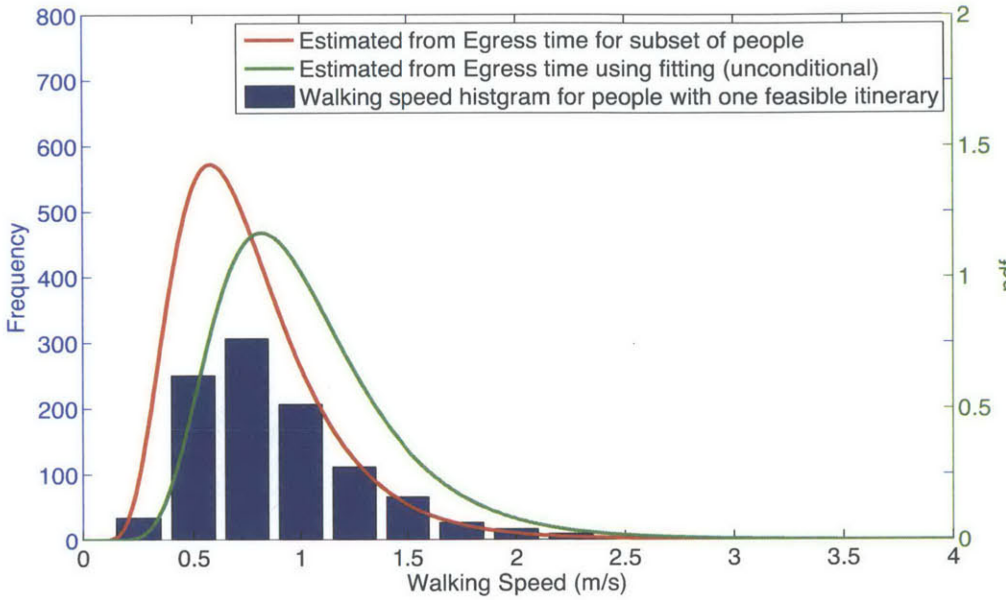
(a) Using Lower Bound on Walking Distance



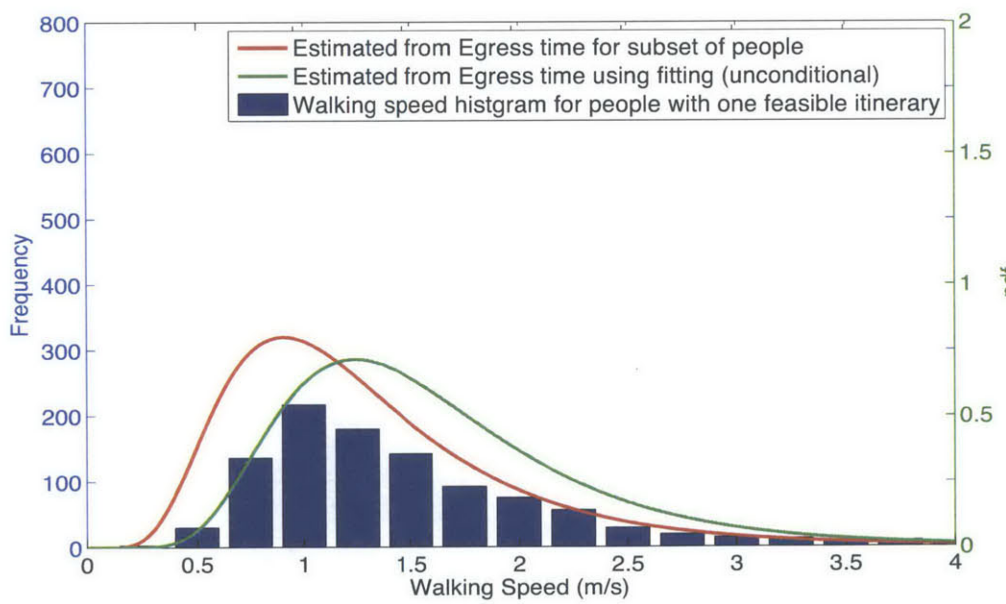
(b) Using Upper Bound on Walking Distance

Figure 5-10: Estimation of Walking Speed Distribution

For comparison purposes, Figure 5-11 shows the estimation results if the passengers with one feasible itinerary are assumed to be representative of the whole population (i.e., the sample is not treated as truncated).



(a) Using Lower Bound on Walking Distance



(b) Using Upper Bound on Walking Distance

Figure 5-11: Estimation of Walking Speed Distribution

The red line shows the walking speed distribution for the full population estimated in the previous section (truncated sample), and the green line shows the one for the subset of passengers with a single feasible itinerary. In both scenarios, with upper bound or lower bound on the walking distance estimation, the subset of people tends to walk faster than the whole population. The results clearly indicate the bias that can be introduced if the sample is not treated properly in the estimation. With the lower bound on the walking distance estimation, the average walking speed for the subset of passengers is 1.02 m/s, which is 32.5% faster than the average for the whole population. With the upper bound on the walking distance estimation, the average speed for the subset of passengers is 1.60 m/s, which is 23.5% faster than the true average of the whole population. As we expect, passengers with a single feasible itinerary are not representative of the whole population if using simple fitting methods to estimate the walking speed distribution.

The results from the estimation are also compared to walking speeds estimated from the manual speed surveys at MTR. The data was collected by surveyors following passengers and recording their walking speeds on different segments of their paths: walkways, stairs, ramps, etc. Tables 5.5 and 5.6 show the MTR walking speed survey data during the morning and evening time periods. Six groups of passengers were examined. The results indicate that male passengers tend to walk faster than females, while elderly, children and passengers with luggage walk slower than the average.

Passenger group	**Sample size**	**Minimum speed [m/s]**	**Maximum speed [m/s]**	**Average speed [m/s]**	**Std [m/s]**
Male	115	0.48	2.11	1.26	0.27
Female	129	0.65	2.04	1.18	0.24
Elderly	30	0.48	1.61	1.07	0.27
Children	22	0.63	1.78	1.04	0.25
Disabled	1	-	-	1.49	-
Passengers with luggage	27	0.65	1.37	1.10	0.17
Average	0.58	1.78	1.19	1.19	-

Table 5.5: Walking Speed Survey Results (Morning Period)

Passenger group	Sample size	Minimum speed [m/s]	Maximum speed [m/s]	Average speed [m/s]	Std [m/s]
Male	65	0.62	1.63	1.10	0.21
Female	79	0.4	1.50	1.03	0.19
Elderly	8	0.73	1.27	1.01	0.18
Children	9	0.40	1.02	0.88	0.19
Disabled	0	-	-	-	-
Passengers with luggage	20	0.67	1.34	1.00	0.21
Average		0.56	1.35	1.00	0.20

Table 5.6: Walking Speed Survey Results (Evening Period)

Table 5.7 compares the average speeds estimated in the previous section to the survey results.

	Mean (m/s)	Std (m/s)
Survey (Morning)	1.19	-
Survey (Evening)	1.00	0.20
Upper Bound	1.30	0.67
Lower Bound	0.77	0.35

Table 5.7: Comparison of the Survey Results and Estimation

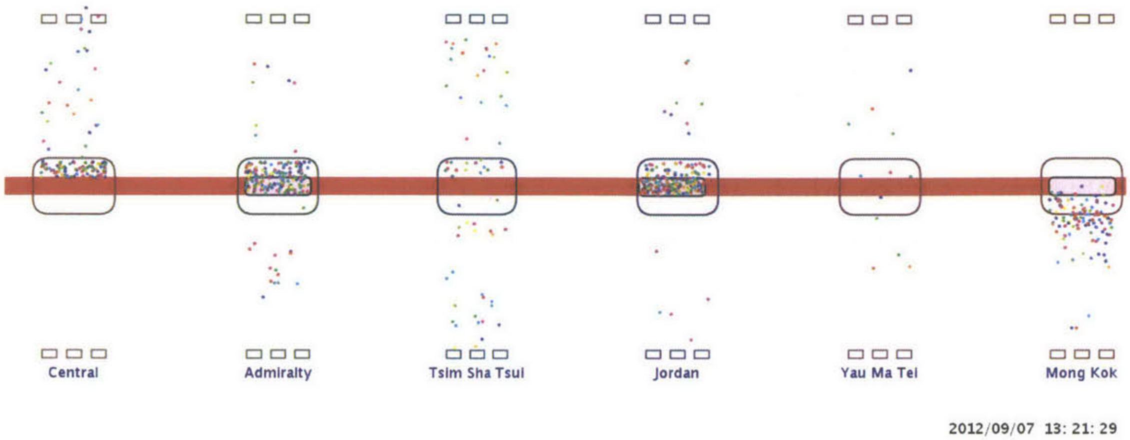
Using the upper bound on the distance estimation where the speed can be overestimated, the walking speed estimation is slightly faster than the average speed in the survey data . However, the walking speed based on the lower bound tends to underestimate the walking speed since passengers' walking distances are underestimated. However, the methodology provided in this research gives a reasonable range of the walking speed solely based on automated data and can be further improved with more detailed analysis. With appropriate modification, maximum likelihood methods can be used to estimate the value of p as well as the impact of the different factors as discussed in section 4.1.

In the PTAM, the estimation of the walking speed based on the survey data with mean and standard deviation as 1.0 m/s and 0.2 m/s is used. Probabilities for each individual to have boarded different trains are estimated given the knowledge of his/her feasible itinerary set and tap-in/out times. A series of applications are presented in the following sections.

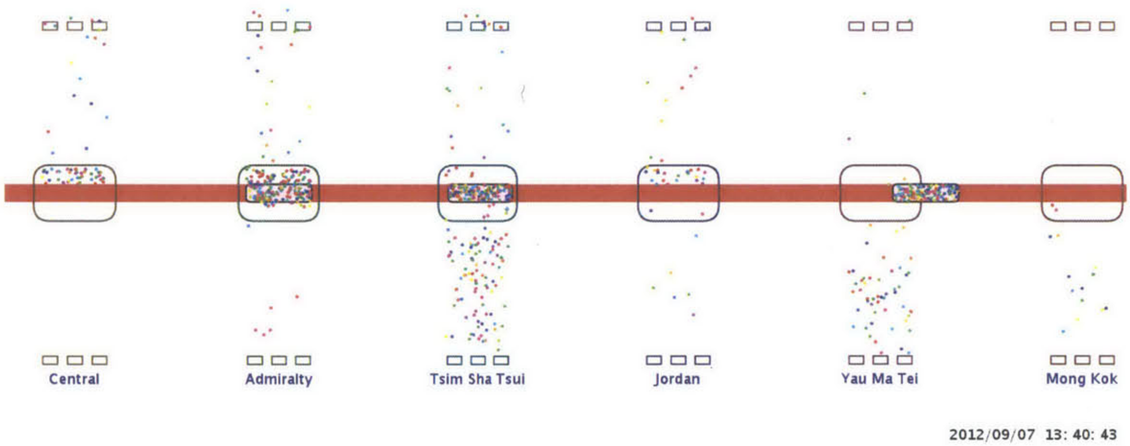
5.5 Passenger Movements

Based on the output of the assignment model and given inferences about the train boarded for each individual trip, we can capture the movements of passengers in the network in great detail. The passengers' locations in the network can be linked to train boarded. An animated simulation has been implemented to show the individual passenger movements over a 3 hour period. The animation is implemented in Java. The inputs to the animation include: the tap-in and tap-out times of the passengers, the estimated probability of boarding each train in their feasible set, and the departure and arrival times of trains at stations. Figure 5-12 illustrates an instance of the animation. At the origin stations, the animation assumes passengers' walking speeds is 1.0 m/s to visualize their movement. At the destination stations, the walking speed is calculated based on the egress time using the train arrival times at destination stations and their tap-out times.

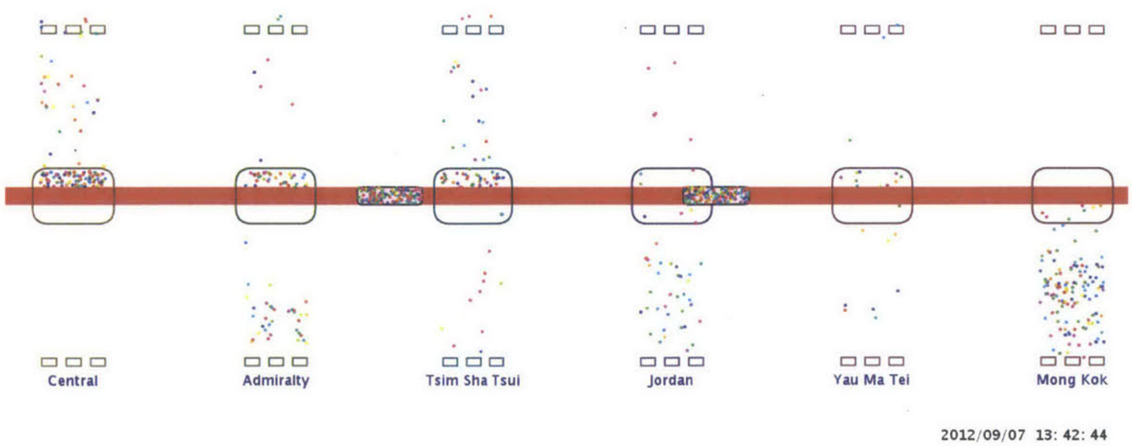
Figure 5-12a is based on an animation with data for 2012/09/07 at 13:21:29 on the Tsuen Wan Line, when a train just arrived at Admiralty. Another train was approaching Jordan and a third train was at Mong Kok with many passengers alighting. The dots represent passengers and the dark area at each station the paid area. The assumption is that after passengers tap-in through the fare gates, they walk towards the platform and wait for the next train. Since Central and Admiralty stations are both busy stations, crowding at platforms was much more severe than at the other stations (see Figures 5-12). The line was heavily used on the segments from Admiralty to Yau Ma Tei and many people alighted at Mong Kok (see Figure 5-12c).



(a) Screen Shot 1



(b) Screen Shot 2



(c) Screen Shot 3

Figure 5-12: Passenger Movement in TWL

On the other hand, many outliers can be observed especially at the Mong Kok station. They exited very slowly from the platform to the tap-out gates. Those may be the passengers who conducted other activities inside the station, such as commercial activities, which are common in Hong Kong.

The animation illustrates the capability of the model to simulate the movements of passengers and trains at the individual level and provides a comprehensive playback of the operations of the system. However, many assumptions are made to visualize the movements which should be relaxed in future research.

5.6 Trainload

At the aggregate level, the trainload is estimated based on the assignment model's output and plotted in a time-space diagram representing the train trajectories (see Figure 5-13).

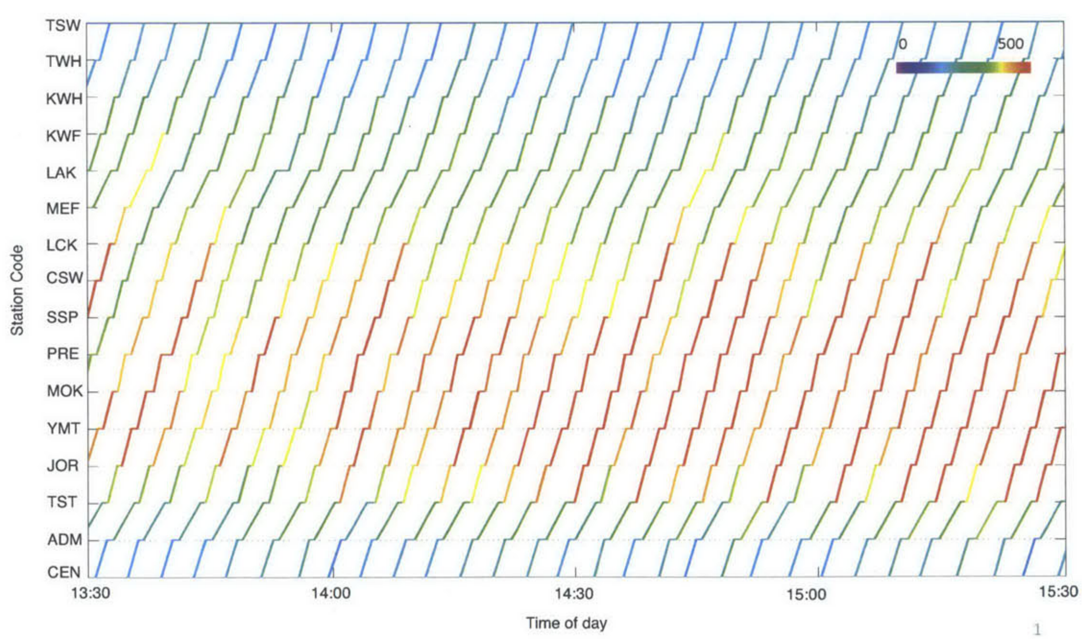


Figure 5-13: Time-Space Diagram for Trainload Estiamtion

The x-axis represents the time of day and the y-axis represents the 16 TWL stations from Central to Tsuen Wan. Each line represents one train itinerary based on the ATR data. The diagonal segments correspond to the train movements between consecutive stations and the horizontal segments the dwell times at stations. The headways were relatively evenly distributed within this period with the exception of the headway for the train that departed from Central at 12:23 PM, which was longer. The color of the line represents the estimated number of passengers on board. Most of the trains were most heavily loaded between Tsim Sha Tsui and Prince Edward stations. With this "heat-map", it is very easy to identify hot-spots and bottlenecks in the network both spatially and temporally.

Figure 5-14 shows the trainload estimation for Trains 8 to 42 which were running between 13:00 and 16:00.

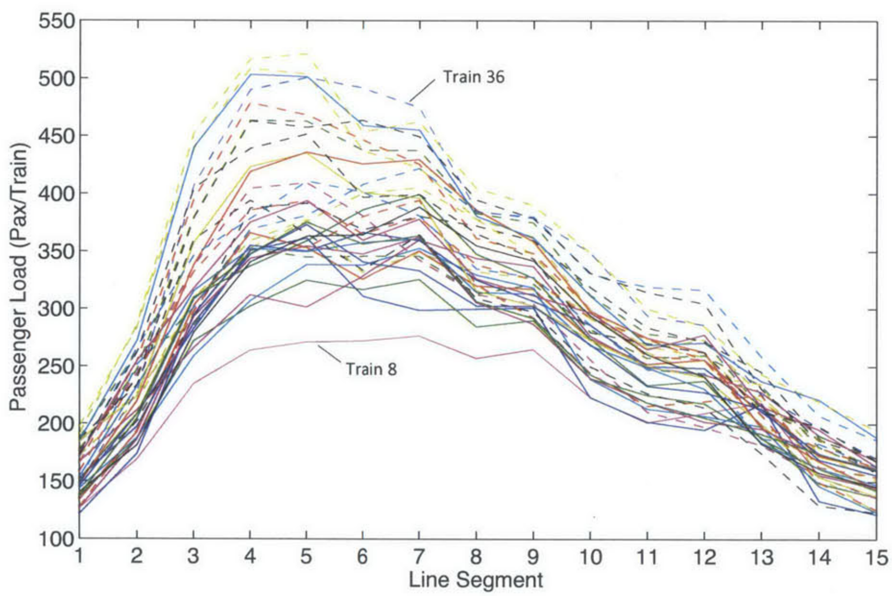


Figure 5-14: Trainload for Trains 8 to 42

The most used segment was between station 3 to station 7, which is from Tsim Sha Tsui to Prince Edward.

Figure 5-15 illustrates the headways at Admiralty, the second station on the TWL. The x-axis represents the train number, and headways longer than 4.2 min are marked in red.

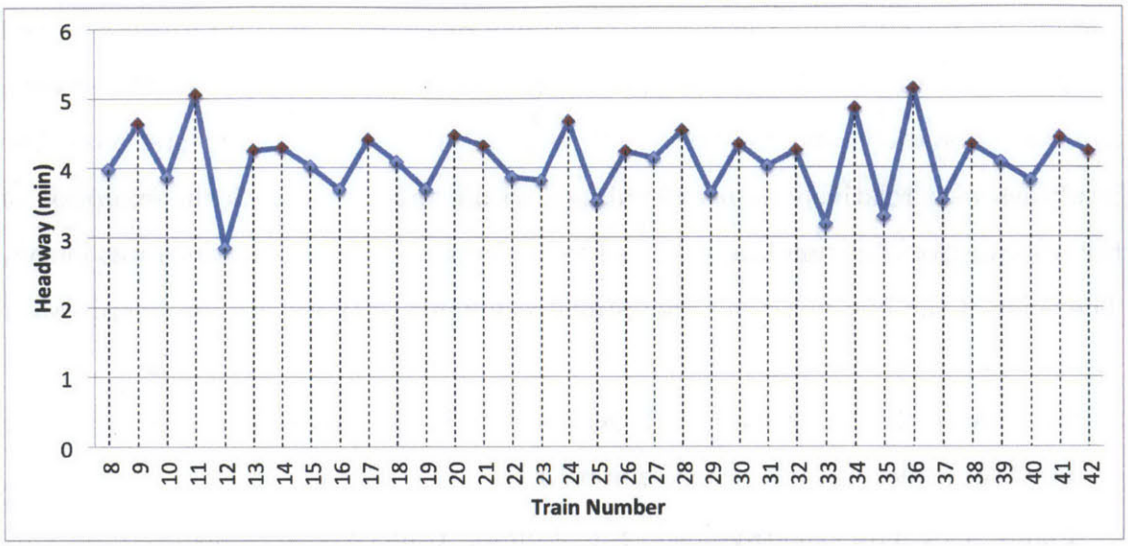


Figure 5-15: Headways at Admiralty

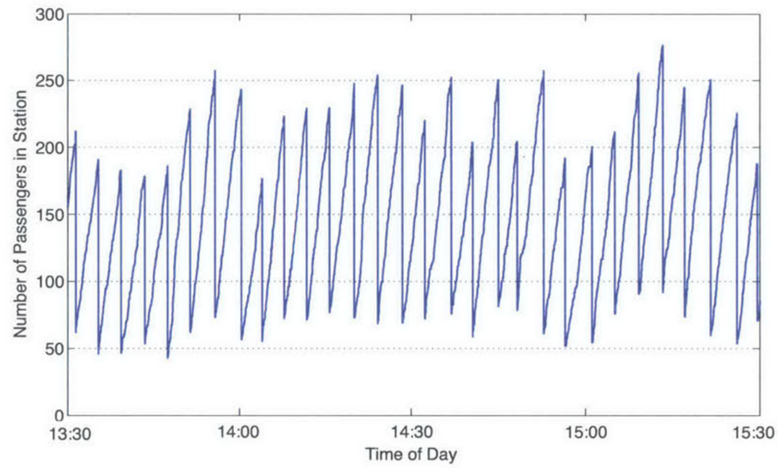
Combining Figures 5-14 and 5-15, we can see that the trains with short headways were usually less crowded. The trains with more than 4.2-min headway are shown with dash line in Figure 5-14, most of which were more heavily used. In Figure 5-14, trains marked in continuous lines were the ones with shorter headways and were less crowded. Train 12, especially, with a 2.8-min headway at Admiralty experienced the least crowding. Note that the heaviest load during this time period was under 550 pax/train, which was far below the train capacity. The service standard of MTR indicates that the full-load at peak hour is 2000 pax/train. However, this estimation is based on trips without transfers hence the estimated load here is the lower bound of the actual load. The capacity constraints are relaxed during the off-peak. We believe that in this case, even accounting for transfer trips, the capacity constraints were not binding.

With relative stable passenger arrival rates during this time period, the trainload is very sensitive to the headway. Therefore, the service reliability can be evaluated from the crowding on trains to measure the performance of the system from the passenger's point of view.

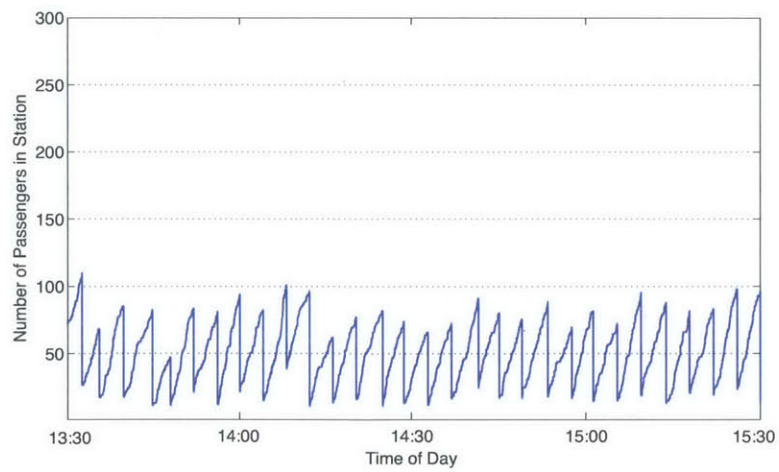
However, the load in this section is derived solely based on passengers without transfers, hence the estimation can only provide a lower bound on the actual trainload. More work is needed to account for trips with transfers to estimate the actual trainload.

5.7 Station Crowding

The PTAM output can be aggregated at different levels. One of them is the crowding at stations. By accounting for the number of passengers that tap-in and those who were able to board a train, the number of passengers at the stations can be estimated. Two stations are examined–Central and Prince Edward (see Figure 5-16).



(a) Central



(b) Prince Edward

Figure 5-16: Crowding at Stations

The saw-tooth line shows the estimated number of passengers inside the station as a function of the time of day. Since Central is a large station, the numbers are usually much higher than at Prince Edward, with more passengers on the stairs, platforms, ramps, etc.. With more and more passengers tapping-in, the number kept increasing during consecutive train departures. After a train departed, the number dropped with a large group of people boarding this train and leaving the station. However, the number is not necessarily zero after the trains' departures since there were passengers inside the station who just tapped-in or were on the stairs/walkways.

The crowding information generated at this level can be very useful, both for passengers to plan their journey, and for operating managers to facilitate the management of crowds at stations. Providing crowding information in real-time has been another important aspect which agencies are interested in exploring. It is one of the important ultimate goals for continuation of this research.

5.8 Summary

This chapter estimated the key parameters for the PTAM and applied the model to the Tsuen Wan Line. The mean walking speed for the population ranges from 0.77 m/s to 1.30 m/s based on the lower/upper bound of the walking distance estimation, compared to the survey results of 1.00 m/s in the afternoon and 1.19 m/s in the morning period. The results confirmed that the subset of passengers with a single itinerary is not representative for the whole population and they are 23.5% to 32.5% faster than the full population, and the proposed method correctly deals with this issue.

Passenger movements were simulated based on the results of the PTAM. The trainload can also be inferred. However, to estimate the actual trainload, trips with transfers should be included since transfer volumes at certain stations are large. The crowding at stations was derived based on the passenger movements by counting the number of passengers inside the stations who had not yet boarded trains.

For peak hour applications, the capacity constraints should be appropriately incorporated into the model to account for denied boardings, as well as transferring passengers. Future work is required in this direction.

Chapter 6

Conclusion

The methodology presented in this research aims developing a Passenger-to-Train Assignment Model (PTAM) to identify the boarding train of each passenger. Such a model provides valuable information at both the disaggregate and aggregate levels. The methodology uses Automatic Fare Collection (AFC) and Automatic Train Regulation (ATR) data. A series of applications based on results from the PTAM are developed to examine the capacity utilization of the MTR system.

Section 6.1 summarizes the research findings, discusses the limitations of the methodology, and outlines the specific contributions of this research. Section 6.2 suggests future directions.

6.1 Summary and Conclusions

6.1.1 Passenger-to-Train Assignment Model

The Passenger-to-Train Assignment Model (PTAM) serves as the main focus of this research. To better address the uncertainty of passenger's behavior in the underground system, a method is developed to estimate the probabilities of passengers to board different trains based on the AFC and ATR data, instead of deterministically assigning a passenger to a single train.

Based on the knowledge of the feasible itineraries (the set of trains that a passenger could possibly have boarded), the distribution of walking speed is input to the model to estimate the probability of having used each itinerary. The trainload model estimates the expected load for every train in the archived data, based on the probabilities.

The application of the model to the MTR network focuses on the situation without capacity constraints and trips without transfers. Over 40,000 trips on Tsuen Wan Line and 50 train itineraries from the ATR data are extracted during 3 hours in the off-peak period. Based on a conservative assumption (passengers' minimum access/egress time is zero), the number of feasible itineraries for each individual is calculated. For the trips between Central to Tsimg Sha Tsui, about 42% of passengers have one feasible itinerary and over 90% have less than 3 feasible itineraries. This might partially due to less congestion during the off-peak period and passengers traveled fast in the underground system. Many outliers can also be observed with over 12 feasible itineraries. Those are possibly passengers who conducted other activities in the paid area, which is common in Hong Kong.

An animated simulation has been implemented to show the individual passenger movements over the same period, which provides a comprehensive playback of the operations of the system. It can be easily observed from the animation that the crowding at platforms at Central and Admiralty stations was much more severe than other stations and the line segments from Admiralty to Yau Ma Tei were heavily used. On the other hand, many outliers can be observed especially at Mong Kok station who exited very slowly.

The trainload for individual vehicles are estimated using the trainload model. A "heat-map" is generated to represent the train trajectories and the corresponding loads for vehicles. It has been noted that the individual trainload is very sensitive to the headway. Therefore, the service reliability can be evaluated from the crowding on trains to measure the performance of the system from the passenger's point of view. The crowding at stations can also be assessed. Two examples are shown at Central and Prince Edward stations. The number of passengers follows a saw-tooth line where the number dropped after the departure of a train. The crowding information generated at these levels can be very useful both for passengers planning their journey, and for operating managers to facilitate the crowds management at stations.

In this application, we assumed that passengers are not denied boarding and the capacity constraints are not binding. This assumption is typically valid during the off-peak (the time period analyzed). But during peak hours, when the demand is very high and trains are crowded, passengers can be left behind for several trains. In that case, the probability of boarding each train should also be influenced by the load of the incoming train, which leads to a more general model as described in Chapter 3.

The transfer demand is also not considered in the MTR application, which results in underestimation of the trainload and the crowding levels. Research into route and transfer station choice int he MTR network will facilitate the treatment of transferring path. A survey was conducted to collect the required information and a route choice model is being developed. The estimated model can be used as input to the PTAM.

6.1.2 Parameter Estimation

In Chapter 4, a walking speed estimation method is developed based on AFC and ATR data. The egress time for the subset of passengers with only a single feasible itinerary was used for the estimation.

A general walking speed model is proposed to explicitly consider different factors that affect passengers' walking speeds at stations (including the individual characteristics, station configuration, the degree of crowding, etc). The access and egress speeds can be formulated using a joint distribution where the correlation between them can be appropriately captured.

Since there is heterogeneity among passengers in terms of their familiarity with the system, the walking distances at stations may vary from person to person. To capture this behavior, an additional parameter is introduced representing the proportion of passengers who "optimize" their walking paths at stations.

Instead of using manual survey data, indirect observations from the automated data based on the subset of passengers with one feasible itinerary are used. The estimation is properly formulated as a maximum likelihood problem that takes into account the fact that the sample is truncated. Synthetic data is generated to test this methodology. The results show that the overall estimation performance is very good. Since the automated data accounts for a very large sample size, this method is very promising to avoid manual data collection.

In the MTR application, a simplified walking speed model was estimated that did not consider the effects of other factors (such as age, gender, or station configurations). The observations of walking speeds for the subset of passengers with one feasible itinerary form a truncated sample with average walking speed 23.5% to 32.5% faster than the overall population. To derive the access/egress time distribution, the walking distance is estimated using the fare gate information recorded in the AFC data. Upper and lower bounds on the walking distance are estimated respectively based on whether (or not) passengers optimize their walking paths. By assuming different walking distances for the whole population (upper or lower bound), two distributions of the walking speeds are estimated respectively. Compared with the survey data, one of the estimated distributions shows faster walking speeds and the other one shows slower estimation. The survey result is in the between.

6.1.3 Methodological Contributions

The methodology presented in this thesis has introduced three innovations compared to previous research.

The PTAM captures passenger behavior at the individual level and estimates passenger movements both at stations and on trains, which provides all the information needed (journey time components, passenger location inference, etc.). Detailed analysis of passenger behavior at stations is conducted on the walking speed and distance for each individual.

Compared with traditional passenger assignment models, the train loads can be inferred for every recorded itinerary. PTAM facilitates the development of more accurate and informative performance metrics, for example the number of passengers left behind. It also presents an improvement over current MTR practice of using passenger flow estimates in 15 minute intervals. Application across lines at this level of resolution may also provide an overall assessment of opportunities to improve capacity utilization, for example through better demand management strategies.

Third, the model negates the need for time-consuming and expensive data collection efforts (for example to collect data about passenger's walking speed). The parameters input to the model are estimated based on the automated data, and the method has proved to provide good estimates of the speed distribution parameters for the whole population.

6.2 Future Work

Much more work is needed to extend the research to deal with congested networks and transfers.

6.2.1 Methodological Enhancements

A general Passenger-to-Train Assignment Model (PTAM) that takes into account capacity constraints is presented in Chapter 3. An iterative process is built into the model to update the feasible itinerary set and the corresponding probabilities for a given passenger based on the available capacity on the train. With capacity constraints, the loading order of the passengers is critical because of denied boardings. Unlike passengers with a single itinerary, the remaining passengers can be loaded based on different service rules, such as "first-tap-in-first-board". These aspects of the model have not yet been tested and need further refinement and validation.

A big challenge is the introduction of transfers in the model. To consider the transfer demand, a route choice model should be integrated with PTAM. The probability of choosing an itinerary is the product of the probability of choosing the corresponding route and the conditional probability of choosing this itinerary given the specific route has been chosen. Each itinerary may consist of multiple trains and the probability of being selected should be a function of the access, egress, transfer times and train running times. More research is needed to develop a comprehensive approach to accommodate the transfer demand.

The definition of the set of feasible itineraries sets can be improved based on further study of passenger behavior at stations. In this thesis, the conservative assumption of zero access/egress time was used to retain all feasible itineraries. However, given that at certain large stations, it is impossible to arrive at the platform within 30 seconds from tap-in, a larger value of the minimum access/egress time can be used to eliminate itineraries with extremely short access/egress times and further improve the assignment accuracy.

For the application presented in this thesis, a simplified walking speed model is used with the mean and variance for the distribution estimated directly. Using automated data, more detailed analysis can be conducted to assess the effects of different factors, such as the individual characteristics, station characteristics, etc. The underlying walking distances can also be modeled more accurately based on assumptions about passenger behavior on the platform and their knowledge of the system. With more detailed analysis, these parameters relating to different factors can be estimated and tested for their significance.

The real-time application of this research is another challenging future research direction. With data becoming available in real-time or near real-time, real-time applications are feasible. A real-time PTAM would require prediction of OD flows in the system. The PTAM can then proceed to estimate the probabilities of passenger using different itineraries. However, since there is no tap-out times information, the set of feasible itineraries set is not well defined.

6.2.2 Model Validation

The model developed in this thesis can be verified with additional data from MTR. At the rail car level, voltage readings from the air pressure sensors installed on 10-15% of MTR trains can be used to estimate the number of passengers on the car. For both model validation and model enhancement, if this information is available on most cars and reliable, voltage readings have data has the potential to support estimates of car loads directly. The data can also be used to validate the PTAM estimates of trainload. However, this data has serious limitations. The data can be fairly noisy and hence the inference of the total car weight may be erroneous; in addition, the inference of the number of passengers from the total load weight depends on assumptions regarding the distribution of individual passenger weight as well as carry-on luggage. Therefore, the translation of the voltage readings to passenger counts will require careful calibration of key parameters. A study by Frumin (2010), with data from TfLs London Overground system, provides initial insight into the issues involved.

6.2.3 Application

A number of other applications can be developed based on the PTAM's output, for example:

- Crowding at different levels, for example on the platform instead station-level crowding.
- Journey time decomposition (access, egress, waiting and in-vehicle times), which can be used to assess the service reliability from the customers' point of view more accurately.
- Estimation of the number of denied boardings.
- Advanced customer information, such as expected crowding, route choice recommendations, etc.

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