TRAIN DWELL TIME EVALUATION
AT HIGH PASSENGER VOLUME STATIONS

A DISSERTATION SUBMITTED TO UNIVERSITY COLLEGE LONDON
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

NATCHAYA TORTAINCHAI

CENTRE FOR TRANSPORT STUDIES, UNIVERSITY COLLEGE LONDON

October 2022
DECLARATION STATEMENT

I, Natchaya Tortainchai, confirm that the work presented in my thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.
PREFACE

Before moving on to the academic report, I would like to share my thoughts on this significant chapter in my life. People say the main product of a PhD is not the output of your work but "you". I began my PhD in 2017 with the confidence that I was fully equipped with research and academic skills. From the beginning of my PhD, I was excited to learn everything. It seemed as though we had dived into a vast ocean and were now exploring something intriguing and brand new. After some time, I realised how vast the ocean of knowledge was and how little we have learned compared to it. What I attempted to do was draw a map of the ocean and learn about what was relevant to my topic. During the first year of my PhD, I was fortunate enough to gain access to Transport for London's office. My supervisor and everyone in the office encouraged me to learn everything I wanted.

After conducting adequate research and getting to know the research challenge, I developed a model at the start of my PhD's second year. I wrote and submitted the paper and wondered if that was all that was needed for a PhD. Finally, the paper was turned down. I never expected to be rejected. At that time, I thought research was simply asking research questions and attempting to answer them using different methodologies and scenarios.

My supervisor mentioned "New Contribution" at the start of the PhD, and I questioned and discussed with him in each of our meetings about what "New" means and how "New" should be defined. Nonetheless, I continued my studies with this thought. I was expected to do an upgrade viva with the research problem and the model I constructed during my second year. In reality, substantial study has been done on the model. I am unable to explain how my model differs from existing models or what has been improved. Many contributions have been made to the advanced level of the models.
Fortunately, the research problem continues to motivate me, and I want to make the most of it. Given the available data and resources, I chose to approach the challenge in a different manner. Then I was overwhelmed by a variety of ideas, tools, and theories. My research focus was altered from what it was at the start. This was possibly the first moment I began to understand how PhDs differed and realised the saying "PhD is a series of disappointments" and this is how we learned from it. I could say that my confidence was at the bottom of the Dunning-Kruger curve at the time. At the very least, I am pleased that I am observing the actual process by which PhD students learn.

Then the exploration of the large London Underground database began. Many different viewpoints on the data were expressed. I began to enjoy data analysis, but trouble arises when there is an abundance of data. The hardest element is not the approach to data analysis, but the skill of selecting data and scoping the analysis. My supervisor often tells me to scope my study, despite the fact that I seem to include everything in my analysis since I believe everything is equally important. It is true that numerous factors are involved in research, that many tools or theories are accessible for usage, and that the research could go in any direction. Then I realised how crucial it is to justify your study when you can't include everything. We need to have our own point of view, which will subsequently become our identity. It reaches a point where there is no longer any right or wrong. It is determined by our values and our areas of expertise. Now I understand why the PhD is named a Doctor of Philosophy; it is all about what we value and what we want to contribute to the area.
ACKNOWLEDGEMENT

The very first person I would like to say thanks to is my supervisor, Dr Taku Fujiyama, who kindly gave me all the support I needed throughout my whole PhD journey. I cannot express my gratitude for his efforts in a few pages, but I would say he completes my PhD journey in every way. He is open-minded, respectful and kind, but he will never compromise on high standards of work. He pushed me to do the very best version of my PhD. He also provided me with opportunities and taught me about the academic career path. I would say he is a role model supervisor who I would love to emulate with my students. I would also like to thank Prof. Benjamin Heydecker, my second supervisor, who gave me ideas and suggestions for my dissertation. His thoughtful suggestions, together with Dr Yihui Wang’s suggestions during the upgrade viva were really helpful for my final thesis. I must mention Dr Bhatti Manni, who gave very useful academic writing skills through her classes, emails, and personal sessions. In addition, I also appreciate Dr Kamalasudhan Achuthan and Dr Marcus Enoch's insightful comments during the viva, which helped polish this thesis.

Secondly, without the case study, this piece of research would not exist or be as useful, and I would not have learned as much. Transport for London (TfL), an organisation with high standards and skilled personnel, kindly provided me with an unforgettable memory in Palestra House. I would like to express my gratitude to David Winslett, Howard Wong, Sandra Weddell, Hayley Oberlander, Richard Smith, and the Transport Service Modelling team for welcoming me at Palestra House and for their assistance in gathering all of the information and suggestions. I would like to thank Zak Khan, Victoria Station Area Manager, who kindly offered me a tour of the whole station.

Anupong Wannakrairot and Dr Chutipong Paraphantakul are two people I would never forget to mention in my acknowledgement. They are the two people who accompanied me from the first to the final year of my PhD. Anupong is the only person who can explain every academic question I have in simple terms. He could understand what I was questioning within a few minutes, while Chutipong had guided me on the PhD path. I followed his steps on the PhD journey. They ensured I was always prepared for whatever came my way on the journey. I greatly appreciate Brenda McQuade's careful proofreading of the papers and thesis.
I would like to thank Dr Jiping Fang, Nattanon Luengboriboon, Dr Yan Cheng, Joe Wright, and other Railway Research Group colleagues. I was very lucky to have all of them during the journey, ensuring that I always had somebody to talk and share the experiences with. In addition, I also had flatmates who shared the rent, food, parties, and many enjoyable moments. Thanks to Tou, Toh, Jee, Natt, Boom, So, Pae, Jom and Friend. During my life here, I can say that I really felt at home as I always have a home in High Wycombe. Milan and Natchapanvira Ongpaiboon are my family in the UK. Any life problems I would encounter would pass smoothly with this couple’s support.

There are many people who always believed in me before I believed in myself. Firstly, I would like to thank my husband, Kittikhun Tortainchai M.D. who sacrificed the most. He never hesitated to encourage me to fulfil my dreams. He has been waiting for me for 5 years, and now I am very ready to begin a new journey with him as a warm family. Secondly, there are my family; Chen Yu Heng, Larphum, Yindee, Surachart, Natnicha, Kittisak, BB Tohyawath, Santisuk, Passapon, Supee, Natwipha, Cholhawan, Likhit, Chusit, who are always proud of everything I do. I could not forget Pawitsarat Tiyapairat and Nillaya Poolpatarachewin as friends for life. Both always let me know that if I failed, they would be there for me. They knew that this degree was important for me to fulfil my lifetime dream of obtaining a PhD. I am also very grateful to Dr Phavika Mongkolkittaweepol, Dr Sanyapong Petchrompo, Dr Tawit Sangveraphunsiri, Taechit Kulthanan, Panicha Boonsanongcheep, Dr Nuttapanita Rapeepongpatana M.D., Pornthep Uenukroh M.D., Jirarat Chongboonwattana M.D. and friends from GS, LJ, TIE for their encouragement and support. They always convinced me that I deserved a PhD.

Lastly, this degree would not exist without the financial support from the Thai Government Scholarship and Mahidol University. I would like to give a special thanks to everyone who supported me throughout the whole PhD.
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In which chapter(s) of your thesis can this material be found?

Chapter 4

Natchaya Tortainchai

27/03/2023
Abstract

Train dwell time is complicated and depends on many factors, one of the dominant ones being passenger volume. High passenger volume on a platform always causes trains to stop longer and consequently delays the service. This research used London Underground’s actual train movement data to evaluate train dwell times on the Victoria line, which is one of the most crowded lines in the London Underground system. In the morning peak of the northbound service of the Victoria line, Victoria station becomes a critical station that determines the line capacity due to the extended dwell time at the platform.

This research introduces the Data Envelopment Analysis to benchmark dwell times at each station on the line in relation to passenger volume at that station, and it suggests that stations be classified based on their demand profile. Stations with the same demand profile as Victoria station (defined as high-passenger-volume stations in this research) would be looked into further. The dwell times at these high-passenger-volume stations are highly variable and dependent on passenger movements. Many studies have found that dwell times at high-passenger-volume stations are difficult to predict accurately using dwell time models. The current method for calculating a dwell time in a train schedule uses the value calculated from the prediction model or the calculation of historical data.

Considering the perspective of the uncertainty inherent in dwell time evaluation, this research proposes a new dwell time evaluation approach to evaluate the likelihood and consequences of dwell time delays at different passenger volume levels. The research contributed to the evaluation framework to evaluate the risk of dwell time delays and found that the best-case scenario with the lowest risk of dwell time delays occurs when the dwell time margin is 20 seconds, and the train is loaded to 70 percent of its maximum capacity prior to arriving at the critical station.
Impact statement

With the increase in passenger demand on many metros around the world, there is a necessity to develop a plan to manage passenger congestion and increase service capacity. This thesis proposes an evaluation framework which supports the planning on a crowded and high frequency system. Firstly, the evaluation provides the optimum solutions for a proactive line-level passenger control strategy which suggests the optimum level of passenger volume on trains before arriving at the critical stations. This optimum level could reduce the dwell time delays, and also balance the level of passengers being controlled. Secondly, it addresses the issue of the length of dwell time margin that should be added into the timetable to absorb the dwell time delay. The suggested dwell time margin determines the service frequency. This evaluation framework strikes a balance between the service capacity and train delays. The evaluation framework could apply with all metros around the world in which their conditions fit the evaluation scope.

In the academic context, this thesis proposes an alternative approach to evaluating dwell time which offers higher accuracy on the dwell time evaluation by focusing on the purpose of preventing delays from passenger crowding at the critical stations (Chapter 6). This dwell time evaluation approach is applied to the risk of dwell time delays evaluation framework to evaluate the consequences of dwell time delays and their probability. The benefit of this evaluation framework is for planning purposes which consider the whole line service performance (Chapter 7). This evaluation framework will be submitted in a high-quality journal paper. In addition, this research proposes the classification of stations according to their characteristics and supports further research to develop different dwell time models for stations with different characteristics (Chapter 4). This study was published in Transportation Research Record: Journal of the Transportation Research Board (1) and was presented in the Transportation Research Board 100th Annual Meeting (2). The proactive line-level passenger control strategy with the aim of reducing the probability of dwell time delays was presented at two conferences, namely UTSG2019 (3) and RailBeijing2021 (4). Finally, the proposed dwell time delay evaluation approach has been accepted to be presented in the Transportation Research Board 102nd Annual Meeting (5) and the INFORMS annual meeting (6). The following are the journal paper and conference lists (the author’s surname has been changed from “Lailomthong” to “Tortainchai”):


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## Terminology

### 1. Definitions

The definitions of the terms used in this thesis are as follows:

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<th>Term</th>
<th>Definition</th>
</tr>
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<tbody>
<tr>
<td><strong>Bivariate delay function</strong></td>
<td>A delay probability function developed in this dissertation which gives the probability of trains having a certain level of passenger volume being delayed by a certain length of time.</td>
</tr>
<tr>
<td><strong>Boarding and alighting time</strong></td>
<td>One of the train dwell time components. It is the time between the first passengers entering or leaving a train to the last passengers entering or leaving a train.</td>
</tr>
<tr>
<td><strong>Critical stations</strong></td>
<td>The stations where dwell times are delayed which become the stations that determine the line capacity.</td>
</tr>
<tr>
<td><strong>Downstream stations</strong></td>
<td>Stations on the line which are located after the critical station.</td>
</tr>
<tr>
<td><strong>Dwell time delay</strong></td>
<td>The time trains stop at stations over the scheduled dwell time.</td>
</tr>
<tr>
<td><strong>Dwell time efficiency</strong></td>
<td>The efficiency of dwell time in this thesis is evaluated by considering the number of passengers at stations compared with the length of dwell time spent at these stations.</td>
</tr>
<tr>
<td><strong>Dwell time passenger-volume factors</strong></td>
<td>Train dwell time factors which are the factors affecting the length of train dwell time. Passenger-volume factors are the factors related to the number of passengers quantitatively. Passenger behaviours are disregarded in dwell time passenger-volume factors.</td>
</tr>
<tr>
<td><strong>Exit-only-station-control (EOSC)</strong></td>
<td>A station control method to control passengers by keeping them outside London Underground’s premises.</td>
</tr>
<tr>
<td><strong>High frequency service</strong></td>
<td>A train operation service which has a train headway shorter than 2 minutes for London Underground’s deep tube line.</td>
</tr>
<tr>
<td>Term</td>
<td>Definition</td>
</tr>
<tr>
<td>-----------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>High-passenger-volume stations</td>
<td>High-passenger-volume stations investigated in this research are stations at which the number of passengers both alighting and boarding trains are high (compared to other stations on the line), and trains arriving are crowded.</td>
</tr>
<tr>
<td>Line-level passenger flow management</td>
<td>The management of passenger flow at a line-level to make efficient movement and reduce congestion problems. It is a management method which manages the number of passengers at more than two stations cooperatively.</td>
</tr>
<tr>
<td>Load on a train</td>
<td>This research refers to the number of passengers on trains as a percentage of the train load. A train with a 100% load in the Victoria line is approximately 1,035 passengers.</td>
</tr>
<tr>
<td>Passenger interactions during boarding and alighting trains</td>
<td>The interactions between dwell time passenger-volume factors which have a strong influence on passenger boarding and alighting time, especially when there is crowding at a platform or on a train.</td>
</tr>
<tr>
<td>Passenger regulation</td>
<td>London Underground’s congestion management approach to manage passenger flow efficiently.</td>
</tr>
<tr>
<td>Passenger weighted journey time (WJT)</td>
<td>An evaluation approach used in Transport for London to quantify passenger value of time on the whole journey.</td>
</tr>
<tr>
<td>Run-out-run-in time (RORI)</td>
<td>Train reoccupation time which is the time for the leading train to run out (RO) and the time for the following train to run in (RI).</td>
</tr>
<tr>
<td>Station control</td>
<td>London Underground’s congestion management approach to restrict or limit passenger movements.</td>
</tr>
<tr>
<td>Station demand profile</td>
<td>The classification of station characteristics which describes different types of passenger volume in terms of “demand profile”. It gives details on different types of passenger-volume factors.</td>
</tr>
<tr>
<td>The optimum load on a train</td>
<td>The suggested level of load on a train before arriving at the critical station to balance dwell time delays at the critical station.</td>
</tr>
<tr>
<td>Acronym</td>
<td>Definition</td>
</tr>
<tr>
<td>---------</td>
<td>------------</td>
</tr>
<tr>
<td><strong>A</strong></td>
<td>The number of passengers alighting a train</td>
</tr>
<tr>
<td><strong>B</strong></td>
<td>The number of passengers boarding a train</td>
</tr>
<tr>
<td><strong>B/A</strong></td>
<td>Boarding/Alighting ratio (the ratio of boarders to alighters)</td>
</tr>
<tr>
<td><strong>BAT</strong></td>
<td>Boarding and Alighting Time</td>
</tr>
<tr>
<td><strong>BCDM</strong></td>
<td>Business Case Development Manual</td>
</tr>
<tr>
<td><strong>BHR</strong></td>
<td>Blackhorse Road station</td>
</tr>
<tr>
<td><strong>BRX</strong></td>
<td>Brixton station</td>
</tr>
<tr>
<td><strong>CDF</strong></td>
<td>Cumulative Distribution Function</td>
</tr>
<tr>
<td><strong>CRS</strong></td>
<td>Constant Return to Scale</td>
</tr>
<tr>
<td><strong>DEA</strong></td>
<td>Data Envelopment Analysis</td>
</tr>
<tr>
<td><strong>DMU</strong></td>
<td>Decision Making Unit</td>
</tr>
<tr>
<td><strong>EUS</strong></td>
<td>Euston station</td>
</tr>
</tbody>
</table>

The risk of dwell time delay
The evaluation of the consequences and probability of dwell time delay.

Train dwell time
The time a train stops at a station, which is the time between the wheel of the train stopping at a station and starting to leave the station.

Train knock-on delay
The delay that occurs when the following trains catch up with the leading train.

Upstream stations
Stations on the line which are located before the critical station.

2. Acronyms and abbreviations
The acronyms and abbreviations used in this thesis are as follows:
f  Train frequency
FPK  Finsbury Park station
GPK  Green Park station
H  Headway
HBY  Highbury & Islington station
KXX  King's Cross St. Pancras station
L  The number of passengers on a train
LU  London Underground
MLE  Maximum Likelihood Estimation
OXC  Oxford Circus station
P  The number of passengers at the platform
PAMELA  Pedestrian Accessibility and Movement Environment Laboratory
PDF  Probability Density Function
PIM  Pimlico station
RORIT  Run Out Run In Time
STK  Stockwell station
SVS  Seven Sisters station
t  Dwell time margin
TfL  Transport for London
tph  train per hour
<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TSM</td>
<td>Train Service Model</td>
</tr>
<tr>
<td>TTH</td>
<td>Tottenham Hale station</td>
</tr>
<tr>
<td>VIC</td>
<td>Victoria station</td>
</tr>
<tr>
<td>VUX</td>
<td>Vauxhall station</td>
</tr>
<tr>
<td>WJT</td>
<td>Passenger weighted journey time</td>
</tr>
<tr>
<td>WST</td>
<td>Warren Street station</td>
</tr>
<tr>
<td>x</td>
<td>Dwell time delay</td>
</tr>
</tbody>
</table>
Chapter 1
Introduction

1.1 Background

Public transportation systems include a variety of transit options such as buses, light rail, ferries, and metros and are an essential part of modern society, especially in urban communities (Kelley et al., 2016). Currently, 56 percent of the world’s population lives in urban areas; this proportion is expected to increase to 66 percent by 2050. Singapore, the Netherlands, Sweden, Chile, Japan, the United States, and the United Kingdom are examples of countries where over 80% of the population lives in urban areas (United Nations Population Division, 2021). In accordance with the criteria for good public transportation, public transportation should be: 1. convenient (door-to-door), 2. Reliable, 3. Direct, 4. Rapid, 5. Attractive, 6. Safe, 7. Cheap (Humphreys, 2016). Metros are one of the most advantageous modes of public transportation. Metros are the fastest and most energy-efficient mode of urban transportation (Eagling and Ryley, 2015). With lines running on separate infrastructure, metros avoid traffic congestion and are able to transport large numbers of passengers, making them the backbone of many cities. Some of the biggest cities in the world are renowned for their metro systems, including London's "Tube," New York City's "Subway," and Hong Kong's "MTR" (UITP, 2019). Metros play a significant role in many urban mobility networks around the world. In 2017, approximately 53 billion passengers were transported by metros in 178 cities. Taking into account the average passenger load of 1.3 per vehicle, metros remove the equivalent of 133 million cars from city streets every day (UITP, 2019).

World metro ridership has increased significantly over the past several decades, and this trend is anticipated to continue. There is a tremendous amount of metro ridership (the number of unique journeys). With an increase in ridership, it is expected that some stations will be more crowded, especially in the peak hours (Mensink, 2017). The congestion was visible in the world’s busiest metros. It is present not only in the London Underground (the research's case study), but also in the Tokyo subway, Beijing subway, Seoul subway, Shanghai metro, Moscow metro, New York subway, MTR Hongkong, and Paris metro (Railway Technology, 2014).
Passenger congestion in trains and metro stations can cause serious issues. It increases the likelihood that a passenger will fall onto the track, along with other serious safety concerns, and causes significant service disruptions (Tirachini, Hensher and Rose, 2013). In addition, it reduces the comfort of passengers, resulting in lower utility for passengers on public transportation and causing people to avoid public transportation. More connections could be missed due to longer access and egress times at the crowded stations. Massive crowds require longer train dwell times at platforms, resulting in a decrease in the overall system's efficiency. Passengers' total travel time can be increased due to longer dwell times, longer access and egress times, and missed connections (Mensink, 2017). Chapter 2 reviews more crowding effects.

Dwell times, or the amount of time the train spends at each station along the line, are a major concern for the improvements that have been studied on many metro systems around the world, including London Underground (Kelley et al., 2016), Swedish railway (Palmqvist, 2022), Switzerland’s suburban railway (Buchmueller, Weidmann and Nash, 2008), Hong Kong MTR (Lam, Cheung and Poon, 1998), Tokyo subway (Kamizuru, T., Noguchi, T., Tomii, 2015), Santiago subway (Suazo-Vecino, Dragicevic and Muñoz, 2017), Dutch railway (Li et al., 2014), etc. Many metro systems are investing in additional capacity by upgrading a variety of technical solutions, such as trains, signalling systems, and automation systems. To achieve maximum capacity, the whole system has to be considered. Capacity can be constrained by train design, train operations and capabilities, signalling systems, track junctions, terminal capacity, and station dwell times. Despite the fact that investments are typically made to solve technical constraints, dwell times could be the significant remaining constraint to maximising capacity. In fact, extended or inconsistent dwell times may restrict the plan's ability to increase capacity from the invested technology (Rail Technology Magazine, 2016).
Dwell times are the main concern of high-frequency metro systems and are a major determinant of line capacity, passenger journey times, and resource needs (i.e., trains and drivers). Extended or inconsistent dwell times lead to longer train journeys, longer passenger journeys, and irregular headways (Rail Technology Magazine, 2016). Extended train dwell times at a station can cause the following train to stop at the signal to wait for passengers to board and alight the train at the platform, thereby delaying the following train. Additionally, passengers at the next station have to wait for the delayed train, resulting in longer passenger waiting times (Wong and Key, 2014). Inconsistent dwell times can cause a "bunching" effect where one train is held and the following trains are bunched together, leading to irregular train headways. The bunching effect has been studied by Krause (2014), Ding (2016), and Wu (2016). The approach to improving dwell times can use existing practices to manage passengers rather than complex engineering solutions, which are expensive. The benefits of reducing dwell times are considerable and worth the effort. Improving dwell times could have advantages in terms of reducing passenger time, increasing capacity, increasing ticket revenues, enhancing passenger satisfaction, and increasing timetable reliability (Rail Technology Magazine, 2016). These benefits can bring about several economic benefits. For example, Donovan estimated the economic benefits of reducing dwell times on Auckland's trains by 30 seconds per stop and identified four economic benefits, which are: cost savings (4.5% of total operational costs could be reduced); existing user benefits (existing rail users will benefit from faster travel times, and this amounts to a value of $10 million per year); new user and decongestion benefits (faster trains will attract new users and lead to decongestion benefits, which are valued at $1.8 million per year) (Donovan, 2017).

The necessity for dwell time improvements becomes more essential when passenger volumes are high, especially in high-frequency metro systems where services are operated at full capacity (the London Underground is one of the cases). Dwell time has the following components: door opening time, passenger boarding and alighting time (BAT), signal delay time, door closure time, and departure time. Approximately 40% of dwell time is on passenger movement (BAT) (McKenna, 1988; Rail Technology Magazine, 2016). Most of the dwell time models and other dwell time studies, including this research, are focused on the passenger boarding and alighting time (BAT) which passenger crowding is related.
The London Underground, one of the world's busiest metros, was the first underground railway. The system carried 1.38 billion passenger journeys in 2019 and operated over 85 million kilometres, making it the seventh-longest metro system in the world (Transport for London, 2019). Being the first underground railway, the system was built with smaller trains and tunnels, giving the London Underground a challenge to manage passenger congestion in the stations and on the platforms (Croome and Jackson, 1993). There are many overcrowded stations on the London Underground, resulting in 547 occurrences of temporary station controls in 2019 preventing passengers from entering stations due to overcrowding. According to data on passenger entries and exits, five of the ten most overcrowded stations are on the Victoria line (Statista Research Department, 2023).

The increase in demand on the network causes the network to become more congested, resulting in the establishment of several projects. One of these is Victoria Line Upgrade (VLU) Project in 2012 to enable the line to run more trains (Rail Engineer, 2013). The project increased the line's capacity by more than 30 percent, allowing it to carry approximately 10,000 additional passengers per hour (Transport for London, 2014). This was followed by the station expansion project in 2018, which is aimed at increasing the space within the overcrowded Victoria station (BBC London, 2018; Mansfield, 2018; Step Free London, 2018). Even though several projects or methods have been implemented to support the growing demand and crowding, the number of peak-hour passengers on the small platform remained high, so the problem of the extended dwell time at the platform has not yet been resolved. More details of the case study are given in Section 3.3.
1.2 Research problems and motivations

Many metros are commonly faced with passenger crowding which leads to train delays at stations. The idea of “high passenger volume leading to service delays” is a common problem for congested metro systems. When there is a high volume of passengers on the platform, the interactions between passengers cause the train to stop longer on the platform and finally delay the service. In the peak-hour service, many critical stations become the stations that determine the line capacity due to dwell time delay at the platform. Signalling technology has been improved to enable trains to run closer. However, the issue that dwell time limits the service frequency still exists and tends to be more critical as time progresses because of the increase in passenger volume. Thus, dwell time delay is the motivation of this research to investigate dwell times at high passenger volume stations.

Dwell time is a complicated component which consists of numerous factors. Dwell time in the crowded environment is more complicated due to passenger behaviours and the interactions between passengers. Much effort has been put into the development of dwell time prediction models; however, dwell time cannot fit consistently with any models because of the nature of the dwell time, which is complicated and uncertain. Section 2.1 gives an intensive review of dwell time factors and dwell time models. This research used the actual operation data from London Underground’s train movement database to evaluate train dwell times at high passenger volume stations. A large amount of the actual operation dataset was used to identify dwell time distributions and evaluate dwell time delays for the different levels of passenger volume. In this research, dwell time has been evaluated from the viewpoint of probability of delay, instead of attempting to inaccurately predict a dwell time value.

Dwell time delays have become one of the most critical problems as they delay the trains at stations and restrict the service capacity, which could lead to delays on the whole network. It is a challenging task for many stations in the London Underground system to manage high passenger volumes on the narrow platforms to avoid delays and accidents and to handle the passenger flow efficiently. The current increase in demand in urban railway leads to an increase in passenger congestion and management only at individual stations is not sufficient to relieve the crowds. This research proposes an
application of the proactive line-level passenger flow management system that would reduce the risk of dwell time delay.

Research problems can be summed up by the following two aspects. More academic and practical reviews linking to research problems are given in Chapter 2 and Chapter 3, respectively.

1.2.1 Stations are crowded causing long dwell times and delaying the line service

Dwell times at high passenger volume stations are the target of improvement of this research. The high passenger volume stations are stations which have long dwell times at the platform resulting in the station becoming the bottleneck of the line and the trains being restricted to entering the platforms. The situation at the platforms of these stations is that there is high passenger volume both alighting and boarding trains, while trains approaching these platforms are also filled to the capacity at the previous stations, causing passengers at critical stations to try to squeeze into the trains. Section 2.1 and Section 3.3 explain these passenger volume factors and their impacts to train dwell times.

1.2.2 Passenger congestion control are carried out at each station individually

Currently, passenger congestion control procedures are carried out in a reactive manner, where station control measures are deployed when there are severe congestions inside the station or on one of the platforms, which may lead to accidents and train delays. When station control is deployed in a reactive way, no passenger is allowed to enter the station/platforms without letting passengers know in advance. This causes uncertainties for passengers. The current procedures involve judgements made at an individual station level that aim to reduce impacts from the congestion at a specific station. Several studies suggested a line-level passenger management approach in which stations on the line are arranged to manage passenger flow cooperatively. More academic and practical reviews regarding passenger congestion management strategies are given in Section 2.2 and Section 3.3, respectively.
1.3 Research objectives

Research objectives are set with the final aim of improving dwell time delays at high-passenger-volume stations, hence improving the overall line service performance. Research objectives include:

- **Benchmark dwell times at each station on the line in relation to passenger volume at that station.** This is to understand the characteristics of the stations and classify stations according to their demand profiles. The stations with the characteristics that could lead to long dwell times are defined as high-passenger-volume stations and would be taken into consideration further.

- **Examine the variability of dwell times using operation data.** This is to examine the variability of dwell times at high-passenger-volume stations and the correlation between dwell times and passenger movements. The variability could make dwell times difficult to represent with existing dwell time prediction models.

- **Define a new method to evaluate dwell times at high-passenger-volume stations.** This is to establish an alternative approach to evaluating train dwell time at high-passenger-volume stations that offers a higher level of accuracy.

- **Propose the dwell time evaluation approach for high-passenger-volume stations.** The approach considers dwell times from the perspective of the risk of dwell time delays, which takes into account the probability and consequences of dwell time delays.

- **Make recommendations for the applications of the proposed dwell time evaluation approach.** This is to fulfil the aim of improving dwell time delays by providing optimum solutions to improve the overall line service performance.
1.4 Research questions and hypotheses

Several research questions and hypotheses are set in this research. Firstly, if dwell times at high-passenger-volume stations cannot accurately be predicted by dwell time prediction models, what could be an approach to evaluate dwell times for the purpose of planning in a crowded system? Secondly, there is always a question in the timetable planning process about how long a dwell time margin or buffer should be added into the timetable. If a length of dwell time margin or buffer is added into the timetable, what would be an approach to justify the balance between train capacity and train delay? Finally, if passenger control strategies can improve dwell time delays, what would be an approach to evaluate the optimum solutions that could maximise the whole line service performance?

1.5 Research scope

The focus of this research is on dwell times at high-passenger-volume stations. High-passenger-volume stations are specific types of crowded stations according to the station classification given in Chapter 4. The research is conducted based on a case study at the northbound service of Victoria line in the morning peak time with a focus on passenger crowding and the impact on train dwell times. The background and full explanations of the research case study are described in Chapter 2. The data analysis in this research is based on data from the London Underground’s database and includes data from NETMIS (data recording each train movements and load on trains at each station) and RODS (Rolling Origin Destination Survey summing a number of passengers who travel to each Origin-Destination pair). Data sources and data limitations are given in Section 3.1.

For the evaluation model of the risk of dwell time delays presented in the final chapter, a specific scenario was selected which has the aim to improve dwell time delays at high-passenger-volume stations and improve the whole line service performance. Lastly, the pre-planning line-level passenger control strategies obtained from the evaluation model only suggest the optimum passenger volume that could maximise the whole line service performance. This research will not include the measures necessary to apply passenger control strategy to achieve the suggested passenger volume. Such specification of the actual control measures could be a topic for future research.
1.6 Structure of the thesis

This chapter gives an overview of the thesis by introducing the research problems and the guidelines to tackle the problems. The research objectives, research questions and hypotheses, and research scopes are stated in this chapter. Other chapters on the thesis are framed as presented in Figure 1-1.

Figure 1-1: Structure of the thesis
Chapter 2 reviews existing studies on train dwell times including dwell time’s factors, the current dwell time evaluation approach and dwell time models. This chapter also reviews existing research on passenger congestion management at the station level and network level. Then, academic gaps are identified, and the contributions of this research are established.

Chapter 3 presents the research’s methodology. This chapter includes descriptions of the data used in the research, methods, and the case study’s justification and context. The current situation of passenger crowding and its effects on train dwell times is described using the case study of the London Underground's Victoria line.

Chapter 4 benchmarks dwell times at high-passenger-volume stations among other stations on the line by introducing the Data Envelopment Analysis to benchmark dwell times at each station on the line in relation to passenger volume at that station. The benchmark approach classifies stations according to their demand profiles and identifies characteristics that could lead to long dwell times. Stations with these characteristics are defined as high-passenger-volume stations and would be taken into consideration further.

Chapter 5 conducts an intensive investigation into train dwell times and passenger volumes to understand dwell times at high-passenger-volume stations. This chapter uses London Underground’s dataset to validate existing dwell time models and demonstrates that dwell times have high variation and are difficult to fit with any dwell time models.

Chapter 6 proposes an alternative dwell time evaluation approach which considers dwell times from the reliability perspective. This chapter develops a dwell time delay probability function which has a passenger-volume factor as a variable (bivariate dwell time delay function).

Chapter 7 applies the bivariate dwell time delay function and evaluates dwell time with a risk-based evaluation approach which is the approach suitable for the evaluation of the current situation. This chapter ultimately addresses and solves the research problems pointed out in Chapter 2 by developing an analytical model to investigate the impacts of dwell time delay and provides the optimum solutions to improve dwell time delays and enhance the whole line performance.

Chapter 8 presents the conclusions from the outcomes of the research which fulfil the research objectives and proposes areas for future studies.
Chapter 2
Literature Review

A good transport system is a system which transport supply could satisfy transport demand at any specific time. Ortúzar and Willumsen (2011) indicated that a good transport system needs to fulfil passenger travel purposes, enhance movements, be connected, support economic and social development. Transport demand which is qualitative and differentiated makes a good transport complicated. Transport supply, considered as a service, is perishable and must be produced tailoring to the demand (Ortúzar and Willumsen, 2011). Most of the time, transport management has to deal with congestion, delays, accidents, and environmental problems (Ortúzar and Willumsen, 2011). The planning of urban railway operations has been studied in order to manage both demand (passengers) and supply (trains). The management on the train side is supply-side management that is related to the management at the capacity level, such as through capacity enhancement, train traffic management, and train scheduling, to name a few. Management from the train side has been extensively studied and implemented. Even though train management has advanced to a certain degree, passenger management must still be considered. For crowded and frequent service, management from the passenger side is essential. Increasing demand for urban railways necessitates a greater emphasis on passenger management to reduce train delays, travel times, passenger discomfort, and accidents (Mensink, 2017).

According to the research problems and motivations regarding the impacts of passenger congestion to dwell time delays, this literature review is framed into two major parts: train dwell time which reviews all studies regarding current dwell time analysis and passenger congestion management in both station and line level.
2.1 Train dwell time

This section intends to review previous studies in train dwell time. The studies in train dwell time are conducted through several aspects. The factors included also relate to several areas such as train specification, platform layout, passenger volume and their behaviours. The previous studies on train dwell time have been conducted through experiments, observations, or from datasets. Some of the research focused on identifying the critical factors impacting dwell time, while some research analysed dwell time data or developed dwell time prediction model. This chapter starts with the definition and composition of train dwell time. Then, experiments and observations studies regarding general factors of train dwell time are presented, after that the review scopes to the passenger factors. Next, the chapter reviews the analysis of the dwell time data which starting from descriptive statistics, distribution functions, and dwell time prediction models.

2.1.1 Definition and train dwell time in general

Train dwell time is known as one of the complicated components in the metro operation field as it is determined by many factors in several perspectives and by passenger behaviours, which is very difficult to predict. The definition of dwell time in London Underground’s Train Service Model (TSM) is the time between wheel stop to wheel start. It is not only the time for passengers to board and alight from the train, but also the technical time for the door opening and closing process (Winslett, 2017). Dwell time can be divided into five components: door opening time, passenger alighting and boarding time (BAT), signal delay time, door closure time, and departure time. The analysis in McKenna’s report presented that BAT, door closure time, and departure time take up most of the overall dwell time. Door closure time and departure time normally take around 10 seconds, however they could take up to 35 seconds if there is a repeated door closure caused by “late runners” (passengers who get on the train while the doors are nearly closed). Since “late-runner” situations occur randomly, they are mostly excluded from the dwell time model (McKenna, 1988). BAT becomes the most significant part of the dwell time model and other dwell time analyses. The dwell times considered in this current research are referred to BAT.
Wong & Key classified factors affecting BAT into 3 groups including passenger-related, platform/station-related, and train-related. Figure 2-1 presented in this report outlines a framework of all factors that could influence dwell time (Wong and Key, 2014). The details of particular factors have been explained in the report. The dwell time factors shown in Figure 2-1 have also been studied in numerous studies.

Figure 2-1: Factors affecting boarding and alighting time
((Wong and Key, 2014), Figure 7, Page 12)
2.1.2 Train, platform, and station-related dwell time factors

This section briefly reviews the train, platform, and station-related factors that can make dwell times vary greatly between different railway systems. It should be noted that while these factors do impact dwell times, our research specifically examines the effect of high passenger volume on train dwell times within a particular system and line where these factors remain constant.

Factors related to the trains are divided into train operator behaviours, carriage layouts, and train doors. Platform or station factors are divided into layout, stepping distance, platform instruments, static initiatives, and station interventions (Wong and Key, 2014). Among these, the factors that most commonly appear in dwell time models are train layout, train door, and platform layout due to their direct impacts on passenger movement and boarding and alighting speeds. For instance, platforms with wider gaps between the train and platform can cause a longer stepping distance; wider platforms provide better capacity, encourage passengers to spread out evenly, and allow for faster boarding and alighting (Karekla and Tyler, 2012); appropriate door width can result in an efficient boarding and alighting process (It should be noted that wider doors can sometimes result in less interior space and take longer to close and open (Railway and Transport Strategy Centre, 2013)); train layouts, such as vestibule width, standback areas, and seating density, can also impact passenger access rates to train doors and cars (Fujiyama, Nowers and Tyler, 2008). Dwell time models that include these factors are including London Underground’s model (Weston and Maunder, 1989), Dwell Time Recalibration (Railway and Transport Strategy Centre, 2013), Karekla’s simulation model (Karekla and Tyler, 2012), Buchmueller’s dwell sub-process time model (Buchmueller, Weidmann and Nash, 2008), etc.

In addition to the factors mentioned earlier, certain factors are often studied as separate qualitative topics rather than being included in dwell time models. For example, platform tools such as signage and passenger information systems have been studied to assess how they can aid in reducing dwell time by helping passengers locate the correct carriage or entrance/exit (Loukaitou-Sideris, Taylor and Voulgaris, 2015). Similarly, train operator behaviours such as the time taken to close the doors and commence train movement can also have a significant impact on dwell time (Wong and Key, 2014).
2.1.3 Passenger-related dwell time factors

Passenger-related factors could be subcategorised into passenger behaviours, passenger types, passengers’ origin and destination, and passenger volume. Among dwell time factor categories, passenger-related factors are the most unstable (Wong and Key, 2014). This is due to the inconsistency of passenger behaviours and other characteristics. Unevenness passenger distribution along a platform is another concern which much research has examined (Szplett and Wirasinghe, 1984; Wiggenraad, 2001; Kim et al., 2014; Smith, 2016; Fang, Fujiyama and Wong, 2019 to name and a few). Unevenness mostly occurs from passengers stay around platform's exits/entrances of origin/destination stations. It causes more passengers to board and alight at the same door (This door is called a critical door). The time at the critical door would determines the dwell time of the whole train. London Underground’s dwell time model which is widely used to predict dwell time also includes this factor as a peak door variable (Weston and Maunder, 1989). The focus of this research is on the part of passenger volume factors as introduced in the research background.

This section focuses on passenger volume factors which refer to the factors according to Figure 2-1 (Wong and Key, 2014). Passenger volume factors are the variables that directly relate to the duration of train dwell time (Basically, the more passenger volume, the more dwell time). Thus, most studies generally include passenger volume as the factors for analysis. This section reviews the most related research and summarises essential passenger volume factors from the results of the following studies.

Fujiyama, Nowers & Tyler conducted an experiment in University College London’s Pedestrian Accessibility and Movement Environment Laboratory (PAMELA) to investigate whether 50 passengers could board and alight at the door of a mock-up of a London Underground train within 27 seconds. The experiment was conducted in 3 scenarios with different boarding and alighting ratios (45Alighters/5Boarders, 45Boarders/5Alighters, 25Alighters/25Boarders). Results showed that the highest number of movements within 27 seconds was achieved by the group of 45Alighters/5Boarders, followed by 45Boarders/5Alighters and 25Alighters/25Boarders, respectively. The case of 25Alighters/25Boarders got the lowest achievement due to the highest number of interactions between passengers. Moreover, the experiment found that if a boarding process continues after the density
of the vestibule reaches 4 passengers per m², the passenger boarding rate will begin to drop. The passenger boarding and alighting flow rate always changes during the door opening time with non-linear distribution. Therefore, using a constant average flow rate to determine the boarding and alighting rate may not be accurate (Fujiyama, Nowers and Tyler, 2008).

Apart from Fujiyama’s study, there have been several research conducted in this laboratory (PAMELA) (i.e., Childs et al., 2009; Howarth et al., 2011; Seriani, Fujiyama and Holloway, 2016; Seriani, 2018; Seriani et al., 2019). Seriani explored the effect of the boarding and alighting ratio (R) with regard to the following aspects: average boarding and alighting rate, sequence of movement, formation of lanes, and the density inside the train. This research found that passenger behaviour can vary when the level of passenger volume is different even when the boarding/alighting ratio is similar. Thus, the numbers of passengers boarding and alighting are crucial factors in the dwell time analysis. In a crowded situation, if boarders are dominant (R=4), a small group of alighters have to interact with a large number of boarders, causing alighters to spend more time per passenger than boarders, and vice versa in an alighter-dominant situation (R=0.25). Regarding the sequence of movement, passengers will always alight from trains first, followed by passengers boarding; however, in a boarder-dominant situation (R=4) the boarding process starts earlier, namely around 10 seconds after the alighting process starts. This research also provided evidence that the boarding flow rate will drop when the density of the vestibule reaches 4 passengers per m². The experiment tried closing the train doors when the density of the vestibule reached 4 passengers per m² and found that this could reduce the total dwell time by 26%, which is about 11 seconds. The authors suggested future work to identify the ideal time to close the doors in a crowded situation (Seriani et al., 2019).

Harris experimented on a mock-up of Southwest Train rolling stock. His research divided BAT into 3 elements: boarding time, alighting time and interaction time, and stated that the interaction time is the most complicated part as it cannot be calculated straightforwardly. The passengers remaining on the train also have an effect on the interaction time. For example, if most passengers alight from the train, more spaces on the train will lead to fewer conflicts, thus passengers can board easily. The interaction time is a part which this research demonstrated that London Underground’s equation is inaccurate at high level passenger flow. The study also revealed that an
increase in the number of passengers leads to a higher BAT with a nonlinear relationship involving a power function between 0 and 1 (which is consistent with London Underground’s model). Regarding the sequence of movement, this research also supported findings that alighting and boarding rates are not constant across alighting and boarding processes. The fastest movement for alighters is right after the doors open as passengers near the doors can get off without obstruction, while the fastest movement for boarders is at the middle of the process as early boarders might be impeded by alighters and late boarders might be obstructed due to the train being nearly full (Harris, 2005).

In the meanwhile, Suazo-Vecino analysed on the subway in Santiago data and found that passenger density inside the train is the most significant variable. Their research conducted on one of the most congested subway stations in Santiago. The study found that the passenger density inside the train takes 73.6% of the whole dwell time, and the number of alighters together with the platform occupancy level accounts for 11.55% of the dwell time. Their research focused on the latter term as they considered that it is controllable by limiting passenger accessibility to the platform which could result in fewer interactions between alighters and passengers on the platform (Suazo-Vecino, Dragicevic and Muñoz, 2017). Kuipers also conducted a comprehensive review of the literature concerning the influence of passenger factors on dwell times, including passenger boarding and alighting behaviour (Kuipers et al., 2021). Table 2-1 gathers the dwell time’s passenger volume factors and exemplifies relevant studies.
Table 2-1: Dwell time’s passenger volume factors

<table>
<thead>
<tr>
<th>Passenger Volume Factors</th>
<th>Impact to passenger boarding and alighting time (BAT)</th>
<th>Examples of relevant studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>The number of passengers boarding (B)</td>
<td>The more boarders, the longer BAT taken</td>
<td>(Szplett and Wirasinghe, 1984; McKenna, 1988; Weston and Maunder, 1989; Puong, 2000; Wiggenraad, 2001; Buchmueller, Weidmann and Nash, 2008; Railway and Transport Strategy Centre, 2013; Yamamura A, Koresawa M, Inagi T, 2013; Fang, Fujiyama and Wong, 2019)</td>
</tr>
<tr>
<td>The number of passengers alighting (A)</td>
<td>The more alighters, the longer BAT taken</td>
<td>(Szplett and Wirasinghe, 1984; McKenna, 1988; Weston and Maunder, 1989; Puong, 2000; Wiggenraad, 2001; Buchmueller, Weidmann and Nash, 2008; Railway and Transport Strategy Centre, 2013; Yamamura A, Koresawa M, Inagi T, 2013; Fang, Fujiyama and Wong, 2019)</td>
</tr>
<tr>
<td>The number of passengers on the train (L)</td>
<td>The crowded train obstructs passenger movement leading to a decrease of boarding and alighting rate</td>
<td>(Weston and Maunder, 1989; Harris, 2005; Yamamura A, Koresawa M, Inagi T, 2013; Wong and Key, 2014; Suazo-Vecino, Dragicevic and Muñoz, 2017; Christoforou, Chandakas and Kaparias, 2020; Harris, de Simone and Condry, 2022)</td>
</tr>
<tr>
<td>The number of passengers at the platform (P)</td>
<td>The crowded platform obstructs passenger movement leading to a decrease of boarding and alighting rate</td>
<td>(Weston and Maunder, 1989; Harris, 2005; Wong and Key, 2014; Suazo-Vecino, Dragicevic and Muñoz, 2017; Harris, de Simone and Condry, 2022)</td>
</tr>
</tbody>
</table>
Apart from considering passenger volume as a single factor, the interactions between these factors are often mentioned in previous research. The interactions between passengers have a strong influence on the dwell time, especially when there are crowding at a platform or a train. The effect of passenger interactions during boarding and alighting process to the dwell time was investigated mostly in the crowding situation (Szplett and Wirasinghe, 1984; Harris, 2005; Fujiyama, Nowers and Tyler, 2008; Konstantina Argyropoulou, Howard Wong, 2014; Seriani, Fujiyama and Holloway, 2016; Seriani, 2018). Some research describes the interactions as Boarding/Alighting ratio (B/A ratio) which is the ratio of boarders to alighters. In the situation when either alighters or boarders are dominant, it makes a shorter boarding and alighting time as there are fewer interactions between passengers compared with the situation when the numbers of boarders and alighters are almost the same (B/A ratio close to 1) (Fujiyama, Nowers and Tyler, 2008; Seriani, Fujiyama and Holloway, 2016; Seriani, 2018)

The evaluation of dwell time with higher passenger interactions is more complicated. Figure 2-2 simply illustrates passenger interactions during a boarding and alighting process. The interactions could occur among any of the passenger volume factors. For example, the interactions of passengers alighting from the train (illustrated in the red box) to the crowded platform (illustrated in the blue box) and the interactions of passengers on platform attempt to board the crowded train. When the train is crowded and some people would like to alight, combined with several passengers attempting to board the crowded train, these interactions could lead to a long dwell time and further train delay (Oberlander, 2014; Seriani, Fujiyama and Holloway, 2016).

Figure 2-2: Passenger interactions during boarding and alighting trains
2.1.4 Train dwell time data analysis

This part reviews the statistical approach specifically for applying on dwell time data analysis. Apart from train dwell time data, this review includes the data analysis approaches on other transportation modes and other train processing time (i.e., delay time, journey time, running time) which are applicable on train dwell time data analysis. For quantitative data like train processing time, descriptive data analysis is commonly used to describe characteristics of variables. Descriptive data analysis includes the calculations of mean, mode, median, percentile, range, standard deviation, etc. These calculations provide representative values which give a rough idea of the dataset and are used on the assumption of deterministic process (Watson, 2001). There are typical statistical approaches used in dwell time research to explore relationships among variables. The common approaches are correlation analysis, regression analysis, and factor analysis. Among these, regression analysis is mostly applied in many studies to predict train dwell times from available data which is used as inputs or factors of the model. The dwell time model represents dwell time in an equation to predict a value of dwell time when several variables are added. The review of dwell time models is provided in Section 3.1.4. There are several research in dwell time data analytics (Bergström and Krüger, 2013; Krause, 2014; Gysin, 2018; Liu et al., 2018; Kuipers and Palmqvist, 2022).

The aforementioned approaches are all deterministic whereas the nature processes of transportation are stochastic. Stochastic is a random pattern of the process that can be analysed statistically but may not be predicted precisely. The nature of dwell times is also stochastic and difficult to predict accurately. Distribution models have been widely used enabling an insight into the variabilities. Probability distributions give complete understandings of data patterns and variabilities by quantifying relative frequency of the random variables as functions. When random processes are established by fitting observation data with the theoretical distribution model, the fitted model can be used to perform many different analyses (Richard A. Johnson, 2017). The examples of standard probability distributions application in transport studies are a poisson distribution for the number of passengers arriving at a station, an exponential distribution for time between successive buses arriving at a bus stop, a normal distribution for sums of mutually independent observations, a lognormal distribution for duration of a journey time in similar circumstances.
The most common distribution models seen in train processing time are Uniform, Normal, Exponential, Gamma, Lognormal, and Weibull distribution (Yuan, Goverde and Hansen, 2010; Lessan et al., 2018). More often, the train processing times usually have a right-skewed characteristic as the times always have a limit or must adhere to a schedule (the earliest or shortest time) (Yuan, 2014). There are several research fitting distribution models to train processing time data. Li’s research used the track occupation data and found that dwell time data at short stop stations fits a lognormal distribution (Li et al., 2014). Yuan also found that lognormal distribution is the best distribution for the arrival times of trains (different between actual and scheduled arrival times) and Weibull distribution is the best fit for non-negative arrival delays (considering only the arrival times that are delayed), departure delays, and free dwell times of late arriving trains (the free dwell time is defined as the necessary dwell time for passenger alighting and boarding regardless of the early arriving trains) (Yuan, Goverde and Hansen, 2010). Lessan proposed distribution functions for the data which has a heavy-tailed distribution (the data which has more of higher values and tend to have many outliers with very high values) to estimate running times and arrival delay distribution as heavy-tailed distributions allow an approximation of larger disturbances. Three common right-skewed, heavy-tailed distributions chosen in this research are Lognormal, Log-logistic, and Weibull (Lessan et al., 2018).

However, some studies found a challenge to fit distributions on large railway dataset or on an originating data from a real process (Harrod, Pournaras and Nielsen, 2019). This dataset may fail the goodness of fit test like Kolmogorov-Smirnov test because the test takes all the number of data points into consideration, and the data points may contain bias or a pattern of behavior (Johnson and Wichern, 2007). Browne and Cudeck suggested that the test should seek for an allowable error, rather than seek for a perfect error sum of zero (Browne and Cudeck, 1993). In addition to standard and single distribution fitting approach, Yuan suggested a fine-tuning the parameters and assessed several applied distribution models to deal with the impact of data outliers and fit the distribution of train delays (Yuan, 2014). Ma fit the delay data with several distributions and suggested that the multi-distribution in one dataset would better fit the data than the single type of distribution (Ma et al., 2016).
There are other studies related in the distributions of train arriving, dwell time, and departure. Goverde used the signal data of Dutch railway to identify train arrival, dwell time, and train departure delay distribution. Based on how the data were distributed, this study found that more than two-thirds of late-arriving trains are likely to increase the dwell time (Goverde et al., 2001). Many studies identified the distributions of input data and developed models to predict the delays. For example; a stochastic model of delay propagation which identifying distributions of late arrival delays and dwell delays, and predicting the distribution of departure delays to support train scheduling (Yuan, Goverde and Hansen, 2002). Lessan developed the stochastic model of train running time to predict train arrival delay and the quality of service. This research built a heavy-tailed distribution for arrival delays based on the running time distributions on previous track sections. The heavy-tailed distribution is used instead of other theoretical distribution models as it allows the prediction of larger delays (Lessan et al., 2018). Martin explained that train delays are usually not equally distributed because the necessity to run according to timetable, thus short delays occur more often than long delays (Martin, 2014).

2.1.5 Train dwell time models

Train dwell time models can be developed from an offline to an online model or from a deterministic to a stochastic model. The model can be a simple one or a very complex one. The degree of model complexity also depends on the input variables. Yang et al. (2019) have conducted reviews of the development of dwell time prediction models over the past forty years. The review categorises dwell time model approaches according to statistical models (linear regression, nonlinear regression, summary plots), simulation models (microscopic, mesoscopic, macroscopic), and other models (fuzzy logic-based, machine learning, mixed approach) (Yang, Shiwakoti and Tay, 2019). The statistical model approach was used in the majority of the research to develop dwell time prediction models, of which regression analysis is the most commonly used method. Other methods for predicting dwell times are uncommon, as they are complicated and difficult to use as an input for further analysis.

In terms of the variables used in dwell time prediction models, some studies only used passenger-related factors, while others included train-related and platform-related factors. One of the most widely investigated model in the UK’s research field is London Underground’s dwell time model which the details have been gathered in
London Underground’s internal documents (McKenna, 1988; Weston and Maunder, 1989; Nicholls, 2010). The original model is one full-page long and includes of variables which cover all three categories (passenger-related, platform-related, train-related factors). In the first term of the equation, the train dwell time includes of 3 elements: boarding factor, alighting factor, and interaction factor. Boarding factor and alighting factor in this model have 0.7 power function which means the increase of dwell time is slow down when there are a greater number of passengers boarding and alighting. Harris (2005) also studied on boarding and alighting factors in his experiments and found that boarding and alighting factors have a power function between 0 and 1. His research showed a significant of the interaction term which is the sensitive term in London Underground model and makes the model overpredict the reality (Harris, 2005). The second and third terms of London Underground model are for the adjustments of vestibule crowding factor and door width factor, respectively. The investigation of London Underground’s dwell time model is demonstrated in Chapter 5.

To investigate and update London Underground model, which was built in the late 1980s, Railway and Transport Strategy Centre (2013) developed dwell time model with a dataset from Imperial College London and the Railway Consultancy Ltd. which includes surveys data of 130 stations around the world. This research used multivariate regression with an iterative process to develop dwell time model. The processes began with testing the correlation between 18 dwell-time variables (passenger, platform, train-related factors) and found that very few correlations are exceeded 0.3. This research developed a model to predict alighting time and a model to predict boarding time separately. The models with the highest performance include all variables, while the simplified models only include seven variables in each model. All variables (which are number of alighters, number of boarders, ratio of alighters/boarders, through passengers in the vestibule, existence of steps in the train, vertical stepping distance, double-sided platform, platform width, seating density, standback width, distance between doors, car area/door width) are statistically significant at higher than 95%. Number of alighters, number of boarders, and ratio of flow are passenger-related variables which are considered highly significant to the train dwell time (Railway and Transport Strategy Centre, 2013).
Another notable researcher in this field is Weidmann who conducted this as doctoral research during 1990s. Most of his documents were not in English, however Railway and Transport Strategy Centre (2013) reviewed some parts of his doctoral research and identified factors which had been investigated in his research which include passenger-related, infrastructure-related, train-related, and service-related factors. Buchmueller, Weidmann, & Nash (2008) developed a dwell time calculation model which have vehicle type, station infrastructure, and demand as input parameters. The data using in this research is collected from automatic passenger counting system and included of number of boarding passengers, number of alighting passengers, and timestamps. In Boarding-Alighting process, the research evaluated Boarding-Alighting process with passenger flow rates (the ratio between number of passengers through doorway and time) and concluded that passenger flow rate decreases when vehicle occupancy is 60% occupied (Buchmueller, Weidmann and Nash, 2008). In the meanwhile, Suazo-Vcino et al. (2017) found that the density inside the train is the most significant variable among other variables in the model. The research developed the dwell time model for one of the most congested subway stations in Santiago (Suazo-Vcino, Dragicevic and Muñoz, 2017). There are numerous other dwell time model research available (Szplett and Wirasinghe, 1984; Lam, Cheung and Poon, 1998; Puong, 2000; Douglas, 2012; Gysin, 2018).

Basically, most dwell time models have at least these two terms: First, boarding flow rate multiplied by number of boarders. Secondly, alighting flow rate multiplied by number of alighters. Some research may include other terms in addition to these two terms. Douglas (2012) and Puong (2000) involved the interaction term among boarders, alighters, and standing through-passengers in their models (Puong, 2000; Douglas, 2012). Puong (2000) observed that if the density of standing through-passengers is over than 5 passengers/m², it would affect train dwell time. Szplett & Wirasinghe (1984) developed different models for different boarding and alighting rate as their research considered that the case of boarding-dominant or alighting-dominant is significant on train dwell time (Szplett and Wirasinghe, 1984). These models were summarised by San & Masirin (2016) and presented in Table 2-2 (San and Masirin, 2016).
Table 2-2: Parameters investigated in other models
(San & Masirin, 2016, Table 2, P.5)

<table>
<thead>
<tr>
<th>Model</th>
<th>Passenger Volume</th>
<th>Mixed Flow Effect</th>
<th>Crowding Effect</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Szplett and Wirasinghe (1984)</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Weston (1989)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Lam and Poon (1998)</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Puong (2000)</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Douglas (2012)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>
2.2 Passenger congestion

In general, passenger congestion could exist in any areas of stations from the ticket concourse, gatelines, passageways, platforms, and trains. This research focuses on platform and train crowding, which has a significant impact on accidents and train dwell times. Figure 2-3 exemplifies the causes and effects of passenger congestion based on reviewing several studies on passenger congestion, including (but not limited to) these studies (Lam, Cheung and Poon, 1998; House of Commons Transport Committee, 2003; Cox, Houdmont and Griffiths, 2006; Li, Yin and Zhou, 2014; Oberlander, 2014; Mensink, 2017; Seriani, 2018; Molyneaux, Scarinci and Bierlaire, 2019; Rail Safety and Standards Board, 2020). The boxes located beyond the green arrows indicate the potential causes of passenger congestion, while the boxes located beneath the red arrows indicate the potential effects of passenger congestion. There are numerous causes of passenger congestion, including trains, passengers, stations, and platforms. Passenger congestion has negative effects on passenger time, safety, passenger satisfaction, operational cost, etc. The grey boxes in the figure depict the relationship between passenger congestion and train dwell time delays, which is the focus of this research. When a train is delayed, passengers waiting on the platform accumulate, resulting in overcrowding. When the train arrives at the crowded platform, it has to stop longer, resulting in a further delay.

This section introduces the literature review on passenger congestion. The reviews cover the fundamentals of passenger congestion, passenger congestion management in general, which aims to reduce the crowding at each station individually, and line-level passenger flow management, which aims to investigate the problems for the whole line.
2.2.1 Fundamental of passenger congestion

When it comes to passenger congestion management, it is necessary to define the term "congestion". The number of passengers per square metre (PPSM), which is used to determine the number of passengers that can be accommodated, is the standard method for measuring crowding levels. The PPSM can vary widely depending on factors such as train and platform design, demand, and cultural norms on personal space (International Association of Public Transport (UITP), 2015). Different countries use varying measures to assess crowding, such as passengers in excess of capacity (PiXC) in the UK (House of Commons Transport Committee, 2003), load factor (passengers per seat) in Australia, and standing passenger area space (square metres per standing passenger) in the US (Li and Hensher, 2013).
It is essential to consider not only passenger standing space, but also how much space passengers have to move around within that area. In this regard, the level of congestion can vary depending on whether passengers are standing or moving. A passenger can be represented statically as an ellipse with an area of 0.30 m². When a passenger begins to walk, this area grows to 0.75 m² because leg and arm movements require additional space. However, in the presence of obstructions (the presence of other passengers in our case), each passenger requires 2 m² (Pushkarev and Zupan, 1975; Gérin-Lajoie, Richards and McFadyen, 2005; Seriani, 2018).

Density is a property used to identify crowds as static. If there are movements of crowds, there are further attributes that explain the phenomenon, which are density, speed, and flow. Fundamental diagrams of traffic flow show how these properties relate (The Highway Research Board, 1965). When density increases, passengers move slower, and when passenger density reaches a point where too many passengers restrict movement, flow begins to decrease.

Fruin has applied the concept of fundamental diagrams to pedestrians. His research led to the development of the level-of-service (LoS) concept, which describes the relationship between volume, speed, and density of pedestrian movement as presented in Figure 2-4. The concept was inspired by fluid flow and by the concept of highway capacity (Highway Research Board, 1965). This concept has also been implemented in the design of pedestrian facilities, including railway stations. A pedestrian level-of-service concept describes pedestrian concentrations in six levels-of-service from A to F (Figure 2-5), which the density for A is the lowest. A higher level-of-service (F) could restrict passenger flow and cause delays (Fruin, 1970). This prompts crowd management in the railway system, including the management of crowded trains, platforms, or stations to keep passenger volume at an appropriate level-of-service.
There is a difference between the physical characteristics of the environment and passenger perceptions of crowding, which is a psychological phenomenon influenced by situational, emotional, and behavioural factors. Cox presented a relationship between perception of crowding and stress level (Cox, Houdmont and Griffiths, 2006). Passenger perceptions are linked to the crowding factor identified by Generalised Journey Time, which considers the perceived quality of various journey segments (Department for Transport, 2022). For example, if a passenger waits on a crowded platform, this may be considered worse than riding on an uncrowded train for the same duration, resulting in a weighted penalty for the different crowding levels and journey segments. These weighting factors are derived from willingness-to-pay surveys and used in various planning processes (Cascetta, 2009).
2.2.2 Passenger congestion management approach

Passenger congestion management strategies are crucial for ensuring trains operate efficiently and safely, especially during peak hours. In addition, congestion management improves service reliability, enhances passenger comfort, decreases passenger travel time, and raises revenues (Mensink, 2017). Passenger congestion can be managed from supply (trains) and demand (passengers) sides. The management from train side has developed to the point where it is now an essential component of railway operation management. There has been a lot of study into train operation, such as train timetabling (e.g. Canca et al., 2014; Sun et al., 2014; Hassannayebi et al., 2017), train delay management (e.g. Gatto et al., 2004; Corman et al., 2017), or train traffic management (e.g. Wu, Liu and Jin, 2018; Zhao et al., 2019).

Train management has been developed to a certain level that trains could run high frequency and maximum capacity is achieved. However, passengers can sometimes be a factor that limits train operation, especially in crowded environments. Passenger congestion can cause train delays and limit line capacity. Management that includes passengers is essential for the crowded and frequent service (Rail Technology Magazine, 2016). The increase in demand for urban railways leads to the greater necessity of managing passenger crowding to improve train delays, passenger times, passenger discomfort, and accidents. The management from passenger side can be managed using techniques such as a time-varying price approach to shift demand from peak periods by varying ticket prices, station inflow control by limiting the number of passengers entering stations or platforms, and passenger regulations such as passenger flow organisation and passenger information provision (Oberlander, 2014).

There are several ranges of passenger congestion management approaches, which vary on different systems. The approaches could range from easy to difficult to apply and from low to high cost. Mensink's research offers a thorough examination of crowd management practices across all railway systems and categorizes these measures (Mensink, 2017). While alternative works, such as Wieringa (Wieringa et al., 2016) and Baelde (Baelde, 2016), also classify crowd management strategies, this research choose Hoogendoorn's approach as it covers a comprehensive range of measures. The categorization divides crowd management into four primary categories: increasing throughput, preventing blockades, distributing traffic, and limiting inflow.
According to Mensink’s research, increasing throughput is the measure to improve passenger flow in crowded areas. Various measures such as separating bidirectional flows on the path (Helbing, Farkas and Molnar, 2002), creating funnel-shaped corridors at the corner, introducing markings on the floor, placing handrails on stairs, creating fast and slow walking lanes (Grice, 2015), and temporarily changing the direction of escalators (Peter D. Kauffmann, 2011) can be taken to increase the throughput. The second strategy focuses on preventing blockades. One effective way to achieve this is by using direction gates on platforms, which can direct people to use a specific exit and avoid crossing flows (Muñoz et al., 2018). Other strategies include relocating gates, kiosks, and vending machines to strategic locations, and creating waiting zones (van den Heuvel, Dekkers and de Vos, 2012). The third strategy is distributing traffic over space or time. Information provision on train stopping position (Molyneaux, Scarinci and Bierlaire, 2017), crowdedness indicators, clear indication of less used exits, and train stopping position adjustment can help distribute the crowded (Van Den Heuvel, 2016). Finally, the fourth strategy is to limit passenger inflow to maintain a density level. This can be achieved through various measures such as using gating measures (the number of access gates to be opened), restricted direction of flow to avoid bidirectional flows (Molyneaux, Scarinci and Bierlaire, 2019), or boarding limits. These measures have been presented with details in Table 2-3.

Among various approaches to managing passenger congestion, platform management is one of the methods that can directly control dwell time on the platform. High passenger volumes on platforms can lead to longer dwell times and service delays (Kuipers et al., 2021). Some metro systems limit dwell times by closing train doors and following schedules regardless of passenger boarding and alighting flows. This approach controls dwell times by interrupting passenger flows, which is a controllable and effective way, but this can lead to passenger dissatisfaction and accidents. Therefore, many metros have to deal with dwell times in a passive way, by which train doors can be closed when passengers stop boarding and alighting. When allowing passengers to board and alight freely, dwell times are more inconsistent and could be prolonged. Hence, some metros involve platform staff to direct passengers. In addition, platform markings, organising the formation of alighting lanes (Seriani, Fujiyama and Holloway, 2016), uses of platform screen doors (Rodríguez, Seriani and Holloway, 2016) are also deployed (Kuipers et al., 2021).
Table 2-3: Crowd management measures (Mensink, 2017)

Table 3.1: Crowd management measures, the field of application, basic strategy used, characteristics (+ indicate a positive effect, - a negative effect), indication on costs (€ up to €10,000, €€ for €10,000-100,000 and €€€ for more than €100,000) and reference to case studies.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Field of application</th>
<th>Strategy</th>
<th>Characteristics</th>
<th>Cost</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>Creation of doors for each direction</td>
<td>Stations with 1 large door</td>
<td>x</td>
<td>-</td>
<td>+</td>
<td>€€€</td>
</tr>
<tr>
<td>Funnel shaped corridors</td>
<td>Large angle corners</td>
<td>x</td>
<td></td>
<td></td>
<td>€€</td>
</tr>
<tr>
<td>Separating bi-directional flows on path</td>
<td>Wide platform with bidirectional flow</td>
<td>x</td>
<td>-</td>
<td>+</td>
<td>€€</td>
</tr>
<tr>
<td>Handrails on stairs</td>
<td>Stairs wider than 6 meters</td>
<td>x</td>
<td></td>
<td>+</td>
<td>€ [61]</td>
</tr>
<tr>
<td>Gates/kiosks/vending machines relocation</td>
<td>Queue interference</td>
<td>x</td>
<td></td>
<td></td>
<td>€€</td>
</tr>
<tr>
<td>Increase attractiveness of route</td>
<td>Predetermined locations of less used exits</td>
<td>x</td>
<td></td>
<td></td>
<td>€€ [50]</td>
</tr>
<tr>
<td>Markings on floor</td>
<td>Crossings</td>
<td>x x</td>
<td>-</td>
<td>+</td>
<td>€ [61]</td>
</tr>
<tr>
<td>Arrival tracks separation</td>
<td>Simultaneous arrival of trains</td>
<td>x</td>
<td></td>
<td></td>
<td>€€</td>
</tr>
<tr>
<td>Fast and slow walking lanes</td>
<td>Longer stretches with more lanes in same direction</td>
<td>x</td>
<td></td>
<td>+</td>
<td>€</td>
</tr>
<tr>
<td>Boarding/desigthing procedure change</td>
<td>Counterflows and pressure when boarding</td>
<td>x x</td>
<td></td>
<td></td>
<td>€€ € [3]</td>
</tr>
<tr>
<td>Arrival pattern offset</td>
<td>Simultaneous arrival of trains</td>
<td>x</td>
<td></td>
<td>+</td>
<td>€€</td>
</tr>
<tr>
<td>Direction gate placement</td>
<td>Large crossing flows towards exits</td>
<td>x x</td>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Headway decrease - pax constant</td>
<td>Large flows after arrival</td>
<td>x</td>
<td></td>
<td>-</td>
<td>€€€</td>
</tr>
<tr>
<td>Object in front of bottleneck</td>
<td>Bottlenecks with arch-forming</td>
<td>x x</td>
<td></td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Information provision on train stopping position</td>
<td>Efficient use of platform length and train doors (first and last wagons)</td>
<td>x</td>
<td></td>
<td>+</td>
<td>€€ [46]</td>
</tr>
<tr>
<td>Light/music/scent</td>
<td>Efficient use of platform length and train doors</td>
<td>x</td>
<td></td>
<td>+</td>
<td>€€ [49]</td>
</tr>
<tr>
<td>Waiting areas</td>
<td>Efficient waiting or preparation for activity locations</td>
<td>x x</td>
<td></td>
<td></td>
<td>+</td>
</tr>
<tr>
<td>Only exiting/entering from station</td>
<td>Many travelers temporarily in same direction</td>
<td>x</td>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Walking time information provision</td>
<td>Inefficient distribution over routes</td>
<td>x</td>
<td></td>
<td>+</td>
<td>€€</td>
</tr>
<tr>
<td>Headway increase</td>
<td>Platforms structurally occupied</td>
<td>x x</td>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Crowdedness indicator</td>
<td>Inefficient use of train doors</td>
<td>x</td>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Train stopping position adjustment</td>
<td>Inefficient use of exits</td>
<td>x</td>
<td></td>
<td>-</td>
<td>€ [69]</td>
</tr>
<tr>
<td>Escalator direction change</td>
<td>Heavy temporary loads</td>
<td>x</td>
<td></td>
<td>x</td>
<td>€</td>
</tr>
<tr>
<td>Holding</td>
<td>Delay of vehicle</td>
<td>x</td>
<td></td>
<td></td>
<td>€ [74]</td>
</tr>
<tr>
<td>Boarding limits</td>
<td>Next vehicle nearby</td>
<td>x</td>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Getting</td>
<td>Demands exceeding capacity</td>
<td>x</td>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Delayed arrival</td>
<td>Platform occupied with passengers from previous train</td>
<td>x</td>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Manual intervention to disperse</td>
<td>Stations where problems are expected frequently</td>
<td>x x x</td>
<td></td>
<td></td>
<td>+</td>
</tr>
</tbody>
</table>
In London Underground, there are many congestion management methods. The choice of methods depends on the physical facilities and management at each station. Oberlander (2014) researched London Underground’s methods for crowd management by reviewing other research, visiting station control rooms, having discussions with staff, and conducting surveys. Types of congestion management in London Underground stations are divided into passenger regulation measures and station control measures. Passenger regulation measures are the methods used to regulate passenger flow through stations. They include arrangement of gatelines and escalators, passenger flow organisation, and information provision to passengers, whereas station control measures are used to limit or restrict passengers during a severe congestion by holding passengers at the station entrance, gatelines, escalators, or passageways (Oberlander, 2014). These measures have been presented in Table 2-4.

Table 2-4: Passenger regulation measures and station control measures

(Oberlander, 2014)

<table>
<thead>
<tr>
<th>Passenger regulation measures</th>
<th>Station control measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Configuration of gatelines</td>
<td>• Closing passageways</td>
</tr>
<tr>
<td>• Configuration of escalators</td>
<td>• Holding passengers at the top of escalators</td>
</tr>
<tr>
<td>• Organising passenger flows</td>
<td>Reducing the number of entry (UTS) gates</td>
</tr>
<tr>
<td>- Separating flows / one-way systems</td>
<td>Holding incoming passengers at the gateline</td>
</tr>
<tr>
<td>- Making routes longer than necessary</td>
<td>• Holding incoming passengers outside the station / closing entrances</td>
</tr>
<tr>
<td>• Other</td>
<td>• Non-stopping trains</td>
</tr>
<tr>
<td>- Position and legibility of signage</td>
<td></td>
</tr>
<tr>
<td>- Announcements on platforms</td>
<td></td>
</tr>
</tbody>
</table>
The Beijing Metro employs several crowd management strategies to reduce congestion and ensure passenger safety (Li, Yin and Zhou, 2014). Station control measures in Beijing are more usual. Station control methods in Beijing metro can be divided into IPFC (Inbound Passenger Flow Control) and TPFC (Transfer Passenger Flow Control), which control passengers at entrances/gates and transfer halls/corridors, respectively (Li and Zhou, 2013). IPFC can be conducted by holding inbound passengers outside station entrances, closing entrances, adjusting the number of gates in service to reduce the crowd inside the station, and segregating inflows and outflows by making entry or exit only. TPFC limits transfer passengers to lower the arrival rate at platforms. TPFC involves controlling transferring passengers by modifying the width of the corridor or making the walk longer. These approaches aim to manage passenger flow, minimize congestion, and prevent safety issues at the station-level in Beijing metro. However, as multiple stations may experience simultaneous passenger flow during peak hours, network level control is commonly implemented in Beijing metro by restricting entry to upstream stations when overcrowding occurs to improve the performance of an overall system (Xinyue Xu, Haiying Li, Jun Liu, Bin Ran, 2018). Network-level control or line-level control measures in this research are reviewed in Section 2.2.3.
2.2.3 Line-level passenger flow management

In addition to station-level congestion management, which aims to reduce passenger congestion at a single station, line-level congestion management can be implemented through the cooperative management of passengers boarding trains at each station. Line-level passenger management is the management of interactions between passengers, stations, and trains at the network level to facilitate the efficient movement of passengers and reduce congestion problems (Wang, Yan and Zhang, 2015). This current research focuses on the management of passenger flow, which is the management of the number of passengers at more than two stations cooperatively, while the number of passengers on the train is also involved.

Cooperative line-level passenger control can be conducted with stations upstream of the station with the highest passenger volume. The purpose of controlling passengers at upstream stations is to reduce the number of passengers on trains and make them less crowded prior to entering the high-passenger-volume station (more spaces on trains when arriving at the crowded station can mitigate the congestion at that station). It is one method to help reduce dwell times at the high-passenger-volume station and enhance the performance of the entire line. There are many studies developing line-level passenger flow management which is essentially the approach to controlling passengers at less crowded stations to make space on trains available for passengers at the overcrowded station (Wang, Yan and Zhang, 2015; Xu et al., 2016; Jiang et al., 2017; Li et al., 2017; Xinyue Xu, Haiying Li, Jun Liu, Bin Ran, 2018).

Managing passenger flow at multiple stations cooperatively is a complex problem. It is necessary to develop a model in order to represent passenger flow on the network. Line-level passenger flow model (LLFM) could be developed using a variety of model types, depending on the required level of complexity. The most common types of models used for problems similar to LLFM are analytical and simulation models (Bradley, Hax and Magnanti, 1977).

Much research has combined passenger flow management with train traffic management. Li developed a real-time train regulation and passenger flow control model to improve the headway regularity and commercial speed. The model included actual train departure times and the passenger load on each train and was solved by the Model Predictive Control (MPC), which is more efficient and faster than other
algorithms for managing passenger flow and train traffic in real-time (Li et al., 2017). Jiang combined a train stop-skipping approach with passenger flow control and maximised the advantages to both passengers who board the train and passengers who have been restricted time (Jiang et al., 2017). Shi brought in a passenger flow control strategy to service-oriented timetable optimisation to reduce the congestion on platforms as service-oriented timetable planning alone cannot satisfy the large travel demands in peak hours (Shi et al., 2018). A similar research framework was also conducted (Liu, Li and Yang, 2020).

The characteristics of transport demand vary, and it spreads unevenly along the line leading to different levels of congestion at each station. There are always overcrowded stations and most of them are highly likely to be interchange stations (Xinyue Xu, Haiying Li, Jun Liu, Bin Ran, 2018). In order to reasonably distribute the crowd, much research has suggested coordinated passenger flow control which basically controls passengers at upstream stations to make spaces on trains available for passengers at the most crowded stations in order to relieve the congestion. Wang suggested that passenger control in coordination with other stations on the line could be effective. The research developed a mathematical programming method to decide entry flow rates for the Beijing Subway in China and aimed to reduce the number of passengers remaining on the platform and balance the ratio of passengers boarding at each station (Wang, Yan and Wang, 2015; Wang, Yan and Zhang, 2015). Xu also developed a dynamic passenger flow control model which includes controlling both inbound and transfer passengers entering from multiple stations and multiple lines at the same time. These dynamic interactions make this model complex and distinctive in this research area. The model developed is a bi-level programming which optimises system performance with different flow control strategies, then considers passengers’ route choice behaviour under a given flow control strategy. In addition, this research addressed the phenomenon that crowding is related to Origin-Destination characteristics. Some stations may have low demand, but the station can be crowded if trains are full at upstream stations (Xinyue Xu, Haiying Li, Jun Liu, Bin Ran, 2018). Overall, results from previous research showed that when stations control passengers independently of other stations, it could lead to overcontrol, and that the average number of passengers waiting on the platform is irregular and at peak times could reach...
an unsafe level. When stations control passengers in a coordinated manner, the average number of passengers waiting on the platform remains below the congested level.

Karekla built a simulation model to evaluate an increased level of service of the whole line from the reduction of train dwell time. When step height between platform and train, and train door width have been improved with the purpose of accessibility, their indirect benefit is the reduction of train dwell time (Karekla & Tyler 2012). This research applied the results from Fujiyama et al. (2008) and estimate the dwell time that would be reduced from the investment project. London Underground’s Train Service Model (TSM) is another useful line-level simulation tool to evaluate LLFM. TSM simulates the movements of consecutive trains on London Underground’s lines and also includes passenger movements and train dwell time. The model reports the total weighted journey time to evaluate all passengers benefit on the whole line and it also presents crowding on trains and platforms (Winslett, 2017). Methods for developing models for LLFM are selected based on the complexity of the problems and the level of detail required. Table 2-5 compares the models that have been used to develop LLFM.

<table>
<thead>
<tr>
<th>Research</th>
<th>Management methods</th>
<th>Model types</th>
<th>Model objectives</th>
<th>Solution approaches</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wang et al. (2015)</td>
<td>Passenger control</td>
<td>Mathematical model (Linear Programming)</td>
<td>Minimise the average passenger delay</td>
<td>Use algorithm in the LINGO software.</td>
</tr>
<tr>
<td>Xu et al. (2018)</td>
<td>Passenger control</td>
<td>Mathematical model (Bi-level Programming)</td>
<td>Minimise the average of passenger time in the system with an acceptable congestion level on platform</td>
<td>Successive averages (assignment problem) embedded into genetic algorithm (search control strategy)</td>
</tr>
<tr>
<td>Research</td>
<td>Management methods</td>
<td>Model types</td>
<td>Model objectives</td>
<td>Solution approaches</td>
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<td>------------</td>
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<td>-----------------------------------------</td>
<td>---------------------------------------------------------------------------------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td>Li et al., (2017)</td>
<td>Passenger control and Train regulation</td>
<td>Mathematical model (Quadratic Programming)</td>
<td>Minimise the delay from train timetable, headway deviation, and the effect of control action</td>
<td>Model Predictive Control (MPC)</td>
</tr>
<tr>
<td>Shi et al., (2018)</td>
<td>Passenger control and train timetable optimisation</td>
<td>Mathematical model (Integer Linear Programming)</td>
<td>Minimise total passenger waiting time at all stations</td>
<td>Heuristic algorithm and CPLEX solver</td>
</tr>
<tr>
<td>Karekla &amp; Tyler (2012)</td>
<td>Evaluate train dwell time reduction benefit to the line level of service</td>
<td>Macroscopic simulation model</td>
<td>Evaluate overall cycle time of trains</td>
<td>Use a spreadsheet</td>
</tr>
<tr>
<td>TSM</td>
<td>Simulate service planning, Test timetable, Evaluate capacity upgrade project</td>
<td>Discrete event simulation model</td>
<td>Evaluate passenger weighted journey time and crowding effects</td>
<td>FORTRAN programming language</td>
</tr>
</tbody>
</table>
2.3 Summary of the literature review

The summary of the literature review is framed into two themes according to the research focus, which are train dwell time and passenger congestion. Each section starts with a summary of the current studies, then the research gaps are identified, followed by the current research’s contributions to address the gaps.

2.3.1 Summary of train dwell time research

Overall, some previous studies have developed the understandings of general dwell time factors. This current research focuses on impacts of passenger-related factors on the train dwell time and highlights the importance of developing the research regarding train dwell time in the congestion environment. Previous studies of train dwell time have been conducted by experiments, by observations from real case, or by collecting data from the available data sources. Some of the research focused on identifying the critical factors impacting dwell time, while some research used dwell time factors to develop dwell time prediction model. Dwell times are naturally complicated and have many factors involved. Dwell times, especially in high passenger volume cases are sensitive to passenger movements and contain a high degree of variation, making them complicated to explain with an equation.

The current gaps in the dwell time evaluation approach are that:

- Dwell times are difficult to accurately predict in situations with a high passenger volume using the existing dwell time models. While the current approach to setting a dwell time is based on an inaccurate dwell time prediction model, it is important from a reliability point of view to set a dwell time that most services can meet.
- Considering dwell times in stochastic, some studies fit dwell time data with the theoretical distribution function. The functions were mainly used as model inputs for other analyses. To the best of our knowledge, there are few studies assessing dwell time distribution by considering different levels of passenger volume. In the high-passenger-volume stations where dwell times are random and show significant variations, it is important to understand how dwell times spread along the different passenger volume levels. Distributions of dwell times for different passenger volume levels can provide a comprehensive understanding of dwell times at stations with high passenger volumes.
This leads to the need of a new dwell time evaluation approach proposed in this research which:

- This research proposes predicting the probability of dwell time delay rather than the average or point estimations, which could provide greater precision. With the probability of dwell time delay evaluation approach, the target dwell time is set first, and then the probability of train delay is calculated using the dwell time delay probability distribution function. This approach is appropriate for the high-passenger-volume stations, where there is a high risk to the service performance if dwell times are delayed.
- This research develops the bivariate dwell time delay function which gives the likelihood of trains having the certain amount of passenger volume being delayed over than the certain amount of delay in second. This bivariate distribution function has a huge benefit on both timetable planning and passenger management in the line-level perspective.
- The new dwell time evaluation approach uses the developed bivariate dwell time delay function to predict the probability of delay, together with the consequences of dwell time delay corresponding to the duration of delays to evaluate the risk of dwell time delays at the high-passenger-volume stations and obtain the solutions to the research problems.

2.3.2 Summary of passenger congestion management research

Most of the passenger congestion management procedures involve making judgments at the individual station level to reduce congestion and its impacts. The primary objectives of these procedures are to minimize crowding, prevent unsafe events, and avoid blockages at the individual station. During peak hours, many stations may be crowded at the same time; therefore, line-level passenger management is necessary. Passenger flow management at a line-level has been researched and applied in many metros. Many studies focused line-level passenger flow management on distributing and balancing the crowd among stations and found that coordinated passenger flow control can reasonably allocate passengers. Most of the studies assumed that services run according to the timetable. In fact, the number of passengers in the system directly relates to train dwell time and leads to train delays and the limitation of line capacity.
The gap in the existing line-level passenger flow management research is that:

- The existing line-level passenger flow management research has not taken account of the impacts of passenger congestion on dwell time delays and the potential reduction in the number of trains run per hour.
- The existing line-level passenger flow model is complicated and does not focus on improving dwell time delays. Most of the current models focus more on finding better ways to optimise passenger flow at each station or solving the problem in real time. A dwell time prediction model is included in some simulation models to predict the amount of dwell time; however, the model lacks accuracy to predict dwell time and takes longer to compute. There is a need for a model that specifically focuses on solving passenger congestion and dwell time delay problems.

The new dwell time evaluation approach quantifies the impacts of dwell time delays on passengers on the whole line, and the analytical model includes all major consequences of dwell time delays, such as knock-on delays, the gap between trains, and the change in headway after the delay. The model suggests the line-level passenger flow management strategy which could improve dwell time delays at high-passenger-volume stations and improve the whole line service performance. This research put passenger congestion management into a pre-planning management system in which stations on the line are arranged to manage passenger flow cooperatively in order to reduce the crowding on trains before arriving at the critical stations. This pre-planning passenger control approach would make passenger control foreseeable compared to the current passenger control approach which deploys the control reactively and causes uncertainties to passengers.
Chapter 3
Methodology

This chapter provides an overview of the research methods, as well as descriptions of the case study and data employed in this research. This research is a data-driven investigation that focuses on evaluating train dwell times in crowded situations when passenger congestion at platforms causes train dwell time delays and limits the capacity of the whole line service. To achieve this, the research uses a case study approach, with the Victoria Line of the London Underground serving as the main focus of analysis. The selection of the Victoria Line as the case study was made because it is one of the busiest lines on the London Underground and is known to experience significant overcrowding at certain times. Additionally, the Victoria Line has load weight data, which provides an opportunity for the research to evaluate dwell times with real-time passenger numbers on trains. The exclusive track use of the Victoria Line could also make the analysis less complicated. The study period chosen for this research is when the line is at its busiest, which is ideal for capturing the impact of passenger congestion on train dwell time delays. More details of the case study and data descriptions are provided in this chapter.

3.1 Research methods

This research proposes the dwell time evaluation method, particularly for the high-passenger-volume situation. The evaluation method introduces a new concept for dwell time evaluation, which considers the estimation of dwell time as the probability of delay rather than its average value. In addition, the effects of various delay durations are quantified. With the aim of the research being to improve dwell time delays, the evaluation method is then applied to determine the optimal passenger control strategies and dwell time settings that could maintain a balance that benefits passengers on the whole line. The research method consists of four steps which the full analysis will be provided in Chapter 4 to Chapter 7:
1. Benchmark dwell times at high-passenger-volume stations among other stations on the line. The objective of this is to classify stations based on their demand profiles and identify the high-passenger-volume stations whose characteristics could lead to long dwell times. This part is presented in Chapter 4.

2. Investigate and develop a dwell time delay perspective to evaluate dwell times at high-passenger-volume stations. This is intended to demonstrate the inaccuracy of the current dwell time evaluation approach and to propose an evaluation approach that considers the probability of dwell time delay. The approaches are covered in Chapter 5 and Chapter 6.

3. Evaluate dwell times with the risk of dwell time delays. The risk of dwell time delays is comprised of two components: a dwell time delay function (derived from previous step) and the consequences of delay, whose impacts are quantified based on passenger time for various delay durations. The optimal solutions to improve dwell time delays are derived from this part which is presented in Chapter 7.

4. Find optimal solutions to improve dwell time delays using the proposed dwell time evaluation approach. Several scenarios are tested, and the best-case scenario is provided in Chapter 7.
3.1.1 Benchmarking high-passenger-volume stations

First, this research uses Data Envelopment Analysis (DEA) to benchmark dwell times at high-passenger-volume stations with other stations on the line to evaluate the efficiency of the dwell time considering the passenger volume that can be delivered. The benchmarking of stations along the line could help understand the characteristics of the stations based on their demand profiles and how demand profiles influence a train’s dwell time. The benchmark approach classifies stations according to their demand profiles and identifies characteristics that could lead to long dwell times.

The reason for using DEA is that different station demand profiles make the dwell time evaluation complicated, and the passenger volume factors are unable to simply add up due to the complex interrelationships of the factors. DEA differentiates passenger volume factors when evaluating performance. The benchmarking of 16 stations on the Victoria line is conducted (the details of the case study are given in the next section). The demand data is derived from RODS, and the dwell time is derived from NETMIS. The data are described in Section 3.3. This analysis employs a deterministic approach to initially assess the overall demand and dwell times at each station. The average values are used to represent demand and dwell times in the analysis. Excel's solver is used to solve DEA using the CCR model.

After benchmarking dwell times of stations along the line, the study highlights the issue at high-passenger-volume stations and identifies characteristics of high-passenger-volume stations that will be considered further in this research.
3.1.2 The probability of dwell time delay

The current perspective of the dwell time evaluation is the prediction of the dwell time’s representative value for use in timetable planning, capacity planning, or operational management. This section evaluates the dwell time data of the high-passenger-volume station with the existing dwell time models. Data analytics is a major approach used to intensively explore dwell times and passenger volume at the high-passenger-volume station. The approaches include descriptive statistics, inferential statistics, and regression analysis. The analysis investigates the passenger volume factors affecting dwell times and demonstrates the variability of dwell times in the actual dataset, which makes it difficult to represent the current dataset with existing dwell time prediction models.

An evaluation approach that considers the probability of a dwell time delay is proposed. The approach is moving from deterministic (point estimation) to stochastic by predicting a probability instead of the average or representative values, which is able to characterise uncertainty and variability situations (United States Environmental Protection Agency, 2022). In fact, the target dwell time that trains should achieve at the high-passenger-volume station has already been established. With this concept, the target dwell time is determined first, followed by the prediction of the probability of achieving. The concept is suitable for the case when the scheduled dwell time is limited and exceeding the limit has significant consequences.

A huge dataset is available on the London Underground system, allowing this research to identify dwell time distributions for different load levels and develop the bivariate dwell time delay function. This distribution function gives the probability of a train having a certain passenger volume level being delayed by a certain length of time. This part mainly uses the data from NETMIS. The data has been divided into two datasets. One for developing the dwell time delay function and another for validating it. The dwell time delay function derived from this part is used together with the consequence function to evaluate the risk of dwell time delay in the subsequent step.
3.1.3 The risk of dwell time delay

An analytical model is developed to represent a new dwell time evaluation concept which is called the risk of dwell time delay in this research. The risk of delay is calculated from the probability and consequences of dwell time delay for each length of delay, where the consequences of delay are quantified based on passenger time for various delay durations. The risk of dwell time delay is calculated for each scenario, and the results of each scenario are compared to find the best-case scenario.

This section takes the approach of developing the model to represent the real situation and to support decisions. This research employs an analytical model that is entirely represented in mathematical terms. An analytical model is simple and easy to understand but can be used in complex decision situations (Bradley, Hax and Magnanti, 1977). Apart from a mathematical model, a simulation model is another option for developing a line-level passenger flow model. A simulation model is an empirical analysis and can represent the real world with uncertainties, but a simulation model will take longer to compute and will not generate an optimal answer. In addition, more variables are needed to complete the simulation model, and some of these variables may not be related to the study (Bradley, Hax and Magnanti, 1977).

Passenger weighted journey time is used to quantify the consequences of dwell time delay, which it is an evaluation approach used in the London Underground to evaluate the benefits of a project. It is also appropriate to use in this research as the major impacts of dwell time delay are on passenger delay. Using passenger weighted journey time allows for the conversion of all major impacts from dwell time delay into passenger time. An analytical model of passenger weighted journey time includes all major consequences, including knock-on delay, the gap between trains, and the change in headway after the dwell time delay.

Lastly, several scenarios are tested. This analysis takes the empirical approach, which increases one variable by a certain value and substitutes the variable into the analytical model. The total of 42 scenarios is tested, and the best-case scenario is determined by comparing the outcomes of each scenario. The best-case scenario enables the planning of passenger control strategies at the upstream stations and the planning of dwell time margins in the timetable.
3.1.4 Improving dwell time delay

This section demonstrates the application of the risk of dwell time delay evaluation approach to improve dwell time delays at a high-passenger-volume station with the objective of minimising total passenger weighted journey time on the entire line. The analysis is first used to determine the optimal passenger control strategy by evaluating various train load levels. Second, it evaluates the various lengths of dwell time specified in the timetable. The longer the dwell time set in the timetable, the better it could absorb the delay and avoid the knock-on delay, but it could also limit the service frequency. The strategy aims not only to improve dwell time delay at the high-passenger-volume station, but also to improve the performance of the entire line.

The current passenger control strategy in the London Underground system is only deployed when stations are overcrowded and can cause accidents. This current passenger control strategy is reactive, which causes uncertainties for passengers. The concept of passenger control strategy in this research is a cooperative and proactive way in which passenger control is planned in advance. The passenger control strategy being considered in the analysis is a coordinated passenger flow control strategy through the management of levels of passenger crowding on trains.

The current dwell time setting for the London Underground uses the 60th percentile of historical data as a scheduled dwell time. This research examines the consequences of various dwell time settings by considering aspects such as demand and capacity, the probability of not achieving the scheduled dwell time, and the consequences of not achieving the scheduled dwell time. The evaluation model determines the appropriate length of dwell time setting by balancing the train knock-on delays caused by setting values too low and the delay from long headway caused by setting values too high.

In addition to determining passenger control strategy and planning dwell time in the timetable, the risk of dwell time delay evaluation approach could also be used for capacity planning, rolling stock planning, staff planning, etc. This dwell time evaluation method is designed to incorporate the probability and consequences of dwell time delay as an indicator for determining multiple planning strategies.
3.2 Case study

This research focuses on problems that are prevalent in many metros when passenger congestion causes train dwell time delays at stations and limits the capacity of the whole line service. This research uses London Underground's Victoria line as a case study, but the methods employed are intended to be applicable to other metro lines as well. This chapter describes the case study's characteristics and the selection of a case study. Then, the current passenger crowding situation, its effect on train dwell time at the case study station and on the entire line are described. Lastly, the current passenger congestion management are presented.

3.2.1 An overview of the case study

The London Underground was the first underground passenger railway in the world. The London Underground consists of 11 lines that cover 402 kilometres and serve 273 stations. In 2019, the system served 1,384 million passenger journeys and operated 85 million kilometres, making it the seventh longest metro system in the world (Transport for London, 2019). Four of the eleven lines are the sub-surface network, which railway tunnels are located just below ground level. The sub-surface lines include the Circle, District, Hammersmith & City, and Metropolitan lines. The trains and tunnels of the sub-surface network are larger than those of the deep-tube lines. Sub-surface lines share stations and tracks with each other. While the Bakerloo, Central, Jubilee, Northern, Piccadilly, Victoria, and Waterloo & City lines are deep-tube network, which railway tunnels lay deeper below ground level. Deep-tube network trains and tunnels are smaller than those of the sub-surface network and generally have exclusive track use (Croome and Jackson, 1993). Figure 3-1 depicts the proportion of London Underground journeys on each line. The Northern, Victoria, Central, and Jubilee lines have the highest and almost the same proportion of journeys. Considering the number of stations on these lines, there are 52, 16, 49, and 27 stations, respectively (RODS, 2017).
Figure 3-1: Proportions of ridership on each line of the London Underground (RODS, 2017)

Victoria line was chosen as the case study as it is one of the busiest lines on the London Underground (Transport for London, 2019). Victoria line is one of the three lines with the highest number of journeys as presented in Figure 3-1, despite having the smallest number of stations. It is the line with the loadweight data that allows this research to evaluate dwell times with the real-time number of passengers on trains. The analysis on the Victoria line could be less complicated as it has exclusive track use. Some of the London Underground's lines share tracks with other lines, making the analysis subject to uncertain variables. In addition, the Victoria line has already transitioned to an ATO (Automatic Train Operation) system in which trains' run-times are more stable; therefore, the variation in trains' run-times can be excluded from the analysis. Figure 3-3 depicts the Victoria line (Blue line) on the map of the London Underground. Victoria line, as a deep-tube line, which was opened 50 years ago with narrow platforms, has a challenging task to manage passenger congestion on small trains and platforms to avoid accidents and handle the passenger flow efficiently (Transport for London, 2014). Currently, the Victoria line serves 16 stations running from Brixton in the south to Walthamstow Central in the north. Comparatively to other
lines in the London Underground system, this line provides high frequent service and short journey times, making it popular for both commuting and leisure purposes (Transport for London, 2019).

Figure 3-2: Victoria line on the London Underground map (Transport for London, 2022)

Figure 3-3: Victoria line map (Transport for London, 2022)
Based on the previous studies on the Victoria line (Oberlander, 2014; Wong and Key, 2014; Winslett, 2018), it was found that several crowded stations (defined as having high passenger volume for boarding and alighting) have higher dwell times compared to other stations in the same direction. These stations could become the critical stations that limit the line's service performance (terminal stations where trains wait longer for new journeys have been excluded). These stations include Victoria in the Northbound direction during the AM peak, King’s Cross St. Pancras in the Southbound direction during the AM peak, and Oxford Circus in the Northbound direction during the PM peak. Figure 3-3 highlights the key stations on the Victoria line map.

Oberlander's analysis of congestion management on the London Underground highlights that Victoria station frequently implements station control measures, including holding passengers at both gatelines and outside the station because the station wasn't built to handle high demand (Oberlander, 2014). Furthermore, as Victoria station is connected to a National Rail terminal, a large number of passengers arrive at the station via National Rail services, increasing the overcrowding issue. Given these factors, the study has selected the morning peak hours of the Victoria Line's northbound service for further analysis.

Considering Victoria station, one of the most crowded stations in the London Underground system, is a central station where the Victoria line, Circle line, and District line are connected (Lawrence-Jones, 2020; Statista Research Department, 2023). It is also an underground station connected to a National Rail terminal. 86% of the passengers accessing Victoria station come from the National Rail station (Transport for London, 2019) and are highly likely to arrive in large numbers, giving Victoria station a challenging task to manage the crowding when large groups of passengers from the National Rail station arrive at the same time. Prior research has examined and considered Victoria station to be the overcrowded station, with frequent entrance closures required, especially during the morning peak on the northbound platform. In addition, platform congestion reduces passenger boarding and alighting rate, causing trains to become delayed at Victoria station's platform (Oberlander, 2014; Wong and Key, 2014; Smith, 2016). These circumstances would be described in Sections 3.2.2 and 3.2.3.
Regarding the rolling stocks being used on the Victoria line, the rolling stocks used on the Victoria line are 2009 tube stocks built by Bombardier Transportation UK. These rolling stocks use radio based ATO and ATC system. Vehicle types on a train include of type A: driving motor car (DM), type B: trailer car (T), type C: non-driving motor car (NDM), type D: uncoupling non-driving motor car (UNDM). Table 3-1 presents the related information on Victoria line’s rolling stocks which is used in the analysis in this research. Rolling stocks are another factor that determines the duration of dwell time, service capacity to carry passengers, platform crowding level, etc. Figure 3-4 shows rolling stocks’ interior and Figure 3-5 to Figure 3-7 show dimensions of rolling stock type A to type D.

Table 3-1: Victoria line’s rolling stock specifications
(Source: Rolling stock data sheet, 2011)

<table>
<thead>
<tr>
<th>Rolling Stock Information</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of trains</td>
<td>47 trains</td>
</tr>
<tr>
<td>Number of cars per train</td>
<td>8 cars</td>
</tr>
<tr>
<td>Number of seats per car</td>
<td>36 seats</td>
</tr>
<tr>
<td>Number of standard-size doors per car per side (1.6-metre width)</td>
<td>2 doors</td>
</tr>
<tr>
<td>Number of narrow doors per car per side (0.8-metre width)</td>
<td>2 doors</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Standing Capacity</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum observed standing capacity (5 customers per m²)</td>
<td>734 passengers</td>
</tr>
<tr>
<td>Maximum full load standing capacity (6 customers per m²)</td>
<td>876 passengers</td>
</tr>
<tr>
<td>Theoretical crush standing capacity (7 customers per m²)</td>
<td>1028 passengers</td>
</tr>
</tbody>
</table>
Figure 3-4: Victoria’s rolling stock interior (Rolling stock data sheet, 2011)

Figure 3-5: Dimensions of rolling stock type A (Rolling stock data sheet, 2011)
B & C Car

Figure 3-6: Dimensions of rolling stock type B and Type C
(Rolling stock data sheet, 2011)

D Car

Figure 3-7: Dimensions of rolling stock type D (Rolling stock data sheet, 2011)
3.2.2 Dwell time and passenger crowding situations

Victoria line is a high frequency service line compared to other metro lines. The line has adopted an automatic train operation system to achieve a shorter headway. Technically, the line is scheduled to run 36 trains per hour in peak time; however, it is sometimes unable to achieve this in practice because most stations require longer dwell times than the threshold.

Figure 3-8 presents the average train time spent at the stations on the northbound service of Victoria line at the busiest morning peak time (8:00-9:00 AM), which is the time when passenger volume is at its highest and trains are often delayed. The main components of the time are composed of:

- Average run out run in time (RORIT) or the train reoccupation time, which mostly depends on signaling and train performance (Blue boxes). RORIT is operational time which is the time for the leading train to run out (RO) and the time for the following train to run into the platform (RI).
- Average dwell time, which is the train stop time at the platform (Red boxes)
- Dwell time’s standard deviation, which is mostly from the inconsistency of boarding and alighting time (Green boxes)
- For lines with automatic train operation, a standard deviation of RORIT is disregarded

When a line is designed to operate 36 trains per hour, the average amount of time a train needs to spend at each station should not exceed 100 seconds. Figure 3-8 shows that most of the stations take more than 100 seconds (indicated as a red line in the figure). Victoria and Seven Sisters stations require the longest time, and these stations could be considered the bottlenecks on the line. The figure illustrates that a 36 trains per hour operation is not achievable because most stations require longer times than the threshold. Focusing on the train dwell time aspect, Victoria station has significantly longer dwell times compared to other stations. The case at Victoria station is challenging as it has to handle high passenger volume and at the same time has to keep the dwell times within the threshold. With the intention being to increase service frequency to 40 trains per hour to support future demand, the necessity to reduce dwell times at Victoria station is more apparent.
Figure 3-8: The breakdown of time at each station on the northbound Victoria line (Transport for London, 2019)

Figure 3-9 and Figure 3-10 show passenger crowding on the platform of Victoria station and on the train. Speaking in terms of dwell time factors reviewed in the previous Chapter 2, it is obvious that all passenger volume factors are high (passengers boarding, passengers alighting, passengers on the train, and passengers on the platform). These circumstances result in passenger obstructions and extremely long dwell times at the station. When passengers are crowded, it causes a longer train dwell time which leads to train delays. Then, passengers accumulate and there is more crowding. Transport for London’s research also investigated these interactions between passengers, platforms and train service reliability, and reported that there are many stations in the system confronted with train service disruptions due to high levels of interaction between passengers on platforms (Wong and Key, 2014). Much research has addressed this problem (Harris, 2005; Railway and Transport Strategy Centre, 2013; Smith, 2016). This makes Victoria station become the station that determines the line capacity because of the long dwell time at the platform. This is because Victoria station is a high passenger volume station and the trains arriving at Victoria station are often full, causing high interactions between passengers (Oberlander, 2014).
Figure 3-9: Passenger crowding on the train and the platform at Victoria station
(Source: Tolga Akmen, LNP)

Figure 3-10: Passenger crowding at the platform of Victoria station
(Source: Oli Scarff)
3.2.3 Current passenger congestion management at the case study station

Victoria station has deployed both passenger regulation and station control. Passenger regulation, which aims to manage passenger flow efficiently, has been deployed at gatelines (arrangement of entry and exit gates), escalators (up/down escalators), and passageways (arrangement of one-way flows and lengthened routes). For the station control approach, which aims to restrict or limit passenger movements, Victoria station has controlled passengers at station entrances, at gatelines, at the top of escalators, and in the passageways before moving to the platform (Oberlander, 2014). Victoria station was one of the stations that deployed station control measures the most. Although station control measures are not preferred by passengers, they have to be deployed when station supervisors consider that there are severe congestions inside the station or on one of the platforms which may lead to accidents and train delays. When station control is deployed, no passenger is allowed to enter the station/platforms for a certain period. The research found that station controls were deployed 39 times at Victoria station during 12 day observations at the morning peak (Oberlander, 2014). When the station or platform is overcrowded, it must be closed for entering and many passengers have to wait outside the London Underground system’s premises, leading to a long queue extending to the National Rail’s premises as shown in Figure 3-11.

![Figure 3-11: Passengers queuing outside Victoria underground station](Source: Tolga Akmen, LNP)
Before the station expansion project was finished in 2018, Victoria station was notable as the station which deployed the exit-only-station-control (EOSC) method the most (Oberlander, 2014). EOSC is a method to control passengers by keeping them outside London Underground’s premises. Apart from controlling passengers outside the station, there are also other passenger control points within the station as shown in the blue boxes in Figure 3-12.

![Figure 3-12: Passenger Control points at Victoria station (Oberlander, 2014)](image)

This research gathered passenger congestion management information through field observations during August 2019, which is when the expansion project is already finished. Figure 3-13 illustrates Victoria station layouts before and after the expansion project. The light green area on the figure shows the area which has been newly built in the expansion project. A new station entrance has been opened to distribute the crowd. However, the entrance from Victoria National Rail is still the area with the highest passenger volume. Therefore, a one-way flow system has been implemented for accessing and egressing from this entrance to avoid interactions between passengers which could lead to accidents and congestions inside the stations. The blue and red
arrows in Figure 3-13 show the paths for accessing and egressing from the northbound platform of the Victoria line. Passengers entering the platform may have to walk a longer distance, but this is one of the strategies to mitigate passenger flow to the crowded platform (BBC London, 2018; Mansfield, 2018). However, if the platform is too crowded, station supervisors still have to temporarily deploy passenger flow control at the passageways or the top of escalators (Control Point C and D in Figure 3-13, respectively) until the congestion is relieved.

The station expansion project was launched to increase the space inside the station to accommodate more passengers and a one-way flow system was implemented to avoid interactions between passengers inside the station (BBC London, 2018; Mansfield, 2018; Step Free London, 2018). However, passenger volume at the northbound platform during peak-time was still crowded and the trains arriving at Victoria station were always filled to capacity, therefore the issue regarding the extended dwell time at Victoria station was not yet solved.

Figure 3-13: Victoria station layout before and after the extension project
(Source: https://www.ianvisits.co.uk)
Apart from the aforementioned passenger management strategies, passengers are also controlled at the station entrances and the entry gates (Control Point A and B in Figure 3-13, respectively) when the controls before the platform are not enough. The passenger control strategy at Victoria station will begin to be implemented from the inside to the outside (from platform to the entrance). First, the passengers on the platform will be managed, and if the situation remains congested, the strategy will shift to the passageways, gatelines, and then the entrances. There is also a control room where the CCTV screens and Trackernet system (TfL’s software to observe the positions and the passenger loads of trains in real-time) are monitored by 2-3 station supervisors per shift (Figure 3-14 and Figure 3-15) to organise passenger flow inside the station. The current objectives of passenger flow management at Victoria station are to reduce the crowding level within the station, to avoid unsafe events, and to avoid any blockages of passenger flow.

Figure 3-14: Monitor screen at Victoria station’s control room

Figure 3-15: TfL’s Trackernet system
3.3 Descriptions of the datasets

This research is data-driven research, which explores data to derive scientific findings or interesting outcomes. Data-driven research has gained popularity in numerous scientific disciplines where large amounts of data are available. The body of knowledge is developed based on discovered patterns or relationships in the available data (Maass et al., 2018). Big data enables the consideration of an entire population rather than a sample of data, reduces the cost of data acquisition (in comparison to traditional modes in which designing studies is required for collecting data to prove theory-driven research assumptions), and enables the exploration of many more correlations from the available data (Harappa, 2020). This research uses actual operation data from the London Underground database to gain insights on dwell time data, develop a dwell time evaluation method, and obtain solutions to the research problem.

The analysis in this research was based on two datasets from the London Underground’s database, which are NETMIS and RODS. NETMIS is a database of actual operation data from London Underground's train movement database, which includes information about each train's movement through stations. The actual and scheduled dwell times are given in NETMIS. RODS, or Rolling Origin Destination Survey, is passenger demand data used in this research that provides origin-destination data on the number of passengers for every pair of stations. RODS is used to estimate the number of passengers boarding or alighting at each station along the line.
3.3.1 NETMIS database

NETMIS contains actual operation data from London Underground’s train movement database, which consists of the data of each train movement through stations. Each row of the data from NETMIS represents one train movement through one station. The arrival/departure times whenever a train arrives and leaves a station are recorded. The samples of the data format obtained from London Underground’s database is presented in Table 3-2. The figures in the table show the sample dataset obtained from NETMIS. Each row of the data represents one train movement through one station. The date, train number, trip number, trains’ arrival/departure time whenever a train arrives and leaves a station are recorded.

Table 3-2: A sample of NETMIS data source

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<tr>
<th>Date</th>
<th>Train Number</th>
<th>Trip Number</th>
<th>Actual Arrival</th>
<th>Actual Departure</th>
<th>Station</th>
<th>Scheduled Arrival</th>
<th>Scheduled Departure</th>
<th>Scheduled Dwell</th>
<th>Load Status</th>
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<td>07:08:43</td>
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<td>07:08:40</td>
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<td>07:10:46</td>
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<td>07:10:45</td>
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<td>78</td>
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<td>38</td>
<td>75</td>
</tr>
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</tr>
</tbody>
</table>
The analysis in this research calculates the actual dwell time by subtracting the train's actual arrival time from its actual departure time. The obtained dwell time consists of passenger boarding and alighting time in addition to other time. This study examines the case based on the assumption that there are no traffic issues and trains depart stations as soon as passengers have completed boarding and alighting. The data from the train movement data also provides the live load of a train as a percentage. A train with a 100% load has approximately 1,035 passengers on it. According to the Victoria line's rolling stock specifications provided in Section 3.2.1, it is roughly equal to the maximum "standing" capacity of 5 passengers per m².

Figure 3-16 shows the process of NETMIS data preparation. By subtracting the arrival time from the corresponding departure time, the train dwell time at the station is obtained. The load on a train before arriving at a station can be obtained by identifying the train, the trip and the station numbers which help track the train moving from one station to another. The difference in the load before and after a train leaves any specific station implies passenger movement in and out of the train. The number of passengers boarding and the number of passengers alighting each individual train can be estimated if the passenger alighting rate at each station is provided. The alighting rate is derived from the Rolling Origin Destination Survey (RODS) data, which sums the number of passengers travelling to each Origin-Destination pair in every 15 minutes. RODS allows estimation of the number of boardings, alightings, and passengers on trains per 15-minute interval. The description of RODS is provided in Section 3.3.2. This research uses the average passenger alighting rate during the focused period.

The train data (NETMIS) of the morning peak time of the Victoria Line's northbound service on weekdays was extracted for study as this is the busiest time on the northbound line (the justification for the selection of the case study is provided in Section 3.2). The data from November 2018 to March 2019 totalling 143,221 rows was extracted. Python3 was used as a data preparation tool because it allows for rapid processing of the large amount of data extracted from the NETMIS dataset.
3.3.2 RODS survey data

The Rolling Origin Destination Survey (RODS) is an annual survey conducted by Transport for London to collect passenger information, including origin and destination stations, travel purposes, interchange stations, etc. This research used RODS data to obtain passenger travel demand for Origin–Destination (OD) matrices. RODS provides the number of trips between station pairs, thereby providing the number of passengers travelling to each Origin-Destination pair every 15 minutes. Table 3-3 provides an example of a 15-minute interval's data format. The origin station is represented in the first column, and the destination station is represented in the first row. The values in the table are the number of passengers who travelled from the origin station to the destination station in that 15-minute interval. With the data in Table 3-3, it allows the estimation of the number of boardings, alightings, and passengers on trains per 15-minute interval.
Table 3-3: A sample of RODS survey data

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<th>VUX</th>
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<th>VIC</th>
<th>GPK</th>
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<td>675</td>
<td>321</td>
<td>485</td>
<td>33</td>
<td>96</td>
<td>370</td>
<td>0</td>
</tr>
</tbody>
</table>

By summing the number of passengers on rows or columns, the number of passengers to board or alight each station is obtained. Figure 3-17 demonstrates the approach to get the number of passengers boarding trains at station C of the northbound service in a 15-minute interval by summing the values highlighted in green which are all passengers who would travel to the downstream stations of station C. The number of passengers alighting trains at station E of the northbound service in a 15-minute interval is also obtained by summing the values highlighted in red which are all passengers who board trains at the upstream stations (station A to D) and alight at station E.
The RODS data of the morning peak time of the Victoria Line's northbound service on weekdays was extracted. The data consists of 12 intervals (every 15 minutes from 7:00 a.m. to 10:00 a.m.), and the average number of passengers boarding and alighting during those 12 intervals was used to represent passenger travel demand for the morning peak time (the justification for the selection of the study period is provided in Section 3.2).

<table>
<thead>
<tr>
<th>Destination</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>0</td>
<td>5</td>
<td>12</td>
<td>25</td>
<td>57</td>
<td>95</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>0</td>
<td>12</td>
<td>37</td>
<td>68</td>
<td>20</td>
</tr>
<tr>
<td>C</td>
<td>12</td>
<td>7</td>
<td>0</td>
<td>6</td>
<td>49</td>
<td>35</td>
</tr>
<tr>
<td>D</td>
<td>17</td>
<td>5</td>
<td>4</td>
<td>0</td>
<td>70</td>
<td>125</td>
</tr>
<tr>
<td>E</td>
<td>43</td>
<td>16</td>
<td>23</td>
<td>66</td>
<td>0</td>
<td>240</td>
</tr>
<tr>
<td>F</td>
<td>30</td>
<td>3</td>
<td>17</td>
<td>41</td>
<td>136</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 3-17: The demonstration of the approach to estimate the number of passengers from RODS survey data.

The RODS data of the morning peak time of the Victoria Line's northbound service on weekdays was extracted. The data consists of 12 intervals (every 15 minutes from 7:00 a.m. to 10:00 a.m.), and the average number of passengers boarding and alighting during those 12 intervals was used to represent passenger travel demand for the morning peak time (the justification for the selection of the study period is provided in Section 3.2).
3.3.3 Data limitations and assumptions

There are some limitations and assumptions made on the data used in this research:

- There is no dataset that could directly provide numerical data about the density on the platform; however, it is possible to infer the crowding on the platform from passenger demand data.

- The data of passenger load on each car of trains is unavailable on the Victoria line’s data. The load considered in this research is for the whole train. Passenger distribution along the platform could be excluded from this research because the considered case study occurs when passengers are crowded on the whole platform, and therefore passenger distribution along the platform may not be considerable.

- The numbers of passengers boarding and alighting each train are estimated from the difference between the load before and after a train leaves a station. The process to obtain these numbers is according to the data preparation process shown in Figure 3-16. Therefore, boarding and alighting volume are not data obtained directly from NETMIS.

- There is no data for identifying unusual cases from the train movement data (i.e., traffic delays, late runners, train rescheduling). Therefore, the dataset might include other delays apart from dwell time delays, as NETMIS simply provides the actual train movement data which includes live data of the load on trains and train arrival and departure time.

- Even if there are some limitations inherent in the NETMIS data, it is still worth investigating train load weight and train movement data, as they are available on the London Underground and other metro databases. Developing an approach to analyse this dataset is therefore of interest and will establish practices in the industry.
Chapter 4

Benchmarking dwell time at stations on the line

This chapter intends to compare dwell time and passenger volume at Victoria station with other stations on the line to see how efficient dwell times at Victoria station are. This would be the first analysis before making an intensive analysis at Victoria station as a case study of high-passenger-volume stations to understand the overall characteristics of each station on the line. The analysis in this chapter took the average train dwell time and passenger demand profile at each station and benchmarked dwell times among stations using Data Envelopment Analysis (DEA) approach. Another purpose of benchmarking stations is to make a clear definition of high-passenger-volume stations that this research works on. This is added as a station classification at the end of this chapter.

Dwell time could be evaluated from different perspectives such as efficiency and reliability. These two aspects are not totally aligned, and the conclusions drawn from each perspective could vary. A station which has long dwell times and delays in service (i.e., Victoria station) might be considered as underperforming if it has a low level of reliability. However, it might perform well in relation to efficiency. Even if it has a long dwell time, it can contribute to many outputs (for example, many passengers alighting and boarding at the station). The efficiency of dwell time in this study is evaluated by considering the number of passengers at stations compared with the amount of dwell time spent at these stations.

The analysis in this chapter used London Underground’s actual train movement data (NETMIS) to calculate the average of dwell times and trains’ loadweight as a percentage at each station (which shows how crowded the trains are). Passenger demand data (RODS) of the case study line is used to estimate the average numbers of passengers wanting to alight and board trains at each station. The case study line is the northbound service of the Victoria line during the morning peak. The case study and data utilised in this chapter are described in Chapter 3.

Considering the various characteristics of stations, it is complicated to evaluate the dwell time. DEA was introduced to benchmark the dwell time at each station and evaluated whether the dwell time spent at the stations is efficient when considering the number of passengers that the stations can serve. Then, different station characteristics
are classified based on the benchmark result to support the accurate evaluation of dwell
time at stations with different characteristics. Parts of the content in this chapter has
been published in Transportation Research Record\(^1\) (Tortainchai \textit{et al.}, 2022).

\textbf{4.1 Station demand profiles on the Victoria line}

This study describes different types of passenger volume in terms of “demand profile”. The demand profile gives details on different passenger-volume factors which are unable to simply add up to indicate the total passenger volume in the station. This is because train dwell times factors have complex interrelationships. The interactions between passenger factors have a huge relation to the duration of train dwell times.

Stations on the line could have different characteristics which influence the duration of dwell times differently. Some stations have more passengers boarding while other stations have more passengers alighting, or some stations have passengers boarding and alighting equally. Several studies have studied different boarding/alighting ratios. Dwell times would be longer when the number of passengers boarding and alighting is almost the same (Fujiyama, Nowers and Tyler, 2008). More literature reviews are given in Section 2.1. This research differentiates the number of passengers boarding and the number of passengers alighting in the analysis. This is because these two factors are opposite vectors which have a different influence on the dwell time in a crowding situation. The following 3 cases could clarify this point. If one considers the passenger volume of these 3 cases as the sum of the passengers, they would all equal 200 passengers per minute. However, these 3 cases affect dwell time differently.

- Case 1: Boarders = 150 passengers per minute, Alighters = 50 passengers per minute
- Case 2: Boarders = 50 passengers per minute, Alighters = 150 passengers per minute
- Case 3: Boarders = 100 passengers per minute, Alighters = 100 passengers per minute

Table 4-1 shows passenger volume and dwell time at each station on the northbound service of the Victoria line during the morning peak hour. The passenger volume shown in the table covers the average of passengers boarding, passengers alighting, and on-board passengers before arriving at the stations (Preload). The boarding and alighting ratio (B/A ratio) presents the direction of passenger movements. If the B/A ratio is further from 1, it represents that either alighters or boarders are dominant at that station. Apart from considering passenger volume which depends on demand at each station, the demand profile shows passenger volume from another perspective that also considers the ratio of different types of passengers at each station (boarding, alighting, and on-board passengers). For example, stations at the beginning of the line would have more passengers boarding and fewer passengers alighting. Stations at the end of the line would have more passengers alighting. This forms the characteristics of each station on the line, which would have different influences on train dwell times.

Table 4-1: Station demand profile of the northbound service of Victoria line

<table>
<thead>
<tr>
<th>Station</th>
<th>Boarders (per minute)</th>
<th>Alighters (per minute)</th>
<th>B/A ratio</th>
<th>Preload (%)</th>
<th>Dwell Time (second)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brixton (BRX)</td>
<td>185.43</td>
<td>0.00</td>
<td>All Board</td>
<td>0</td>
<td>24.00</td>
</tr>
<tr>
<td>Stockwell (STK)</td>
<td>190.08</td>
<td>23.93</td>
<td>7.94</td>
<td>28</td>
<td>36.06</td>
</tr>
<tr>
<td>Vauxhall (VUX)</td>
<td>113.45</td>
<td>16.42</td>
<td>6.91</td>
<td>51</td>
<td>33.89</td>
</tr>
<tr>
<td>Pimlico (PIM)</td>
<td>29.20</td>
<td>7.67</td>
<td>3.81</td>
<td>65</td>
<td>28.63</td>
</tr>
<tr>
<td>Victoria (VIC)</td>
<td>174.25</td>
<td>107.98</td>
<td>1.61</td>
<td>69</td>
<td>48.56</td>
</tr>
<tr>
<td>Green Park (GPK)</td>
<td>38.97</td>
<td>100.57</td>
<td>0.39</td>
<td>77</td>
<td>33.77</td>
</tr>
<tr>
<td>Oxford Circus (OXC)</td>
<td>53.13</td>
<td>213.85</td>
<td>0.25</td>
<td>67</td>
<td>38.72</td>
</tr>
<tr>
<td>Station</td>
<td>Boarders (per minute)</td>
<td>Alighters (per minute)</td>
<td>B/A ratio</td>
<td>Preload (%)</td>
<td>Dwell Time (second)</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-----------------------</td>
<td>------------------------</td>
<td>-----------</td>
<td>-------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>Warren Street (WST)</td>
<td>4.40</td>
<td>62.85</td>
<td>0.07</td>
<td>42</td>
<td>32.42</td>
</tr>
<tr>
<td>Euston (EUS)</td>
<td>19.32</td>
<td>64.27</td>
<td>0.30</td>
<td>33</td>
<td>27.74</td>
</tr>
<tr>
<td>King’s Cross St. Pancras (KXX)</td>
<td>23.83</td>
<td>72.55</td>
<td>0.33</td>
<td>26</td>
<td>31.82</td>
</tr>
<tr>
<td>Highbury &amp; Islington (HBY)</td>
<td>19.22</td>
<td>48.00</td>
<td>0.40</td>
<td>18</td>
<td>24.55</td>
</tr>
<tr>
<td>Finsbury Park (FPK)</td>
<td>11.10</td>
<td>34.18</td>
<td>0.32</td>
<td>13</td>
<td>30.13</td>
</tr>
<tr>
<td>Seven Sisters (SVS)</td>
<td>2.40</td>
<td>29.85</td>
<td>0.08</td>
<td>8</td>
<td>33.55</td>
</tr>
<tr>
<td>Tottenham Hale (TTH)</td>
<td>2.17</td>
<td>12.12</td>
<td>0.18</td>
<td>5</td>
<td>23.60</td>
</tr>
<tr>
<td>Blackhorse Road (BHR)</td>
<td>0.00</td>
<td>6.63</td>
<td>0.00</td>
<td>3</td>
<td>24.47</td>
</tr>
<tr>
<td>Walthamstow (WAL)</td>
<td>0.00</td>
<td>15.58</td>
<td>All</td>
<td>2</td>
<td>81.64</td>
</tr>
</tbody>
</table>

Figure 4-1 illustrates the demand profiles and the dwell times at each station. The information noted above each data point gives the station abbreviation and the average dwell time spent at that station. The slope of the line demonstrates the B/A ratio. The stations located on the upper area of the line, which the slope equals “1”, are the stations with more boarding passengers. 11 out of 16 stations on the northbound service of Victoria line are stations with more alighting passengers and most of them have low numbers of passengers (the points clustered at lower left of the scatter plot). The marks in red represent the stations with the load on trains before arriving the stations (Preload) over 60% (the 60% loadweight is roughly 4 passengers / m²) which is the level of density where passenger movements in and out of trains begin to be restricted (Fujiyama, Nowers and Tyler, 2008; Seriani et al., 2019).
When stations on the line have different characteristics, the duration of the dwell time may be affected differently. Some stations with alighter-dominance or boarderdominance may have fewer passenger interactions. Some stations at which passengers move in a bi-directional flow in and out of trains may deal with higher passenger interactions. However, the level of interactions also depends on the passenger volume and the density on trains. Considering the various characteristics of stations, it is complicated to evaluate the dwell time performance as the passenger volume factors are unable to simply add up due to the complex interrelationship of the factors. Consequently, this study employs DEA as the method to differentiate passenger volume factors when benchmarking the performance of dwell times across stations, instead of traditional data analytics, in which different types of passenger volume are simply added together.
4.2 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) or frontier analysis is a non-parametric approach to compare the relative efficiency of units (Decision Making Units (DMUs)). It is a performance benchmarking method which allows multiple inputs and multiple outputs in the analysis and identifies a best-practice frontier from a set of the units that have the highest efficiency compared to others. The approach focuses on best-practice frontiers rather than central tendencies of the data. DEA allows comparison between units without requiring a formulated model (Charnes, Cooper and Rhodes, 1978; Assaf and Josiassen, 2016; Beasley, 2020). The original DEA model was presented in Charnes, Cooper, and Rhodes (CCR) (Charnes, Cooper and Rhodes, 1978) and called the CCR DEA model. The ratio of outputs to inputs is used to evaluate the relative efficiency of any DMUs, thus the model is formulated in the ratio form and converted into the linear programming form, which is easier to solve. The modified linear programming model will set the denominator of the objective function equal to one and add it as a constraint.

In addition, the denominator of the efficiency function will be multiplied by a scale factor. This model can be transformed with this approach as it has a single degree of freedom. (The approach to convert the problem into the modified linear programming form is demonstrated in Beasley’s OR-Notes (Beasley, 2020)). This research used the Solver add-in in Microsoft Excel to solve the linear programming model.

The current research applies the CCR DEA model to compare the efficiency of the dwell time at each station on the Victoria line. CCR is one of the methods for determining the best-practice frontier from the most efficient units, while less efficient units are compared to the best-practice frontier. The dwell time efficiency in this analysis is measured by the number of passengers demanding to alight and board trains at individual stations (Considered as outputs in this analysis) and the dwell time spent at these stations (Considered as an input in this analysis). If the station has a shorter dwell time or higher passenger volume, the efficiency score evaluated with DEA could be high. To evaluate the dwell time efficiency of station i, the model can be formulated as shown in Equation 1 to Equation 4.
Maximise \( E_i \)  

Subject to:

\[
E_j = \frac{w_{ai}A_j + w_{bi}B_j}{v_{di}D_j}, \quad \forall j \in \{\text{Station } j = 1, 2, ..., n\} 
\]

\( 0 \leq E_j \leq 1 \)

\( w_{ai}, w_{bi}, v_{di} \geq 0 \)

Where:

\( i \) = the station being evaluated
\( j \) = all stations being compared relatively with station \( i \)
\( w_{ai} \) = the weight assigned to alighters when evaluating efficiency of station \( i \)
\( w_{bi} \) = the weight assigned to boarders when evaluating efficiency of station \( i \)
\( v_{di} \) = the weight assigned to dwell time when evaluating efficiency of station \( i \)
\( A_j \) = the number of passengers demanding to alight at station \( j \)
\( B_j \) = the number of passengers demanding to board at station \( j \)
\( D_j \) = Dwell time being spent at station \( j \)

The concept of the DEA model is to maximise the efficiency of the station being evaluated by deciding the weights for each input and output. The optimisation has to be repeated by changing the station being evaluated (the maximum function in Equation 1) to find the optimum efficiency for all stations. Equation 2 defines the efficiency of each station as a weighted sum of outputs divided by a weighted sum of inputs. The weights \((w_{ai}, w_{bi}, v_{di})\), which are the decision variables, are allocated to find the best efficiency of the station being evaluated, thereby presenting the particular station in the best possible practice. For example, if the model is aimed at evaluating Victoria station efficiency, the weights are chosen in order to maximise Victoria’s efficiency \( E_{\text{Victoria}} \) and the same weights will be applied to other stations so that their efficiency can be compared relatively. The constraint in Equation 3 is set to make all station efficiency scores fall between 0 and 1, therefore the best possible efficiency is 1. If applying the same weights makes the efficiency of any station above 1, the allocated weights will be adjusted according to the constraint of Equation 3 resulting in a lower efficiency at Victoria station (the station being evaluated) compared relatively to other stations. Equation 4 sets the weights to be positive. There is no weights restriction added in the
model’s constraint which means that all factors are equally significant. The model will apply the higher weight to the associated factor in which the station being evaluated performs better in order to maximise its efficiency. Therefore, it could be interpreted that if the weight assigned to any factor is high, it implies that this factor is outstanding at the station being evaluated.

With the DEA approach, stations with different characteristics or different demand profiles can be evaluated from their best potential. When stations that are being evaluated obtain the highest efficiency score (E=1), these stations will form the efficient frontier. The stations with lower efficiency will be evaluated by being compared relative to the frontier.

4.3 The evaluation of dwell time efficiency at each station

This section aims to evaluate train dwell time of the stations with different demand profiles by applying the DEA approach. DEA benchmarks the efficiency of the dwell time spent at each station by considering the number of passengers the stations can service, especially in the case when the stations have different demand profiles as mentioned in the previous section. DEA makes it possible to evaluate the dwell time at each station when the different types of passengers are not comparable.

Passenger volume is first considered in relation to two factors, which are the number of passengers wanting to alight and the number of passengers wanting to board the train at individual stations. The DEA approach examines the two factors individually. Table 4-2 shows the results of the dwell time efficiency scores derived from the DEA approach. The efficiency scores and related values are calculated by a DEA-Solver on Microsoft Excel provided in Beasley’s OR-notes (Beasley, 2020). The method used in this DEA-Solver is referred in Equation 1 to Equation 4 as shown in the previous section.
The model evaluates the relative efficiency from the ratio of the weighted outputs to the weighted input. The two outputs of this analysis are the number of passengers alighting (denoted as $A_j$) and the number of passengers boarding (denoted as $B_j$), and the input is the dwell time (denoted as $D_j$). One of the key results from this analysis is the efficiency scores of each station which are derived from benchmarking among stations on the line under a constant return to scale (CRS) assumption (Banker et al., 2011). A best-practice frontier line is established from the most efficient stations. The highest efficiency score ($E=1$) is given to the stations which are the most efficient in utilising the dwell time. In addition to the efficiency scores, the analysis provides the projected dwell time for the stations which have a lower efficiency score ($E<1$). This projected dwell time suggests the length of the dwell time necessary in order for the less efficient stations to meet the same efficiency level as the most efficient stations ($E=1$).
Table 4-2: Data Envelopment Analysis (DEA) benchmarking results

<table>
<thead>
<tr>
<th>Stations</th>
<th>Rank</th>
<th>Efficiency Score (E)</th>
<th>Boarders (per minute)</th>
<th>Alighters (per minute)</th>
<th>Current Dwell Time (second)</th>
<th>Projected Dwell Time (second)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brixton</td>
<td>1</td>
<td>1</td>
<td>185.43</td>
<td>0.00</td>
<td>24.00</td>
<td>24.00</td>
</tr>
<tr>
<td>Stockwell</td>
<td>4</td>
<td>0.777</td>
<td>190.08</td>
<td>23.93</td>
<td>36.06</td>
<td>28.02</td>
</tr>
<tr>
<td>Vauxhall</td>
<td>6</td>
<td>0.503</td>
<td>113.45</td>
<td>16.42</td>
<td>33.89</td>
<td>17.04</td>
</tr>
<tr>
<td>Pimlico</td>
<td>12</td>
<td>0.171</td>
<td>29.20</td>
<td>7.67</td>
<td>28.63</td>
<td>4.90</td>
</tr>
<tr>
<td>Victoria</td>
<td>3</td>
<td>0.793</td>
<td>174.25</td>
<td>107.98</td>
<td>48.56</td>
<td>38.51</td>
</tr>
<tr>
<td>Green Park</td>
<td>5</td>
<td>0.593</td>
<td>38.97</td>
<td>100.57</td>
<td>33.77</td>
<td>20.01</td>
</tr>
<tr>
<td>Oxford Circus</td>
<td>1</td>
<td>1</td>
<td>53.13</td>
<td>213.85</td>
<td>38.72</td>
<td>38.72</td>
</tr>
<tr>
<td>Warren Street</td>
<td>10</td>
<td>0.351</td>
<td>4.40</td>
<td>62.85</td>
<td>32.42</td>
<td>11.38</td>
</tr>
<tr>
<td>Euston</td>
<td>8</td>
<td>0.435</td>
<td>19.32</td>
<td>64.27</td>
<td>27.74</td>
<td>12.07</td>
</tr>
<tr>
<td>King's Cross St. Pancras</td>
<td>7</td>
<td>0.436</td>
<td>23.83</td>
<td>72.55</td>
<td>31.82</td>
<td>13.88</td>
</tr>
<tr>
<td>Highbury &amp; Islington</td>
<td>9</td>
<td>0.392</td>
<td>19.22</td>
<td>48.00</td>
<td>24.55</td>
<td>9.63</td>
</tr>
<tr>
<td>Finsbury Park</td>
<td>11</td>
<td>0.217</td>
<td>11.10</td>
<td>34.18</td>
<td>30.13</td>
<td>6.52</td>
</tr>
<tr>
<td>Seven Sisters</td>
<td>13</td>
<td>0.161</td>
<td>2.40</td>
<td>29.85</td>
<td>33.55</td>
<td>5.40</td>
</tr>
<tr>
<td>Tottenham Hale</td>
<td>14</td>
<td>0.093</td>
<td>2.17</td>
<td>12.12</td>
<td>23.60</td>
<td>2.19</td>
</tr>
<tr>
<td>Blackhorse Road</td>
<td>15</td>
<td>0.049</td>
<td>0.00</td>
<td>6.63</td>
<td>24.47</td>
<td>1.20</td>
</tr>
<tr>
<td>Walthamstow</td>
<td>16</td>
<td>0.035</td>
<td>0.00</td>
<td>15.58</td>
<td>81.64</td>
<td>2.82</td>
</tr>
</tbody>
</table>
4.3.1 Evaluation based on passenger demand volume

Firstly, the results are presented by grouping low- and high-demand stations. Figure 4-2 presents the results of the passenger volume - efficiency score chart. It can be seen that stations on the chart are clustered into low and high passenger volume stations. In the lower passenger volume stations, the efficiency score increases relative to the increase in passenger volume (without differentiating between the numbers boarding and alighting) and the dwell times are all lower than 35 seconds. These stations have very low usage demand, thereby having low relative efficiency scores. However, it should be noted that the analysis excludes Walthamstow, as it is the terminal station and has longer dwell times compared to other stations. This is because trains have to wait for a certain amount of time before starting their return journey, which leads to longer dwell times.

Figure 4-2: Plot of stations on passenger volume - efficiency score chart
Considering the recorded dwell time spent at the low passenger volume stations, it does not clearly present an increase relative to the passenger volume. This is because the duration of the dwell time of the low passenger volume stations depends more on the rail traffic and timetable. The duration of the dwell time spent at these stations might be longer than the time needed for passengers to board and alight trains (BAT). The dwell time at these stations has to follow the schedule of the timetable even when passengers have already finished boardings and alightings (non-BAT dominance).

The dwell times at the low passenger volume stations (uncrowded stations) are already short and they are not the main problem causing train delays. This research will therefore not consider improving the dwell times at the uncrowded stations. Table 4-2 shows the projected dwell times derived from the DEA analysis (the suggested duration of dwell time in order to improve dwell time to the efficiency level), which is inapplicable to the low passenger volume stations. (For example, the suggestion that Tottenham Hale should take 2.19 seconds of dwell time in order to improve the efficiency to the frontier whereas this is not necessary for a low passenger volume station.)

The focus of the research problem is on the higher passenger volume stations where the dwell times result in train delays. In contrast to the low passenger volume stations, Figure 4-2 shows that dwell time efficiency scores of high passenger volume stations are not increased relative to the passenger volume, and the dwell times at each station also show a great variation. There are other factors that have a stronger influence on dwell times at high passenger volume stations.
4.3.2 Evaluation based on Passenger Movement Direction

Referring to the research reviewed in the previous section, the differentiation between boarding and alighting is another crucial factor that affect dwell times at high passenger volume stations. The results from DEA in Table 4-2 present that the stations which have the highest efficiency score are Brixton station and Oxford Circus station (E=1). Both stations have a much lower dwell time than Victoria station (VIC) which has the third highest efficiency rank (efficiency score = 0.795). Considering the demand data in Table 4-1, passengers at Brixton and Oxford Circus move in a one-way flow in or out of the trains. All passengers at Brixton are boarding passengers (Brixton is a terminal station of the Victoria northbound line) and most of the passengers at Oxford Circus are alighting passengers (B/A ratio = 0.25). Dwell times at both stations are less than 40 seconds. There is only Victoria station which has a bi-directional flow (the numbers of boarders and alighters are not widely different) and has an extremely high dwell time.

Figure 4-3 shows the DEA approach in a graphical chart which plots the high passenger volume stations based on the ratios of the numbers of passengers per second of dwell time for boardings and alightings calculated separately. The chart visually compares the relative efficiency of the stations by differentiating boardings and alightings. The information noted above each data point gives the station abbreviation, the dwell time spent at that station, and trains’ loadweight as a percentage before arriving at that station, respectively.

The stations with the highest value on the y-axis or on the x-axis are preferred from the efficiency point of view, as they represent higher ratios of the number of passengers per second. A best-practice frontier would be formed from the stations with the highest efficiency compared with other stations. Considering the results under the constant return to scale assumption presented in Table 4-2, Brixton and Oxford Circus stations have the highest efficiency score (efficiency score = 1) where one station has the highest boarding rate, and the other has the highest alighting rate.
Considering loadweights on trains before arriving at high passenger volume stations in Figure 4-3, it shows that 3 out of 6 stations are the stations with the pre-load on trains over 60% (roughly 4 passengers / m²). Among these stations, it is obvious that the dwell times at Victoria station are exceptionally high. Other high passenger volume stations, which have much lower dwell times of less than 40 seconds, have a predominantly one-way flow movement. In this case study, there is only Victoria station which has a bi-directional flow. The crowding inside trains could affect the stations with uni-directional flow and bi-directional flow differently.

The number of passengers on trains (on-board passengers before arriving at the stations) is another crucial factor that contributes to the high level of passenger interactions. It has been studied in much research as reviewed in Section 2.1. Even passengers on trains are not the actual demand for the stations being evaluated by the DEA, they have a significant impact on dwell times, particularly in crowded situations. Thus, the number of passengers on trains before arriving at stations is also included as a factor to classify stations in the next section.
4.4 Station Classification

The benchmarking of stations along the line in the previous analysis evaluates stations with different characteristics or different demand profiles from their best potential. This could help in understanding the characteristics of the stations based on their demand profiles and how demand profiles influence dwell times. This study examines dwell times at stations with varying demand profiles and classifies stations according to their demand profiles.

This study proposes the classification of stations according to their characteristics and supports further research to develop different dwell time models for stations with different characteristics. Table 4-3 shows different station characteristics, the example of stations under the categories, the amount of dwell time and dwell time efficiency score. Finally, the short conclusions about the dwell times for each category are added. Stations are classified based on passenger volume, passenger movement direction, and crowding inside trains. This study classifies stations to find demand profiles that have different effects on dwell times.

There is a limitation on this classification. This classification is based on the analysis of the Victoria Line only, as the main purpose of classifying stations here is to compare dwell times on the case study line and identify types of demand profiles that result in an exceptionally high dwell time. This classification is a preliminary setting which based on the benchmarking results and data from the case study line. More research should be done specifically to classify the stations for the purpose of evaluating dwell time.
Table 4-3: Types of stations and train dwell time evaluation

<table>
<thead>
<tr>
<th>Station characteristics</th>
<th>Sample stations</th>
<th>Current dwell time</th>
<th>Dwell time efficiency score</th>
<th>Concepts for dwell time model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Low passenger volume stations</td>
<td>BHR, TTH, SVS, FPK, etc.</td>
<td>All are lower than 35 seconds.</td>
<td>All are lower than 0.5.</td>
<td>Dwell times depend more on the traffic and timetable. Passengers boarding and alighting time (BAT) rarely causes any train delay and could be simply calculated by multiplying the passenger movement rate by the number of passengers without differentiating boardings and alightings.</td>
</tr>
<tr>
<td>2. High passenger volume with uni-directional flow</td>
<td>BRX, STK, OXC</td>
<td>All are lower than 40 seconds.</td>
<td>Stations could become the most efficient stations depending on passenger volume. With fewer passenger interactions, it could deliver a high number of passengers with less dwell time.</td>
<td>Dwell times mainly depend on passenger volume in the dominant direction. (Boarding dominance or Alighting dominance)</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Station characteristics</th>
<th>Sample stations</th>
<th>Current dwell time</th>
<th>Dwell time efficiency score</th>
<th>Concepts for dwell time model</th>
</tr>
</thead>
<tbody>
<tr>
<td>3. High passenger volume with bi-directional flow, but low passenger volume on trains</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>There is no case study fitting in. Dwell time might depend on passenger volume plus the interactions between passengers boarding and alighting.</td>
</tr>
<tr>
<td>4. High passenger volume with bi-directional flow, and high passenger volume on trains</td>
<td>VIC</td>
<td>An average dwell time is approximately 49 seconds with 9 seconds of standard deviation.</td>
<td>Due to significantly high dwell time, Victoria station has lower dwell time efficiency score than scenario 2.</td>
<td>Dwell time and its variation would be high as there are high interactions between passengers. Passenger behaviours should be included in this case. Predicting the dwell times of this scenario may result in low accuracy outputs. Further analysis is presented in Chapter 5.</td>
</tr>
</tbody>
</table>
4.5 The summary and application of benchmarking outcomes

This chapter attempts to obtain insight into the complexity of dwell times by comparing and identifying types of demand profiles that would result in high dwell times. Stations on the northbound service of the Victoria line during the morning peak time have been analysed regarding their different characteristics, namely the number of passengers boarding, the number of passengers alighting, passenger movement direction. The study applied a Data Envelopment Analysis approach to evaluate and compare train dwell times at each station. Results provide that the dwell times of the low-volume stations are all less than 35 seconds, and the dwell time efficiency score increases relative to the increase of passenger volume. In the low passenger volume stations, there are fewer passenger interactions. The general dwell time prediction models being developed are more reliable on the low-volume stations. However, as mentioned earlier, the actual dwell times in low passenger volume stations might be dominated by train traffic issues which may lead to a longer dwell time than necessary. In the case of high-volume stations, it is necessary to differentiate between the numbers alighting and boarding or to consider passenger movement direction (uni-directional or bi-directional flow). In addition, the density on trains is related as it results in high levels of interaction between passengers. The density on trains could affect the stations with uni-directional flow and bi-directional flow differently.

The focus is on stations with similar characteristics to Victoria station (which has to handle high passenger volume with bi-directional movement, and the trains arriving at Victoria station are additionally crowded). The challenge is that these stations have to handle high passenger volume and at the same time have to keep the dwell time within the threshold. The further analysis in this research would deal with this type of high-passenger-volume station. High-passenger-volume stations mentioned later in this research are those that have a high passenger volume, have bi-directional flow, and have trains arriving that are crowded. This characteristic would result in high interactions between passengers, thus making an exceptionally high dwell time.
Chapter 5

The investigation of dwell times at high-passenger-volume stations

This chapter conducts an intensive investigation of train dwell times and passenger volumes to understand dwell times at high-passenger-volume stations. This chapter investigates Victoria station data as a case study, but the evaluation approaches presented in this chapter could be applied to other high-passenger-volume stations. The definition of high-passenger-volume stations in this chapter is the stations with a high number of passengers boarding and alighting trains at the platforms and the trains arriving are also crowded according to the station classification given in the previous chapter. The high passenger volume stations considered in this chapter could become critical stations that determine the line capacity. Dwell times at these stations are complicated due to the interactions between passengers and the variations of passenger behaviours. Dwell times at high-passenger-volume stations are sensitive to any change of factors, leading to a high variance. Estimating dwell times at high volume stations with any representative values or models could be inaccurate. Hence, this chapter examines the data from Victoria Station to demonstrate the variability of the data and to compare the actual dwell time to the predicted dwell time using existing models. Section 5.1 conducts a data analysis to review dwell times and the related factors at the case study station. Then, the current dwell time models are explained and tested in Section 5.2.
5.1 Dwell time data analysis

This study analyses dwell times in the crowding situation during morning peak on weekdays, which is when dwell time is delayed and the station deploys passenger control the most, referring to the case study selection in Section 3.3. This analysis is aimed at understanding current dwell times, the related passenger volume variables, the interaction effects, and correlations between variables in a crowded situation. A comprehensive review of dwell time data could reveal gaps in the current dwell time approaches. The tools used for data analysis and visualisation are Microsoft Excel and Tableau. Each record of the data from NETMIS provides the train dwell time, the train load before arriving at a station (L), and any difference in the load before and after a train leaves a station (to estimate the number of passengers boarding (B) and the number of passengers alighting (A)).

5.1.1 Preliminary analysis

First, the descriptive statistics of the variables used in this research are summarised in Table 5-1, which presents the average, standard variation, and the coefficient of variation of the variables in the crowding environment during the morning peak time at Victoria station. The histograms of dwell times and passenger volume are presented to preview data patterns of the variables. The histograms are shown in Figure 5-1 to Figure 5-4. The descriptive statistic data shows that dwell time is the variable which has the highest coefficient of variation, while passengers alighting and load on trains have the lowest variation.
Table 5-1: Descriptive statistics on 1778 trains stopped at Victoria station throughout the study period.

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Standard Deviation</th>
<th>Coefficient of variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dwell time (sec)</td>
<td>48</td>
<td>9.5</td>
<td>0.196</td>
</tr>
<tr>
<td>Passengers boarding at</td>
<td>182</td>
<td>29.8</td>
<td>0.164</td>
</tr>
<tr>
<td>(passengers per train)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Passengers alighting</td>
<td>161</td>
<td>15.6</td>
<td>0.097</td>
</tr>
<tr>
<td>(passengers per train)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Load on trains before arriving at the station (passengers per train)</td>
<td>752</td>
<td>63.5</td>
<td>0.091</td>
</tr>
</tbody>
</table>

The histogram in Figure 5-1 shows that the lengths of dwell times during the peak period are right-skewed and cluster around 41-50 seconds, which is higher than the scheduled dwell time (38 seconds). Dwell times during the morning peak vary greatly and range from 21 to 90 seconds. Considering passengers boarding trains, there are a few more passengers who want to board than alight trains at Victoria station. Most of the numbers of passengers boarding during the peak period are clustered at 161-200 passengers per train as shown in Figure 5-2.

![Histogram of dwell time](image)

Figure 5-1: Probability density function of dwell times at Victoria station
Figure 5-2: Probability density function of the number of passengers boarding trains at Victoria station

When considering passengers alighting trains in Figure 5-3, the histogram has almost the same shape as the histogram of passengers on trains in Figure 5-4. This is because the number of passengers alighting is derived from the load on trains. The histograms of passengers alighting and passengers on trains are right-skewed and cluster at around 141-170 passengers and 600-750 passengers, respectively.

In the morning peak, there are a few more passengers who want to board trains at Victoria station on the northbound line than passengers who want to alight. The average of the boarding and alighting ratio is around 1.13. When the ratio between the number of passengers boarding and alighting is close to one, this indicates that passengers are moving in bi-directional flows. In addition, 94% of trains arriving at Victoria station have a load of more than 600 passengers (standing density approximately 3 passengers per m²). This could lead to the higher dwell times due to the interactions between passengers.
Figure 5-3: Probability density function of the number of passengers alighting trains at Victoria station

Figure 5-4: Probability Density Function of the number of passengers on trains before arriving at Victoria station
Dwell time's passenger volume factors (i.e. passenger alighting, passenger boarding, passenger on trains) often have correlations with each other, which makes dwell times more complicated. Figure 5-5 shows the correlation plot between the selected variables. All the plots show positive low correlation coefficients. No precise trend could be identified due to high variations of the data, except the correlations between the number of passengers on trains and the number of alighters, which almost form linear relationships (correlation close to 1). This is because of the data calculation process, by which the number of alighters is estimated from the load on trains multiplied by the alighting rate.

Considering correlation coefficients of the variables, all of them show positive correlations. The correlations between the independent variables (boarders, alighters, previous load) could cause difficulties when conducting multiple regression analysis. Considering the correlation coefficients of dwell time with the other three variables, the values are around 0.2 - 0.3 which represent small positive correlations. The load on trains is the variable which has the highest correlation coefficients with dwell time. Even though the number of alighters has a higher correlation coefficient with dwell time than the number of boarders, it cannot be concluded that the number of alighters itself has stronger relationship than the number of boarders as this might be due to the effect of the relationship between the load on trains and the number of alighters.

Overall, the data shows that the variables have a low positive correlation with dwell times. One of the reasons that the data shows low correlation coefficients is because dwell times at high-passenger-volume stations contain high variations.
Figure 5-5: Correlation plot
5.1.2 The interaction effects of the variables

Dwell times in the crowding environment is complicated and includes the interaction effects of the variables which would make dwell time inconsistent. A different volume of each variable would have unequal effects on the train dwell times. Figure 5-6 and Figure 5-7 investigate dwell times with relation to this complicated interaction over two major variables. The number of passengers alighting is disregarded in this interaction analysis because of the data limitation that the numbers are directly estimated from the load on trains multiplied by the alighting rate. The interaction effects of the load on the trains should already represent the interaction effects of passengers alighting.

Figure 5-6 is the graph of the average dwell time over the load on the train. Each line represents a range of boarders for every 20 passengers and the labels show the upper bound of the ranges. All lines show the upward trend over the load on the train which means that the higher number of passengers on the train causes a longer dwell time. It seems that the number of boarders at 120-220 passengers has similar interaction effects. When the number of boarders exceeds 220 passengers, the slope of the lines is steeper, showing that the number of passengers on the train affects the dwell time more when there are higher number of passengers boarding. The slope for 220-240 boarders is 0.075 and the slope for 240-260 boarders is 0.116.
Figure 5-6: The investigation of interaction effects of numbers of passengers boarding

Taking up another aspect, Figure 5-7 plots the average dwell time over the number of boarders and each line now represents the range of the load on the train for every 50 passengers. The slope of the line increases when the range of the load on the train increases. The steepest line (0.131 second/passenger) represents the scenario when the number of passengers on the train exceeds 800 passengers. This implies that, at this level of train crowding, every 1 boarder will make the dwell time increase by 0.131 seconds.
Figure 5-7: The investigation of interaction effects of the load on the trains

Figure 5-6 and Figure 5-7 show that there are interaction effects between the number of passengers on the train and the number of boarders. The higher the number of passengers on the train, the more the number of boarders affect the dwell time, and vice versa. However, when processing the data with regression analysis, this interaction term is not significant in the model. The regression analysis result is presented in Table 5-2. This can happen because the interaction between variables exists when the number of boarders and passengers on trains reaches a specific level. There could be a few of the data that could reach this level; however, the impact of this interaction can cause severe delays.
5.1.3 Scatter plots

The previous analysis demonstrates that passenger volume level has a significant effect on train dwell times and especially when in the higher passenger volume ranges, the interaction effects are stronger. Since dwell times contain high variations, making an analysis with average values may not be enough to represent all dwell time patterns.

This section took all observation values and presented them in scatter plots with colour labels. Dwell time is plotted on the y-axis, while one dwell time factor is plotted on the x-axis, and another factor is represented with colour labels. The scatter plot in Figure 5-8 classifies different load levels on trains with different colours. The green points represent lower train loads, and the blue points represent higher loads. The plot shows a small positive correlation for both low and high train loads. This shows that dwell time has a high variation (Even at similar numbers of passengers, dwell times vary considerably). The scatter plot in Figure 5-9 shows similar results but from another perspective.

Figure 5-8: Scatter plot showing dwell times and numbers of passengers boarding trains
The next scatter plot presents train dwell times with colours for the given combinations of the number of passengers on trains and the number of passengers boarding. Figure 5-10 represents dwell times with ranges of colours from green to red (showing dwell times from 30 seconds to 60 seconds). The data points plot the number of passengers on trains and the number of passengers boarding. It can be observed that the data on the lower left (where both variables have low values) have lower dwell times. When moving toward the upper right, the dwell time increases. This figure raises the prospect of evaluating dwell time in term of the likelihood of meeting or delaying the scheduled dwell time. For example, if the loads are lower than 700 passengers and passengers boarding are lower than 200 passengers, there should be a lower likelihood of delay than the combination of 850 passengers on trains and 240 boarders.
This research has investigated several plots on the morning peak data with different segmentations, in addition to the plots shown in this report, but discovered that none of them forms a strong trend or clear segmentation. This study supports earlier findings that dwell time data in crowded scenarios cannot easily fit well into any line models or will achieve only a low goodness of fit performance. This research aims not to fit dwell time data into any dwell time models (which have been studied in much research ranging from simple to complicated models). The research ambition is not to try to predict any representative values of dwell times but rather to consider dwell times on the reliability perspective. This alternative dwell time reliability evaluation approach will be presented in Chapter 6.

Figure 5-10: Dwell times showing on a plot between previous load and boarders
5.2 The evaluation of existing dwell time models at high passenger volume stations

To give more support to this research assumption that dwell times for high-passenger-volume situations cannot be accurately predicted with dwell time models, this section took the real dataset from NETMIS, substituted the data into existing dwell time models, and evaluated the prediction performance. This section demonstrates that dwell times are difficult to fit with a single model as each tries to predict a value of the dwell times despite the fact that the dwell times contain a lot of variations.

Many studies have developed dwell time models. Some studies only used passenger-related factors, while some studies included train-related and platform-related factors. Most of the dwell time models used regression analysis approaches. This current research tested different models including the London Underground model, regression models from other research, and other multiplicative functions. Tests of actual data sets on different dwell time models are presented in

Table 5-2. All the calibrated regression models gave around 0.08-0.26 of R-square. Among the models from other research, the current data fit London Underground’s model the best. This is because different metro systems require different dwell time models. This research used London Underground as a case study, thus testing with London Underground’s dwell time model was the most suitable.

London Underground’s dwell time model is one of the most widely investigated models in this research field. Details of this model have been gathered in London Underground’s internal documents (McKenna, 1988; Weston and Mauder, 1989; Nicholls, 2010). The model was derived from the findings of previous research and London Underground’s strategic survey outcomes. The original model is very complicated and is a full page long. The variables considered in this model cover all three categories (passenger-related, platform-related, train-related factors). The model investigated in this study is a simplified version of London Underground’s dwell time model in which some parameters are replaced with constant values.
Dwell Time = BAT + OT \hspace{1cm} (1)

\[
BAT = \left[ (F \times \frac{B}{D})^{0.7} + (F \times \frac{A}{D})^{0.7} + 0.027 \times \left( F \times \frac{B}{D} \right) \times \left( F \times \frac{A}{D} \right) \right] \times \left[ 1.4 \times \left( 1 + \left( \frac{F}{VC} \times \frac{T-S}{D} \right) \right) \right] \times DWF \hspace{1cm} (2)
\]

Where BAT = Boarding and Alighting time

- A = number of alighting passengers
- B = number of boarding passengers
- D = number of doors
- F = peak door/average door Factor
- S = number of seats
- T = number of passengers standing in the vestibule

(0.88*Load on train approximately)

DWF = Door Width Factor

VC = Vestibule Capacity

OT = Other Time (Door opening, Signal checks, Door closure and departure)

London Underground’s dwell time model is composed of two main components which are boarding and alighting time (BAT) and other time (OT) as shown in Equation 1. In the first term of the BAT equation (Equation 2), it is divided into 3 elements: boarding factor, alighting factor, and interaction factor. Boarding factor and alighting factor both have a 0.7 power function, and the interaction term has a constant factor of 0.027. The second and third terms of the BAT equation are for the adjustments of the vestibule crowding factor and door width factor, respectively.

Harris (2005) showed in his research that the London Underground’s model is fit for predicting the dwell time at low volume stations, but it might not fit in the crowding situation because passenger interactions in crowded scenarios are more complicated. Harris & Anderson (2007) also demonstrated that London Underground’s model might be applicable on other metros. However, the research suggested adjusting the parameters such as the boarding and alighting power factor, which is 0.7 in London Underground model, but which could range from 0.45-0.9 in other metro models.
This current research uses the northbound platform of Victoria station as a case study, thus platform-related and train-related parameters are constant. Several factors (D, F, S, DWF, VC, OT) are substituted in the model. The following values are used to substitute in the dwell time model; D = 30, F = 2, S = 288, DWF = 1, VC = 33, OT = 19.2 (based on the values used in London Underground’s Train Service Model (Nicholls, 2010) together with London Underground’s internal notes (Weston and Maunder (1989) Table 1 Page 2)). The other passenger volume variables are taken from the actual train operation data (NETMIS) and substituted in the dwell time model, then the predicted dwell times are obtained.

Finally, the predicted dwell time and the actual dwell time are compared to evaluate the model’s goodness of fit. The goodness of fit test describes how well the prediction fits a set of observations. It tests the difference between actual values and predicted values from the model with statistical hypothesis testing. The accuracy is presented in $R^2$ to show in what percentage of the calculations, the dwell time model could represent the actual dwell time. The regression and error sum of squares are calculated, then the following $R^2$ which measures the overall quality of the model is obtained. It was concluded that only 23% of the dwell time data during the morning peak of Victoria station can be represented with the London Underground’s dwell time model.

$$R^2 = \frac{SSR}{SSR + SSE} = \frac{46766}{46766 + 156927} = 0.23$$

Figure 5-11 shows the plot between the predicted dwell time and the actual dwell time. Figure 5-12 shows the predicted dwell time with residual error, while the residual plot between the residual error and different number of passengers are presented in Figure 5-13 and Figure 5-14. It can be roughly seen in Figure 5-11 that the model could be both overestimated and underestimated randomly. The residual plots in Figure 5-12 to Figure 5-14 show that the model is evenly distributed or balanced across the residual errors. There is no clear heteroscedasticity and the residuals do not have a clear trend at any points. The residual errors have high variations throughout the X-axis.
Figure 5-11: Predicted and actual dwell time of the current model

Figure 5-12: Residual plot between residual error and predicted dwell time
Figure 5-13: Residual plot with number of boarders

Figure 5-14: Residual plot with number of passengers on train
The high variations of residual errors could be due to the nature of dwell times in crowded scenarios which are unpredictable due to passenger behaviours. Another presumption to explain residual error variations is that there might be some omitted variables. Dwell time is influenced by more than 50 factors. This research analyses at the data regarding Victoria station in which the physical factors of the platform and train are constant and already substituted. The possible variables which have not been included in the model are behaviour variables (for both passengers and train drivers). Behaviours, especially at the high-passenger-volume stations, are the most complicated and unpredictable variables. There are studies of passenger behaviours in crowded situations. Passengers with certain characteristics, such as vision, hearing, mobility, age, culture, and gender, may require additional space to move around in high-density situations (Seriani, 2018). In addition, behaviours such as walking purpose, route unfamiliarity, carrying luggage, and using smartphones can lead to inconsistent dwell times (D’Acierno et al., 2017). In addition to passenger behaviours, train driver behaviours, including door-closing speed, are another factor that could cause a high variation in dwell times, which can have a knock-on effect and bunching of trains following (Wong and Key, 2014). These passenger and driver behaviours can be difficult to predict due to the variance in the behaviours (Kuipers et al., 2021). Attempting to estimate dwell times based on point estimation under such conditions can lead to poor performance predictions. The tests of the research dataset on other models are concluded and shown in Table 5-2.

The first model being tested is London Underground’s dwell time model, which is demonstrated, and the results are provided in this Section. The Railway and Transport Strategy Centre’s dwell time model is then evaluated. This model is chosen because it is the calibrated version of the London Underground’s model; however, the fitting performance on this model is low. This is because this model considers the general crowding level and is not specifically conducted for the crowding environment, whereas the data used for testing is the data during the crowding period. The third model being tested considers the model that was developed specifically for the crowding case. This model still does not adequately fit the research dataset. This model was developed for the dwell times of the subway in Santiago. The last two models consider using regression analysis on the current dataset, with average dwell time and average log of dwell time as dependent variables, respectively. The model with the log of dwell time
fits better than the model with the average value, but the best-fitting model ($R^2=0.26$) still has poor fitting performance.

Table 5-2: Tests of the actual dataset on different dwell time models

<table>
<thead>
<tr>
<th>Model</th>
<th>Descriptions</th>
<th>Variable terms</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. London Underground’s model</td>
<td>The terms represented here already have the constant parameters (platform, train parameters) substituted</td>
<td>$BAT = f(k_1B^{0.7}, k_2A^{0.7}, k_3AB, k_4B^{0.7}L, k_5A^{0.7}L, k_6ABL, k_7B^{0.7}A, k_8A^{1.7}, k_9A^2B)$</td>
<td>0.23</td>
</tr>
<tr>
<td>2. Railway and Transport Strategy Centre (2013)</td>
<td>This model considers the general crowding level and is not conducted specifically for the congestion environment. The model predicts alighting time and boarding time separately</td>
<td>$(1) BR = f(k_1B, k_2mod_A^A, k_3T_{VC}^{1.6}, k_4W, k_5S, k_6SB, k_7(\frac{VC^*AD}{DD+W})^{-0.5})$</td>
<td>0.08</td>
</tr>
<tr>
<td>3. Suazo-Vecino, Dragicevic and Muñoz (2017)</td>
<td>This model is developed for the congestion environment, but with limited observations</td>
<td>$(2) DW = f(k_1B, k_2A*T_B, k_3TA, k_4e^L)$</td>
<td>0.09</td>
</tr>
<tr>
<td>4. Regression analysis from current dataset</td>
<td>Developing regression analysis from the current dataset</td>
<td>$DW = f(k_1B, k_2A, k_3L, k_4BL)$</td>
<td>0.18</td>
</tr>
<tr>
<td>5. Regression analysis from current dataset with log of dwell time</td>
<td>Developing regression analysis from the current dataset with log of dwell time as a dependent variable</td>
<td>$\log(DW) = f(k_1B, k_2A, k_3L, k_4BL)$</td>
<td>0.26</td>
</tr>
</tbody>
</table>
Overall, the performance of the current dwell time models in crowding situation is still not accurate enough. In addition, dwell time could not be represented well in a simple regression model. There are limitations in fitting dwell times with a regression approach. For example, there might be an omission of some variables. It is highly likely that some variables are missing from the model (especially passenger behaviour variables) which make the model fail to fit the data. The second crucial limitation is the interaction between variables which causes a disturbance in the data and makes the model’s coefficients unstable when adding or deleting variables.

In conclusion, this chapter demonstrates the high variation of dwell times in a crowded environment. Dwell times in a crowded situation could be difficult to fit with any models or to predict accurately with any equations. This is because general dwell time models try to predict any representative values of the dwell times, while the nature of dwell times contains a high degree of variation. The scatter plot of dwell time versus passenger volume factors reveals weak correlations, and no clear relationships could be identified. Therefore, it is possible that there are no reliable models capable of accurately predicting the representative value of dwell times in a crowded situation.
Chapter 6
Dwell time from the probability of delay perspective

Previous dwell time analyses in Chapter 5 reveal complications, uncertainties, and variabilities involved in the dwell times at high-passenger-volume stations. The analysis supports that dwell times at these stations are complicated and current dwell time models are not suitable for predicting them. The investigation results show that train dwell times at such stations consist of interaction effects between the dwell time factors, thus dwell time models are sensitive to the change of variables. In addition, dwell times are also influenced by passenger interactions and behaviours, which cause high variations of dwell times, making them difficult to fit with any models.

This chapter proposes an alternative approach to addressing the gap of evaluating dwell times at high-passenger-volume stations. The approach is to evaluate dwell times in terms of the reliability or the probability of delays, instead of trying to predict a dwell time value. The evaluation focuses on high-passenger-volume stations which have high chance and high impact from dwell time delay and could become critical stations that determine line capacity.

6.1 The concept of dwell time delay evaluation

Reliability in general is the invariability of the service and can be considered in past studies from several perspectives. Dwell time reliability can be characterized as both early and delayed. This research considers the crowding situation when there are always many passengers on the platform waiting to board crowded trains. Therefore, early departure is not considered in the evaluation. Train delays are one of the performance measures of the reliability of the service and are usually calculated from the percentage of the train delays over the expected length of time. In general, train delays can occur at the beginning, during the journey, while stopping at stations, and at the terminus (Goverde et al., 2001). Train delay is a common problem in the railway operation. The term of delay can be defined in two ways. First is the delay from the train timetable which is usually used on the low frequency service which passengers plan to arrive according to the train timetable. The second is the headway regularity. This is usually for the high frequency service, especially the mass transit which passengers arrive without relying on the train timetable. In this case, the regularity and the duration of
headway is important as it is related to passenger waiting time on high frequency service system (Ma, Ferreira and Mesbah, 2014). There are strategies to determine the amount of delayed time that should be counted as a delay. Each railway operator may have different criteria to consider the delay. The determination of the delay threshold value can be based on minimum headway, recovery time, level of passenger expectation, etc. (Martin, 2014). There are several recent research studied dwell time delays including but not limited to Bergström and Krüger (2013), D’Acienro et al. (2017), Palmqvist, Tomii and Ochiai (2020), Kuipers and Palmqvist (2022), Palmqvist (2022).

The current scheduled morning peak dwell time at Victoria station is set at 38 seconds. However, few trains in a crowding situation can achieve this scheduled dwell time. From the train service planning viewpoint, it is important to set an appropriate dwell time which is achievable by most services. Delays in the schedule can affect the service performance but the length of dwell time setting in the schedule also trades off against the service capacity. For example, setting a longer scheduled dwell time to improve delay performance can reduce the train frequency. The balance between the performance criteria depends on the service policy. The evaluation of this consequence is presented later in Chapter 7.

Figure 6-1 illustrates the concept of dwell time reliability by showing the probability of train delay and train on-time for different load levels on trains. The figure is derived from the case study dataset described in Section 3.5. The delay cut-off here is the point where the length of dwell times is over the target dwell time to achieve the current service frequency. The figure shows the probability of trains having a lower and higher dwell time than the target dwell time which is considered as on-time and delayed, respectively. A lower load on trains has a higher chance of achieving the target; however, most of the trains with a higher load could not achieve this target dwell time.
Figure 6-1 demonstrates the concept of an increase in the probability of trains being delayed over an increase in train load. This research focuses on improving the dwell time delay; therefore, the delay part (the right tail of the distributions) will be taken into consideration in the further analysis to focus on the pattern and the spread of dwell time delays.

The determination of the delay threshold is varied and depends on how the service performance is evaluated. The further analysis will refer to the current scheduled dwell time which has been set at 38 seconds as a dwell time delay threshold, however, this delay threshold can be varied in different situations. Dwell times which are lower or equal to the schedule will be considered as on-time (delay = 0). Dwell time delays are defined as when trains spend longer than the scheduled time and can be calculated from “Actual train dwell time” minus “Scheduled dwell time” with the unit in seconds.
6.2 Dwell time and passenger volume on trains

This chapter focuses specifically on train load before arriving at the critical station. Even this chapter shows the evaluation on the train load factor, the proposed approach aims to be also applicable to other passenger volume factors. There are several reasons why this chapter focuses on the train load factor to adopt a dwell time evaluation approach. The reasons for this choice are as follows:

- Victoria station has already deployed station controls. However, there is high passenger volume at Victoria station and trains are still delayed at the station. Thus, further control of passengers at other stations is examined to determine if it could improve dwell time and line capacity.
- There are already several passenger management approaches deployed at a station-level. This research considers line-level passenger management which could be conducted by managing the train load along stations on the line.
- Train load data can be obtained directly from NETMIS data, while other factors are estimated values.
- With regard to this research’s problem and scope, the case being considered is when stations are crowded, and platforms are full of passengers waiting to board trains. Therefore, the number of passengers boarding trains is consistently considered to be at capacity across all analyses.
- If too many factors are considered, it makes the evaluation dynamic because of the interaction effect between the dwell time’s factors.

This chapter focuses on the number of passengers on trains and the relationship of this to train dwell time. The number of passengers on trains is presented as a percentage of the train’s full capacity, which is the number directly extracted from the data system. Higher density on the trains arriving at the crowded stations can lead to a longer dwell time and higher chance of being delayed. The higher density on the train could also naturally lead to a higher number of passengers alighting from trains as trains would be carrying a higher number of passengers (considering the constant proportion of passenger alighting). With a larger number of passengers alighting at a high passenger volume station, passengers would move in a more bi-directional flow in and out of trains (causing higher interactions between passengers) leading to a longer dwell
time. There are also many other factors related to the train dwell time as mentioned previously but taking too many factors into consideration will make the evaluation dynamic. The scope of the analysis here is therefore limited to the number of passengers on trains before arrival and train dwell times.

Figure 6-2 gives an overview of the dwell time for different percentages of load on trains before arriving at Victoria station. The chart shows the data on the northbound platform of Victoria station. It presents that a smaller load on trains (less crowding on trains) could lead to a shorter average dwell time. When the percentage of the load on trains is over 60%, the average train dwell time is dramatically increased.

![Figure 6-2: Average dwell time with different load level at Victoria station](image)

\[
y = 0.3095x^2 - 1.3094x + 46.308 \\
R^2 = 0.9469
\]
In the high passenger volume stations where dwell time values are random and show considerable variations, it is important to understand how dwell times spread along the different passenger volume levels. To the best of our knowledge, there are not many studies assessing dwell time distribution by considering different levels of passenger volume (the literature review regarding this is presented in Section 2.1.3), however, identifying distributions of dwell times for the given ranges of the load provides a thorough understanding of dwell time values at high passenger volume stations and how distribution parameters are changed at the different levels of passenger volume. The loads from 60% to 90% of the trains’ full capacity are examined as 90% of the selected data has loads on trains falling into these ranges. The loads lower than 60% have insufficient data to identify distributions. Given that Victoria station is the fifth stop on the northbound service, it is sensible that the majority of morning-peak trains arriving at the station are crowded.

Figure 6-3 shows distributions of the dwell time for ranges of the loads on trains from 60% to 90% of the trains’ full capacity. It appears that dwell time distributions of all ranges are likely to have right-skewed distributions in which most values cluster on the left. A right-skewed distribution is a characteristic of data which has a limit. For example, dwell times in cases of crowding are limited by the scheduled dwell time, thus most values are clustered near the scheduled dwell time. The averages of dwell times for ranges of the loads on trains are all higher than the clusters. When considering the higher levels of loads, the length of dwell times and their deviations shift to the higher values. The shapes and locations of the distributions are changed in response to the varying levels of crowding on trains.
Figure 6-3: The probability distribution of the dwell time for the given ranges of the load
6.3 Probability distribution fitting

To make a deeper analysis and allow broader investigations, dwell time data will be fitted to theoretical distribution functions. Fitting the data to theoretical distributions supports the understanding of characters and patterns of dwell times and delays and allows the estimation of probability in many possible scenarios. In addition, fitted distributions are also applicable in other forms of analysis such as simulation models, optimisation, or other analytical models.

6.3.1 Dwell time probability distribution fitting

This section intends to fit dwell time data with theoretical functions. The analysis starts with fitting the dwell time values by conducting multi-modal distribution validations by fitting all data points with candidate distributions which have similar patterns to the empirical distributions. The research used the library called “Auto-fitter” in Python3 as a tool to fit the data. The python script auto-fits candidate distributions and shows the candidate that is the most aligned with the actual dwell time dataset. Lognormal is the closest distribution that all ranges of load are almost fitted to. Maximum Likelihood Estimation (MLE) is used to identify parameters of lognormal distribution for given ranges of the load on trains. The parameters obtained are those which minimise the sum squares of error between predicted and actual density.

A chi-squared goodness of fit test is used to validate the goodness of fit of dwell time on each interval (dwell time is a continuous dataset and needs to be divided into intervals of 5 seconds. The interval width is calculated from the characters of the operational dataset). Principally, a chi-square goodness of fit test compares the number of observations that fall in each interval with the expected number that fall in each interval of the hypothesized distribution (being calculated from Cumulative Density Function (CDF)), then evaluates the differences between them and converts the data into a proportion (Rossetti, 2021).

When testing the chi-square, the null and alternative hypotheses are demonstrated below. If the p-value is more than the confidence interval, it means that H₀ would not be rejected, and the empirical data fits with the hypothesized distribution. The null and alternative hypotheses for the chi-square goodness of fit test are the following:
**H₀:** The empirical data follows Lognormal distribution.

**Hₐ:** The empirical data does not follow Lognormal distribution.

Table 6-1 shows a demonstration of the chi-square tests for load at 60-65%. The analysis shows that the number of observations on each interval of dwell time is nearly equal to the expected number of the hypothesised distribution. As a result, the chi-square value is low. Figure 6-4 depicts a plot of the cumulative probability of empirical data versus the cumulative probability of the Lognormal distribution for each interval of dwell time for load at 60-65%. The plot depicts a linear line, which indicates that the empirical data follows a Lognormal distribution.

### Table 6-1: The chi-square goodness of fit test for the dwell time of load at 60-65%

<table>
<thead>
<tr>
<th>lower interval</th>
<th>upper interval</th>
<th>#Observation</th>
<th>CDF(upper)</th>
<th>CDF(lower)</th>
<th>#Hypothesis</th>
<th>chi-square</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>35</td>
<td>58</td>
<td>0.0874</td>
<td>0.0131</td>
<td>57.32</td>
<td>0.01</td>
</tr>
<tr>
<td>35</td>
<td>40</td>
<td>159</td>
<td>0.2724</td>
<td>0.0874</td>
<td>142.65</td>
<td>1.87</td>
</tr>
<tr>
<td>40</td>
<td>45</td>
<td>216</td>
<td>0.5228</td>
<td>0.2724</td>
<td>193.06</td>
<td>2.73</td>
</tr>
<tr>
<td>45</td>
<td>50</td>
<td>168</td>
<td>0.7422</td>
<td>0.5228</td>
<td>169.12</td>
<td>0.01</td>
</tr>
<tr>
<td>50</td>
<td>55</td>
<td>90</td>
<td>0.8823</td>
<td>0.7422</td>
<td>108.00</td>
<td>3.00</td>
</tr>
<tr>
<td>55</td>
<td>60</td>
<td>40</td>
<td>0.9531</td>
<td>0.8823</td>
<td>54.63</td>
<td>3.92</td>
</tr>
<tr>
<td>60</td>
<td>65</td>
<td>24</td>
<td>0.9833</td>
<td>0.9531</td>
<td>23.23</td>
<td>0.03</td>
</tr>
<tr>
<td>65</td>
<td>70</td>
<td>12</td>
<td>0.9945</td>
<td>0.9833</td>
<td>8.67</td>
<td>1.28</td>
</tr>
<tr>
<td>70</td>
<td>75</td>
<td>4</td>
<td>0.9983</td>
<td>0.9945</td>
<td>2.93</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Sum of Chi-square</td>
<td>13.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>p-value</td>
<td>0.10</td>
</tr>
</tbody>
</table>
Figure 6-4: The plot between the cumulative probability of empirical data and Lognormal for load at 60-65%.

Table 6-2 shows the lognormal parameters and chi-squared p-value for all ranges of load. The location (\( \mu \)) in lognormal distribution represents the mean of the natural logarithm of dwell time while the scale (\( \sigma \)) represents the standard deviation of the natural logarithm of dwell time.

The results of the goodness of fit test in Table 6-2 present that dwell times for the ranges of the load at 60-75% can fit the lognormal distribution with 95% confident interval considering chi-squared p-value greater than 0.05. However, dwell times for the ranges of the load over 75% have a random shape (as shown in Figure 6-3), thus the fitting performance is not good.
Table 6-2: Parameters and goodness of fit test of dwell time distribution

<table>
<thead>
<tr>
<th>Load on trains</th>
<th>Location (µ)</th>
<th>Scale (σ)</th>
<th>Chi-squared</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>60-65%</td>
<td>3.796</td>
<td>0.178</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>65-70%</td>
<td>3.838</td>
<td>0.182</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>70-75%</td>
<td>3.860</td>
<td>0.172</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>75-80%</td>
<td>3.873</td>
<td>0.176</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>&gt;80%</td>
<td>3.989</td>
<td>0.175</td>
<td>0.0004</td>
<td></td>
</tr>
</tbody>
</table>

The Probability Density Function (PDF) of the lognormal distribution with the parameter µ, σ is as follows:

\[ f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp \left(-\frac{(\ln(x)-\mu)^2}{2\sigma^2}\right) \] (1)

6.3.2 Dwell time delay probability distribution fitting

To improve the distribution fitting performance, the further analysis disregards the distributions of the on-time part as it does not have to lose the performance to fit the pattern of the on-time dwell time data. Dwell times which are lower or equal to the schedule are all considered as on-time (delay = 0). The extended dwell times are considered as the ranges of every 5 seconds and fit on the theoretical distribution functions again. Figure 6-5 presents the distributions of dwell time delays for the given ranges of load on trains. It is obvious that the ranges of lower load have right-skewed distributions in which most values cluster on the left and the distributions tend to spread more and move toward left-skewed when the load on trains increases.
Figure 6-5: Distributions of dwell time delays for the given ranges of load on trains.
The process of distribution fitting is repeated by fitting all data points on each range of load on trains with theoretical distributions using the library called “Auto-fitter” in Python3. The dwell time delays for different ranges of load on trains now commonly fit with Weibull distribution. Weibull distribution is usually used in risk analysis to evaluate the failure rate. It is a flexible and adaptable distribution (Frost, 2022).

The process of fitting dwell time delay distribution is the same as fitting dwell time value with lognormal distribution. Maximum Likelihood Estimation (MLE) is used to identify parameters of Weibull distribution for given ranges of load on trains. A chi-squared goodness of fit test is also used to validate the goodness of fit of dwell time delay on each interval. The null and alternative hypotheses are demonstrated below. If the p-value is more than the confidence interval, it means that $H_0$ would not be rejected, and the empirical data fits with the hypothesized distribution. The null and alternative hypotheses for the chi-square goodness of fit test are the following:

$H_0$: The empirical data follows Weibull distribution.

$H_a$: The empirical data does not follow Weibull distribution.

The p-value results in Table 6-3 show that all the ranges have better fit performance than fitting dwell time data (as the variations at the on-time part has been omitted). Table 6-3 presents the goodness of fit test and fitted parameters of the dwell time delay for each range of load on trains. The dwell time delay for all ranges of load has a good fit to the Weibull distribution. In terms of the parameters, shape and scale are both increased according to the increase of the load on trains. The scale parameter represents the variability in the distribution. Delays tend to have higher variability when the load is higher. The shape parameter tells the shape of the distribution. For the Weibull distribution, the smaller shape parameter indicates that the distribution tends to have a more right-skewed distribution which means that the lower load on trains is likely to cluster at lower dwell time delays. The shape parameters of dwell time delay distributions range from 0.9 to 2.
Table 6-3: Parameters and goodness of fit test of delay distribution

<table>
<thead>
<tr>
<th>Load on trains</th>
<th>Shape (k)</th>
<th>Scale (λ)</th>
<th>Chi-squared</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>60-65%</td>
<td>0.9575</td>
<td>8.8443</td>
<td>8.8443</td>
<td>0.28</td>
</tr>
<tr>
<td>65-70%</td>
<td>1.1570</td>
<td>11.6419</td>
<td>11.6419</td>
<td>0.10</td>
</tr>
<tr>
<td>70-75%</td>
<td>1.2527</td>
<td>12.5289</td>
<td>12.5289</td>
<td>0.45</td>
</tr>
<tr>
<td>75-80%</td>
<td>1.6950</td>
<td>15.8810</td>
<td>15.8810</td>
<td>0.29</td>
</tr>
<tr>
<td>&gt;80%</td>
<td>1.9679</td>
<td>20.5086</td>
<td>20.5086</td>
<td>0.24</td>
</tr>
</tbody>
</table>

The Probability Density Function (PDF) of the Weibull distribution with the parameter $k, \lambda$ is as follows:

$$f(x) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^k}$$  \hspace{1cm} (2)

6.4 The bivariate dwell time delay function

This section further develops the bivariate dwell time delay function for applying on the analytical dwell time delay evaluation. This dwell time delay function is aimed to represent the probability of delay for all ranges of the load on trains. A bivariate function with load and dwell time delay variables is defined under the assumption that dwell time delays follow the Weibull distribution. Figure 6-6 illustrates the dwell time delay distributions on the x-axis for different levels of train load (z-axis) to illustrate the distributions in 3 dimensions and introduce the probability distribution with 2 variables.
According to the Weibull parameters presented in Table 6-3, both shape and scale parameters of dwell time delay distributions have an increasing trend when the load on trains increases. This research fits Weibull’s shape and scale parameters with the regression analysis, thus functions of parameters with the load factor (L) as a variable are obtained and substituted into the Weibull function. The models and R-square of shape and scale parameters obtained from regression analysis are as follows:

Weibull’s shape model: \[ k = 0.106 \times e^{0.0365 \times L} \text{ with } R^2 = 0.9765 \] (3)

Weibull’s scale model: \[ \lambda = 0.819 \times e^{0.0399 \times L} \text{ with } R^2 = 0.9788 \] (4)

The Weibull’s parameter models in Equation (3) and (4) are substituted into the Weibull PDF function (Equation 2), thus the dwell time delay probability function with load (L) as a variable is obtained as in Equation (5). This function gives the probability of trains having L% of the load on trains being delayed at the certain length of \( x \) seconds.

\[
f(x, L) = \frac{0.106e^{0.0365\times L}}{0.819e^{0.0399\times L}} \times \frac{x}{0.819e^{0.0399\times L}} \times e^{-\left(\frac{x}{0.819e^{0.0399\times L}}\right)^{0.106e^{0.0365\times L}}} \] (5)
In addition to the bivariate Probability Density Function (PDF), the bivariate Cumulative Distribution Function (CDF) of the Weibull distribution could be used to evaluate the likelihood of trains being delayed over a certain length of delay and this requires the cumulative probability of the delay. The CDF of dwell time delay is composed of 2 variables which are the amount of delay (x) and percentage of the load on trains (L). This function gives the likelihood of trains having L% of the load on trains being delayed more than x seconds (x could be called the delay cutting point or delay threshold). The bivariate dwell time delay function obtained is as follows:

\[ p(delay > x, L) = F(x, L) = e^{-\left(\frac{x}{0.819e^{0.0399L}}\right)^{0.106e^{0.0365L}}} \]  

The bivariate dwell time delay function was validated with the observation data using the Kolmogorov-Smirnov (K-S) test and it was found that it gives 78% of R-square. The K-S test was selected to validate the goodness of fit of this function because both variables in the function are continuous and are not dependent on the data interval. The K-S test validates the bivariate model by testing with matrices (delay (x), load (L)) of all data points. The K-S test compares the model CDF with the empirical CDF without specifying intervals. The K-S test is more powerful than the chi-square test as it uses all the data observations in the test (Law, 2007).

Figure 6-7 shows the P-P plot which is the plot between empirical and theoretical cumulative probability. Figure 6-8 shows the residual plot across the delays, and it presents that the delay function has around -10% to +10% error and that more variations are at the lower levels of delay. One of the reasons is that the number of observations at the lower levels of delay is much higher and the cumulative density at the higher levels of delay is closer to 1.

The overall performance of the delay function in predicting the probability of dwell time delays is quite satisfactory. Predicting dwell times based on the probability of delay could be more accurate than predicting the average or the representative value of dwell times.
Figure 6-7: The plot between the cumulative probability of empirical data and the model

Figure 6-8: The residual plot across the delay
6.5 An application of the dwell time delay function

When the delay function is established, it enables the testing of the probability of delay on different values of delay (x). The likelihood of delay varies according to different levels of the load on trains (L). The dwell time delay function has a huge benefit on dwell time and dwell time margin setting in the train scheduling. In the planning process, several lengths of dwell time setting can be tested, and the probability of delays from the setting could be obtained from the dwell time delay function. When varying dwell times and margins in the timetable, the planning can target different amounts of train service frequency by setting different lengths of dwell time. Several planning strategies can use this dwell time delay function to evaluate the service performance. For example, if the target is to run 36 trains per hour, it ideally means that the trains at the critical stations should have a maximum of 100 seconds headway. The breakdown of time presented previously shows that the maximum train dwell time is 52 seconds (assuming constant Run-out-run-in time (RORI) at 48 seconds). It should be noted that maximum dwell time here means the upper limit of the dwell time, which consists of scheduled dwell time and dwell time margin, that could make 36 trains per hour achievable. The dwell time delay function would evaluate the probability that this target dwell time could be achieved.

Table 6-4 compares this alternative dwell time delay perspective with the current dwell time perspective. The current dwell time approach predicts dwell time values, which can be inaccurate when passenger volume is high. In situations with a high passenger volume, dwell time delays have significant effects on service performance and passenger delay. This alternative perspective on dwell time delay takes into account the dwell time delay, which is more accurate and suitable for high-passenger-volume stations.
Table 6-4: Comparison of the current and the proposed dwell time delay perspectives

<table>
<thead>
<tr>
<th>Criteria</th>
<th>The current dwell time perspective</th>
<th>The probability of dwell time delay perspective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Types of the estimation</td>
<td>Estimates dwell time value</td>
<td>Estimates the probability of dwell time delay</td>
</tr>
<tr>
<td>Accuracy</td>
<td>Inaccurate in high-passenger-volume situations as taking the point estimation of the high variation data. The current dwell time model tested in Chapter 5 gave 23% of the accuracy</td>
<td>More accurate as using a range estimation. The bivariate dwell time delay function tested in this Chapter gave 73% of the accuracy.</td>
</tr>
<tr>
<td>Application on the types of stations</td>
<td>Suitable for low passenger volume stations which dwell times have less variations, as the model can provide an accurate dwell time prediction</td>
<td>Suitable for high passenger volume stations which dwell times have high variations. Dwell time delays have a significant impact at high passenger volume stations in a high frequency service, so being able to predict dwell time delays accurately is critical</td>
</tr>
<tr>
<td>Application on the timetable planning</td>
<td>Estimates the representative value of dwell time for use in the timetable planning</td>
<td>Dwell time is set according to the target service frequency, and then the method evaluates the probability of dwell time being delayed over the target dwell time</td>
</tr>
</tbody>
</table>
Criteria | The current dwell time perspective | The probability of dwell time delay perspective
--- | --- | ---
Application on the risk of delay evaluation | One representative value is estimated; thus, it is not applicable to evaluate the risk of several lengths of dwell time delay. | The probability is used together with the consequences of dwell time delay corresponding to the probability to evaluate the risk of several lengths of dwell time delay. This will be demonstrated in Chapter 7

The cumulative probability function of train delay considers the probability, or the percentage of trains being delayed over certain amount is another indicator that could be used to evaluate the service reliability. The cumulative probability of train delay provides the probability of trains being delayed over certain amount which is a cut-off point of the delay. The bivariate Cumulative Distribution Function (CDF) of the Weibull distribution could be used to evaluate this probability. For example, if setting the cut-off delay (the point taken into account as a delay threshold value) extending from the scheduled or target dwell time at 5 seconds, the probability of delay over 5 seconds would be the summation of the probability of the right-tail of the probability distribution \( \int_{5}^{\infty} f(x)dx \) where the amount of delay is all over 5 seconds.

Figure 6-9 demonstrates the cumulative probability of train delays on different ranges of passenger volume level. The higher volume on trains definitely has a higher likelihood of delay. A bivariate dwell time delay CDF allows the estimation of the probability of trains having a certain level of passenger volume being delayed over a certain length of time. The figure shows that the probability of delays is high for all load levels when the delay is less than or equal to 0 (on-time). When the cut-off delay is increased to 10 seconds, the probability of delays decreases and varies depending on the load level. The figure shows several cut-off delays to demonstrate the amount of dwell time margins being set in the timetable and the probability of achieving them.
Figure 6-9: The probability of delay for different percentage of load on trains

Figure 6-10 presents the probability of delay from 0 to 1 with a heatmap. The dark red colour in the lower left of the chart represents the highest probability of delay which is when high passenger volume trains (90% of the full load) and the cut-off delays at 5 seconds are set. In the timetable planning, if setting higher dwell time (providing more margins), there will be a lower probability of delay. The lighter colour in the chart shows a lower probability of delay.

Figure 6-10: The probability of delay’s heatmap
With this dwell time delay evaluation approach, the target dwell time and train load can be set first. Then, the probability of a train with a certain load being delayed over the target dwell time can be evaluated. This cumulative probability of train delay is used as one of the indicators to demonstrate the service reliability of different passenger control strategies on the line-level passenger flow model demonstrated in Appendix A. However, the evaluation in Appendix A only gives the result as a probability of delay without considering the impact of delay. When considering the delay over a certain point, it does not take an account of the duration of delay, which has different levels of impact (5-second delay has less impact than 20-second delay). Long dwell times at high-passenger-volume stations can have a significant impact on passengers on the whole line.

Chapter 7 will evaluate and optimise the line-level service performance with the risk of dwell time delay using the bivariate dwell time delay function obtained in this chapter. The consequences of each length of dwell time delay will be considered in Chapter 7. The dwell time delay function used in Chapter 7 would be a PDF function, which gives the probability of trains with a certain level of passenger volume being delayed by a certain amount of time. This is in contrast to the CDF function, which returns the sum of the probability of all delays of a given length, regardless of the amount or consequences of the delay (if the cut-off delay is set at 5 seconds, the delays over 5 seconds are regarded as having the same consequences, whereas in fact the higher length of delays may impact the service performance more).
Chapter 7

The risk of dwell time delays at a high passenger volume station

In many metro lines, there is sufficiently high signaling and train capability to run a high frequency service, but in practice the trains are delayed at the critical stations due to trains stopping at the station longer than the scheduled headway. These critical stations can become the stations that determine the line capacity. This chapter evaluates the risk of dwell time delays at these high passenger volume stations on high frequency service systems. In the previous chapter, dwell time delays are assessed with the probability of having a certain length of delays. The analysis in this chapter adds the consequences of dwell time being delayed at a certain length and presents the outcomes with the risk of dwell time delays. The risk of dwell time delays in this research takes into account both the probability and the effects of such delays.

The dwell time evaluation in the previous chapter shows different dwell time delay probability functions at different levels of passengers on trains. The lower levels of load on trains before arriving at critical stations are highly likely to cause less dwell time delays. This chapter considers the proactive line-level passenger control strategy to control passengers at the upstream stations and get a lower load on trains before arriving at critical stations, which would consequently lead to a lower risk of delay. The key to this evaluation is the trade-off between passenger control and train delay. The more passengers being controlled at the upstream stations to get lower passengers on trains before arriving at the critical station basically leads to a lower dwell time delay at the critical station. To balance between passenger control and train delay, this research considers the consequences of passenger control and train delay according to London Underground’s Business Case Development Manual (TfL Programme Management Office, 2013) which uses the passenger weighted journey time. This chapter develops an evaluation framework to assess the risk of dwell time delay on various load levels and suggests the optimum train load for various ranges of dwell time margin.

Dwell time margin is an essential component of the timetable, especially for high frequency service systems, and it is used to absorb delays. When assessing the consequences of a dwell time delay, the dwell time margin is a crucial factor to consider. Setting a higher dwell time margin can reduce the impact of delays and train
knock-on effects, but it also reduces the service frequency (varying dwell time margins also mean evaluating different scheduled headways or service frequencies). More explanations are given in section 7.2.2. This chapter evaluates the risk of dwell time delays for different amounts of dwell time margin and different levels of load and gives the best-case scenario.

7.1 The risk of dwell time delays

This section focuses on the evaluation of the risk of dwell time delay, and this needs a clear scope and scenario for the purpose of the evaluation. This research evaluates the risk by evaluating the impact of each length of dwell time delay together with the likelihood that this length of delay could exist (the likelihood of delay is obtained from the previous Chapter 6). There is a specific scenario which this delay evaluation is used for. The term dwell time delay in this chapter is defined as when trains stop at the critical station over the scheduled dwell time. This research focuses on a station where the dwell times are frequently delayed. The evaluation is only made for the effect of the dwell time delay at this critical station, regardless of the other delays. The assumptions that this research made for this evaluation are:

- There is no other delay from the other stations.
- Only the dwell time margin is taken into account. Run-time margin is disregarded because the focused system employs the Automatic Train Operation (ATO) system.
- The focus is at the crowding situation which full of passengers waiting to board trains at the platform of the critical station.
- This evaluation is for the busy line where dwell times at the critical station is limited, thus this research assumes trains leave the critical station as soon as passengers finish boarding and alighting, which in fact in the non-crowded case there might be some trains arrive earlier and have to stay longer to follow the schedule.
- All trains in the analysis are subject to the same conditions specified for each planning scenario (pre-plan load on trains and dwell time margin). With the same pre-plan load, the probability distribution would be identical, and the calculation process takes into account all possible lengths of delays in the probability distribution.
- No delay recovery at any points of the system is considered to demonstrate the case setting in this evaluation framework when passengers are full on both the platform and trains, thus there is no chance of the next trains to improve the delays, even the trains already take longer than the scheduled departure time.

7.1.1 The configuration for evaluating the risk of dwell time delays

The evaluation concept is to balance the impact of delays at the critical station, passengers being controlled at upstream stations, and passengers waiting to board trains at all stations. It is highly likely that there will be more dwell time delays at the critical station if the trains carry more passengers, resulting in delays for passengers on the delayed trains and on the trains that follow. The duration of the delay and the dwell time margin are the primary determinants of whether the trains will have a knock-on effect. To evaluate these consequences, the assessment areas have been divided into three sections: the upstream stations, the critical station, and the downstream stations as shown in Figure 7-1.

Figure 7-1: Evaluation framework at 3 assessment areas
The evaluation is demonstrated on the northbound service of the Victoria Line as shown in Figure 7-2 (more explanations about the line are given in Chapter 3), which is divided into three sections according to the assessment areas. Prior to passengers arriving at the critical station, the stations upstream have to control passengers cooperatively to achieve the suggested load. Lastly, stations downstream of the critical station are the stations where passengers are impacted by train delays at the critical station.

Figure 7-2: Assessment areas on the northbound service of Victoria line (Mather, 2003)
The evaluation's objective is to minimise the risk of dwell time delay from all assessment areas. In this analysis, the risk of dwell time delays considers both the consequences and probability of dwell time delays. The decision variables are the predetermined train load before arriving at the critical station \((L)\) and the dwell time margin that should be added to the timetable \((t)\). The expected outcomes of the analysis are the risk of delay for each combination of load level and dwell time margin.

The evaluation demonstrates scenarios for planning a load level and dwell time margin and provides an assessment of the risk of delay for various scenarios using the passenger weighted journey time (WJT) function, in which the effect of all passenger delays would be incorporated into the analysis. A passenger weighted journey time analytic model is developed to evaluate the risk of delay for each combination, allowing for the determination of the best-case scenario. The passenger weighted journey time is chosen for evaluation because this study employs a passenger-based methodology that considers all effects from the passengers' time perspective. The impact of both train delays and passenger controls are quantified and determined by the amount of time passengers spend on the system.

### 7.1.2 The calculation of the risk of dwell time delays

The risk of dwell time delays could be calculated from the summation of the dwell time delay probability function and the passenger weighted journey time (WJT) for all lengths of delays. This is to evaluate the impact of each length of delays and the chance of having this length of delay. The total passenger weighted journey time (Total WJT) represents the risk of delays of each scenario by summing the probability and WJT of all dwell time delay values. The calculation will begin by analysing the consequence of delay (WJT) with a 1 second dwell time delay \((x=1)\) and the probability of having a 1 second dwell time delay. The calculation proceeds until \(n\) seconds of dwell time delay, at which point its probability approaches 0.

The probability function \(f(x, L)\) is the bivariate delay function obtained from the previous chapter 6. This function gives the likelihood of trains having the \(L\%\) of load on trains before arriving at the critical station being delayed by \(x\) seconds. The passenger weighted journey time (WJT) function is demonstrated in the next section. The total WJT for the preset dwell time margin \(t\) and load \(L\) is represented as:
\[ Total\ WJT(t, L) = \sum_{x=1}^{n} f(x, L) \cdot WJT(x, t, L) \] (1)
\[ f(x, L) = \frac{0.106e^{0.0365x}}{0.819e^{0.0399x} \cdot L} \cdot \frac{x}{0.819e^{0.0399x} \cdot L} \cdot e^{-\left(\frac{x}{0.819e^{0.0399x} \cdot L}\right)^{0.106e^{0.0365x} \cdot L}} \] (2)

*Where:* \( x = \) Amount of dwell time delays evaluated in seconds = \((1, \ldots, n)\)

\( L = \) The percentage of the load on a train before arriving at the critical station

### 7.2 Passenger weighted journey time

Passenger weighted journey time (WJT) is an evaluation approach used in TfL to quantify the benefits of a project (TfL Programme Management Office, 2013). In this analysis, it is used as a function to represent the consequences or impacts of dwell time delays on passengers. WJT considers passenger value of time unequally for different activities or stages of a journey. When passengers are restricted from boarding the trains, they may value the time more highly than they value spending time at other stages. The weights applied in this research will be based on Business Case Development Manual (BCDM) (TfL Programme Management Office, 2013).

BCDM is the TfL’s manual for the evaluation of project benefits compared to the cost of the projects. Appendix E of the manual include the principles of passenger benefit quantification. Weights for elements of journey time are presented in Table E-5 of the manual in which the values are derived from the research by TfL (TfL Programme Management Office, 2013). The weights of passenger time consider the case when passengers waiting at crowded and uncrowded differently which this current research will refer to the weights given in the BCDM. The weights for elements of journey time which relate to this research are presented in Table 7-1.
Table 7-1: the weights given to the WJT (TfL Programme Management Office, 2013)

<table>
<thead>
<tr>
<th>Journey Time Element</th>
<th>Weighting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delay at ticket gate or control point</td>
<td>4.0</td>
</tr>
<tr>
<td>Standing or sitting in a crowded train</td>
<td>1.0 + RF²</td>
</tr>
<tr>
<td>Waiting for trains on uncrowded platform</td>
<td>2.5</td>
</tr>
<tr>
<td>Waiting for trains on crowded platform</td>
<td>2.5 + CF³</td>
</tr>
</tbody>
</table>

The total passenger weighted journey time is calculated from a summation of passenger time at each time term. Each time term is the product of three other variables: the weights or impacts of each term, the number of passengers being affected, and the amount of time spent. The WJT can be expressed as:

\[ \text{Weighted journey time (WJT)} = \text{Weights} \times \text{Number of passengers} \times \text{Time} \]

7.2.1 An analytical model of passenger weighted journey time

This section presents an analytical model to evaluate the consequences of delays in different scenarios. Passenger weighted journey time (WJT) is used as the model’s performance indicator. Passenger weighted journey time included in this research is concluded in Table 7-2 and can be explained as:

\[ \text{RF} = 0.09 + (2.11 - 1.13Y) \times X \]
where \( Y = 0.254 \) for Victoria line and
\[ X = \frac{\text{train load}}{\text{train seats}} / \frac{\text{crush load}}{\text{train seats}} = 0.60 \]
RF = 1.18 for Victoria line

\[ \text{CF} = 0.667 \times (P - 0.5)^2 \]
where \( P \) is platform crowding level and values between 0.5 and 2, CF = 1.5 when \( P \) is greater than or equal to 2, CF = 0 when \( P \) is less than 0.5 (Source: Rolling stock data sheet, 2011) CF = 1.5 for Victoria line
(Transport for London, 2011)
• Column 1 is passengers restricted time at the upstream stations \( (T_u) \): Passengers are affected by being restricted from getting onto trains as this causes a delay to the restricted passengers.

• Column 2 is passengers denied boarding time at the critical station \( (T_{c1}) \): When trains arrive at the critical station with a high load, there would be passengers being denied to board trains at the critical station, i.e., passengers who cannot board the train due to a lack of space on the trains.

• Column 3 is passengers being delayed on trains at the critical station \( (T_{c2}) \): Delays on trains are composed of dwell time delays at the critical station, and train knock-on delays if train dwell time delays at the critical station are over the dwell time margin resulting in following trains catching up. These delays would cause delays to passengers already on the trains.

• Column 4 is passengers waiting for trains at the downstream stations \( (T_d) \): Passengers at the downstream stations could be affected by the extended dwell time delay if trains are dwelling over the dwell time margin at the critical station.

Passenger weighted journey time evaluates the consequence of train delays at all assessment areas. Passengers being denied to board trains at the critical and upstream stations indicates the cost associated with the passenger control whereas passengers being delayed on trains and passengers waiting for trains at the downstream stations represent the cost associated with train delays. Table 7-2 outlines all components that would ultimately be added together to get the total WJT which represents the consequences of delays.
Table 7-2: Components of passenger weighted journey time

<table>
<thead>
<tr>
<th></th>
<th>1. Upstream Stations</th>
<th>2. Critical Station</th>
<th>3. Downstream Stations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Restricted Delay</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>($T_u$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Denied Boarding Delay</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>($T_{c1}$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>In-vehicle Delay</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>($T_{c2}$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Delay on platform</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>($T_d$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Passenger control</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Train delay</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Weights**

- The weight for passengers being controlled ($w_u = 4$)
- The weight for passengers waiting on a crowded platform ($w_{c1} = 4$)
- The weight for passengers being delayed in vehicle ($w_{c2} = 2.18$)
- The weight for passengers waiting on an uncrowded platform ($w_d = 2.5$)

**Number of passengers affected per hour**

- The demand per hour ($D_u$)
- The demand per hour ($D_{c1}$)
- The demand per hour ($D_{c2}$)
- The demand per hour ($D_{d}$)

- The capacity per hour is the total number of passengers being carried per hour ($S_u = f_a \times L$)
- The capacity per hour is the total number of passengers being carried per hour ($S_{c1} = f_a \times (100 - L)$)
- Passengers on trains before arriving at the critical station ($f_a \times L$)
- Passengers waiting to board trains at the downstream stations ($D_{d}$)

**Passengers restricted from getting onto trains at upstream stations** ($\text{Max}(0, D_u - S_u)$)

**Passengers being denied to board at the critical station** ($\text{Max}(0, D_{c1} - S_{c1})$)

**Duration of time**

- Time for restricted passengers to wait for next trains equals scheduled headway ($H_u$)
- Time for denied boarding passengers to wait for next trains equals achieved headway ($H_a$)
- Amount of dwell time delay at the critical station ($x_i$)
- Accumulated time of train knock-on delays when trains dwell time delay over dwell time margin ($t$) ($\text{Max}(0, x_i - t) \times (f_a^{-1})^2$)
- Time for passengers waiting for the next trains equals achieved headway ($H_a$)
An analytical model of the passenger weighted journey time can be formulated as:

\[ WJT = T_u + T_{c1} + T_{c2} + T_d \]  
(3)

\[ T_u = w_u \times Max(0, D_u - S_u) \times H_s \]  
(4)

\[ T_{c1} = w_{c1} \times Max(0, D_c - S_c) \times H_a \]  
(5)

\[ T_{c2} = w_{c2} \times (f_a \times L) \times (x_i + Max(0, x - t) \times \frac{(f_a+1)}{2}) \]  
(6)

\[ T_d = w_d \times D_d \times H_a \]  
(7)

**Where:**
- \( L \) = The percentage of the load on a train before arriving at the critical station
- \( t \) = Dwell time margin
- \( x_i \) = A parameter in the analysis represented a length of dwell time delays evaluated. All the possible values of dwell time delays are taken to evaluate the consequences and their probabilities = \((1, 2, 3, ..., n \text{ seconds})\)
- \( w_u, w_{c1}, w_{c2}, w_d \) = Weights or impacts of each term
- \( D_u, D_c, D_d \) = Demand at each assessment area per hour as a percentage of a train at full capacity
- \( S_u, S_c \) = Capacity or passengers being carried for each assessment area per hour
- \( H_s \) = Scheduled headway (seconds)
- \( H_a \) = Achieved headway at the critical station (seconds)
- \( f_s \) = Scheduled train frequency (trains per hour) = \(\frac{3600}{H_s}\)
- \( f_a \) = Achieved train frequency (trains per hour) = \(\frac{3600}{H_a}\)
7.2.2 Scheduled and achieved headway

Train headway is the time difference between 2 services. Basically, it is decided by the signaling and train stop time at the station. Run-out-run-in time (RORI) is a headway component which evaluates the signal and train performance time at each station. It is a train reoccupation time which is the time for the leading train to run out (RO) and the time for the following train to run in (RI) (Winslett, 2019). This research assumes a constant RORI, and the scheduled dwell time as explained in the previous Chapter 3. The dwell time margin would be a variable in the analysis. Figure 7-3 presents the scheduled and achieved headway.

Scheduled headway in this research refers to the planned length of time between two trains. It includes the dwell time margin which is the buffer time provided for the delay (the delay in this research refers to dwell time delay). When the dwell time margin is varied, different numbers of scheduled headways (or train frequency targets) are investigated. For the achieved headway, this research evaluates achieved headways at the critical station where dwell time delays take place. Dwell time delay according to the dwell time delay function from previous Chapter 6 is the delay beyond the scheduled dwell time. If the dwell time delay (x) is lower than the dwell time margin (t), the achieved headway will be within the scheduled headway. When the dwell time delay exceeds the margin, it begins to extend the achieved headway. If early departure is not considered, the achieved headway can be obtained as:

\[ H_a = H_s + \text{Max}(0, (x_i - t)) \]  

Figure 7-3: Components of scheduled and achieved headway
7.2.3 Train knock-on delay

Train knock-on delay is the delay caused when the following trains catch up with the leading train. Train knock-on delay in this research takes place when the length of the dwell time delay \( x \) exceeds the dwell time margin \( t \). This causes the leading train dwelling longer at the critical station’s platform and the following trains catch up with the leading train. Figure 7-4 and Figure 7-5 present train graphs for the case of trains with and without knock-on delay. RORI is considered constant in the analysis, therefore a specific length of operational time is required to replace a train at the platform with the following train (Winslett, 2019). The length of dwell time delay of the leading train which is extended from the dwell time margin will affect the arrival time of the following train. For example, if the leading train’s dwell time extends 3 minutes from the dwell time margin, the next train will also be delayed by 3 minutes. This research assumes the same conditions for all trains and no delay recovery at any points of the system, therefore trains will all have the same length of extended delay.

Figure 7-5 presents train knock-on delay accumulation when all trains have the same length of extended delay. When the first train has an extended dwell time delay, the second train’s knock-on delay is \( 1 \times \) the extended delay, and the third train’s knock-on delay is \( 2 \times \) extended delay. This sequence continues up to \( f \) trains per hour. The equations of the accumulated train knock-on delay can be written as:

\[
\text{if extended delay} = x_i - t \\
\text{\( i^{th} \) train knockon delay} = (i - 1) \times (x_i - t) \\
\text{Accumulated train knockon delay} = (x_i - t) \times \sum_{i=1}^{f_a} (i - 1) = (x_i - t) \times \frac{(f_a-1)f_a}{2} \quad (9)
\]
In this research evaluation’s assumptions, there is no early departure or no recovery (more explanations are given in section 7.1). In fact, when there are knock-on delays, the train following may have a dwell time shorter than the scheduled dwell time in order to recover and run according to the timetable. Therefore, there might be shorter extended delay being carried to the next trains.
7.3 Calculation methods

The calculation will be made in 2 parts: the analysis to achieve the Victoria line target train frequency and the analysis with all possible scenarios. The objective of the calculation is to obtain the optimum scenario (the combination of load level and dwell time margin) which gives the lowest total passenger weighted journey time. The optimum scenario enables the planning of passenger control strategy at the upstream stations and the planning of dwell time margin to be added into the timetable.

The analysis first demonstrates the risk of dwell time delays in the calculation of the current target train frequency on the Victoria line. The Victoria Line is aimed at running 36 trains per hour. This means that the trains should have 100 seconds of headway in order to keep the trains running according to the planned frequency. The run-out-to-run-in time is set constantly at 48 seconds, and the scheduled dwell time is set at 38 seconds according to the morning peak timetable. The rest of the time is considered as a dwell time margin (14 seconds). The calculation baseline sets a 14-second dwell time margin (t=14), and no passenger control is deployed at upstream stations. No passenger control is the case when trains arrive at the critical station with the full load at 90% (the load at 100% is not taken into consideration as it is an invalid value which does not exist in the real dataset). Then, the calculation starts by evaluating the consequence of a delay (WJT) with a dwell time delay of 1 second (x=1) and the probability of having 1 second of train dwell time delay. The analysis continues discretely up to n-seconds of dwell time delay, where its probability closes to 0. The summation of the consequences of each length of delay and the probability of having this length of delay for all lengths of delays provides a total passenger weighted journey time (representing the risk of dwell time delays) of the base line case. The total passenger weighted journey time is continuously calculated for other load levels, thus the optimum load for the current target train frequency on the Victoria line is achieved.

Another analysis takes the empirical approach, which increases one variable by a certain value and substitutes the variable into the analytical model. The analysis varies the dwell time margin from 0 to 25 seconds for every 5 seconds and varies the load on trains before arriving at the critical station from 60% to 90% for every 5%, which are feasible values for the current system (i.e., the load at 55% is not considered, as it would require overcontrolling passengers at upstream stations to achieve this load level. In
addition, the remaining capacity for the critical station exceeds the station's demand). Six margin values and seven load levels are evaluated, resulting in a total of 42 tested scenarios. Then, the best-case scenario is determined by comparing the outcomes of each scenario.

7.4 Results

7.4.1 The analysis for the current target train frequency

This section demonstrates the analysis for the Victoria Line's current target train frequency. First, the scenario is examined in which trains arrive at the critical station with a full load and without passenger control (L=90%). Table 7-3 displays the analysis for the baseline scenario (dwell time margin = 14 seconds; load level = 90 percent). The total WJT is calculated by adding the risk of dwell time delays between 1 and 70 seconds in the final column. This scenario has a total WJT of 1,988,830 seconds. Considering WJT for each length of delay, the WJT increases as the length of dwell time delay increases, and it increases dramatically when the dwell time delay exceeds the dwell time margin (x=15 in this scenario). When the dwell time is delayed by more than 14 seconds, it results in an extended delay from the dwell time margin and a longer headway being achieved. Subsequent trains are affected by knock-on delays when the dwell time delay is longer than the margin. The probability of delay derived from the delay function, which provides the probability that trains carrying L percent of the total load will be delayed by x seconds, shows that there is a higher probability on a higher length of delay. Thus, the weight on the probability is higher for a longer length of delay, causing a higher risk of delay.
Table 7-3: Baseline analysis with a 14-second dwell time margin and no control at upstream stations

<table>
<thead>
<tr>
<th>dwell time delay in second (x)</th>
<th>Achieved train frequency ( (f_a) )</th>
<th>( T_u )</th>
<th>( T_{c1} )</th>
<th>( T_{c2} )</th>
<th>( T_d )</th>
<th>WJT in second</th>
<th>Probability of delay</th>
<th>WJT * Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>36</td>
<td>0</td>
<td>273,600</td>
<td>7,063</td>
<td>270,000</td>
<td>550,663</td>
<td>0.0002</td>
<td>106</td>
</tr>
<tr>
<td>2</td>
<td>36</td>
<td>0</td>
<td>273,600</td>
<td>14,126</td>
<td>270,000</td>
<td>557,726</td>
<td>0.0007</td>
<td>383</td>
</tr>
<tr>
<td>3</td>
<td>36</td>
<td>0</td>
<td>273,600</td>
<td>21,190</td>
<td>270,000</td>
<td>564,790</td>
<td>0.0014</td>
<td>812</td>
</tr>
<tr>
<td>4</td>
<td>36</td>
<td>0</td>
<td>273,600</td>
<td>28,253</td>
<td>270,000</td>
<td>571,853</td>
<td>0.0024</td>
<td>1,389</td>
</tr>
<tr>
<td>5</td>
<td>36</td>
<td>0</td>
<td>273,600</td>
<td>35,316</td>
<td>270,000</td>
<td>578,916</td>
<td>0.0036</td>
<td>2,108</td>
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<tr>
<td>15</td>
<td>35.64</td>
<td>0</td>
<td>277,776</td>
<td>233,028</td>
<td>272,700</td>
<td>783,504</td>
<td>0.0236</td>
<td>18,522</td>
</tr>
<tr>
<td>...</td>
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<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>20</td>
<td>33.96</td>
<td>0</td>
<td>298,656</td>
<td>832,170</td>
<td>286,200</td>
<td>1,417,026</td>
<td>0.0333</td>
<td>47,250</td>
</tr>
<tr>
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</tr>
<tr>
<td>25</td>
<td>32.43</td>
<td>0</td>
<td>319,536</td>
<td>1,329,144</td>
<td>299,700</td>
<td>1,948,380</td>
<td>0.0376</td>
<td>73,277</td>
</tr>
<tr>
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<td>...</td>
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<td>The summation of WJT*probability</td>
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The following scenario compares the result when passengers are controlled at upstream stations with the outcome when no passengers are controlled. Table 7-4's analysis illustrates the situation when train loads are limited to 60% before arriving at a critical station. This scenario has a total WJT of 836,746 seconds.
In the case of trains with a load of 60%, the probability of delay is greater for shorter dwell time delays; consequently, the WJT multiplied by the probability is greater at the beginning. Even though there are greater impacts from passenger control, the impact of train delays at shorter dwell times is relatively low due to the lower train load.

Table 7-4: The analysis with a 14-second dwell time margin and passenger control at upstream stations

<table>
<thead>
<tr>
<th>dwell time delay in second (x)</th>
<th>Achieved train frequency (f_a)</th>
<th>( T_u )</th>
<th>( T_{c1} )</th>
<th>( T_{c2} )</th>
<th>( T_d )</th>
<th>WJT in second</th>
<th>Probability of delay</th>
<th>WJT * Probability</th>
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<td>270,000</td>
<td>711,418</td>
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<td>270,000</td>
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<td>33,696</td>
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</table>

The summation of WJT*probability

836,746
Figure 7-6 compares the results of the WJT multiplied by the probability for different values of dwell time delays in the cases of passenger control and no control. With passenger control, dwell time delay is clustered at the lower values according to the dwell time delay probability function. Therefore, the shorter dwell time delay will impact the total WJT more because most of the passenger weighted journey time is due to passengers being controlled at the upstream stations. In the case of no control, dwell time delay is clustered at the higher values, therefore the dwell time delay extending from the dwell time margin will have more impact on the total WJT.

Figure 7-6: Passenger weighted journey time multiplied by probability for the case of control and no control

Figure 7-7 summarises the results for different levels of pre-set loads on trains before arriving at the critical station for the Victoria line’s current target headway. The results show that the total WJT increases dramatically when the load is over 70%. The optimum load level, where the total WJT is the lowest, is at 65%.
4.2 The analysis on different dwell time margins and load levels

This section evaluates 42 combinations of dwell time margins ranging from 0 to 25 seconds per 5 seconds and train loads prior to arrival at the critical station ranging from 60 to 90% per 5%. Figure 7-8 provides an overview of the results on different dwell time margins through changes of the load on trains before arriving at the critical station. The lower margins (0-10 seconds) have less buffer to absorb delays, thus the results indicate that the lower numbers of passengers on trains before arriving at the critical station give the better results. In the lower margins, it is crucial to control the load on trains prior to their arrival at the critical station; otherwise, the total WJT can reach its maximum level due to the severe delays caused by the overcrowded trains. The setting of a shorter dwell time margin also results in a shorter train headway. Passengers on the platform would spend less time waiting for trains, but if the margin is too small, trains would catch up with one another.

Figure 7-7: Total WJT for the Victoria line's current target headway
The higher margins (15-25 seconds) allow more spare time for passengers to board and alight trains at the critical station. Dwell time margins can absorb the dwell time delay. Thus, the control of passengers at upstream stations can be less in order to avoid the cost of passengers being controlled. The optimum load on trains for the higher margins is around 65-75%, which provides the optimal balance between the cost of controlling passengers and the cost of train delays.

![Graph showing Total WJT for different dwell time margins](image)

**Figure 7-8: Results for different dwell time margins**

The optimal scenario has a 20-second dwell time margin and a 70 percent pre-load. Table 7-5 presents the analysis of the optimal scenario. Setting the load level to 70% would result in passengers being restricted to board at both upstream and critical stations. With a dwell time margin of 20 seconds, the train headway would be longer than in other scenarios with shorter headways, resulting in longer passenger waiting times at all stations. However, this has been traded off with fewer train delays, resulting in the lowest WJT total. The result could be divided into two parts when the dwell time delay is less than or equal to 20 seconds and greater than 20 seconds as illustrated in Figure 7-9. When the dwell time delay is lower than the margin, passenger control and scheduled headways will dominate the results and when the dwell time delay exceeds the margin, the impacts will depend on train delays.
Table 7-5: The analysis with 20-second dwell time margin and 70% load on trains

<table>
<thead>
<tr>
<th>Dwell Time Delay in Second (x)</th>
<th>Achieved Train Frequency ($f_a$)</th>
<th>$T_u$ (s)</th>
<th>$T_{c1}$ (s)</th>
<th>$T_{c2}$ (s)</th>
<th>$T_d$ (s)</th>
<th>WJT in Second</th>
<th>Probability of Delay</th>
<th>WJT * Probability</th>
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The summation of WJT*Probability: 823,181
Table 7-6 presents the results with the optimal load for different dwell time margins. The lower dwell time margins (0-10 seconds) need more passenger control at the upstream stations; thus, the optimal load is at its lowest feasible value (60%). In the higher dwell time margins (15-25 seconds), a slightly higher load is allowed, but passenger control is still necessary. Overall, the total WJT for the optimum load is reduced when the dwell time margin is higher. The total WJT starts to increase again when the dwell time margin reaches the point when adding more margins would result in a capacity shortage.
Table 7-6: The optimum load on trains for different cut-off delays

<table>
<thead>
<tr>
<th>Margin (t)</th>
<th>Scheduled frequency</th>
<th>Optimum Load</th>
<th>Total WJT in seconds</th>
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<td>39.56 tph</td>
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<td>980,200</td>
</tr>
<tr>
<td>10</td>
<td>37.50 tph</td>
<td>60%</td>
<td>864,456</td>
</tr>
<tr>
<td>15</td>
<td>35.64 tph</td>
<td>65%</td>
<td>828,867</td>
</tr>
<tr>
<td>20</td>
<td>33.96 tph</td>
<td>70%</td>
<td>823,181</td>
</tr>
<tr>
<td>25</td>
<td>32.43 tph</td>
<td>70%</td>
<td>863,793</td>
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</table>

The evaluation in this chapter shows that cooperative passenger congestion management by controlling passengers at upstream stations to limit the load on trains before arriving at the critical station can reduce the risk of dwell time delay at the critical station. Setting the optimum load in a passenger management plan would be considered as a proactive passenger management approach as it could make the control foreseeable compared with the current approach which deploys the control reactively and causes uncertainties to passengers. For the planning of dwell time margins in the timetable, setting the lower dwell time margin could reduce train headway and increase train frequency, but it also has to consider train knock-on delays if trains are running too close to each other. The analysis in this research suggests setting a 20-minute dwell time margin which gives a capacity of around 34 trains per hour capacity while setting the load at 70 percent. This is the result that fits best for Victoria line’s current demand and conditions. However, it should be noted that this result is based on setting passenger weighted journey time as the objective function.
The evaluation in this chapter addresses the bivariate dwell time delay function to the risk of delay evaluation model to find the optimum scenario which aims to minimise the total passenger weighted journey time from the whole line perspective. There are limitations on using the passenger weighted journey time as the model’s objective. The passenger weighted journey time only considers all impacts in terms of the time dimension. There would be other consequences from this proactive passenger management approach which have not been considered in this research. For example, a smaller number of rolling stocks would be required due to shorter total journey times, there would be higher reliability from a shorter dwell time standard deviation, and a higher probability of trains being on time (trains running according to the timetable), etc. This could make the evaluation function more complicated.

When deploying passenger control strategy on metro systems, it brings several consequences which relate to many aspects of the service performance. The consequences of the control strategy give both benefits and disbenefits to the service system. Table 7-7 demonstrates the consequences of the passenger flow control strategy which considers both benefits and disbenefits of passenger control strategy to the system. The evaluation framework develops in this research only considers one aspect of the consequences. In fact, there are also other aspects to consider. This depends on the service policy to evaluate the worthiness of controlling passengers. Further research may develop other objective functions which include other effects.
Table 7-7: Benefits and disbenefits of the control strategy

<table>
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<tr>
<th>Benefits</th>
<th>Disbenefits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less crowding on trains before trains arrives at the critical station due to restricting passengers on trains</td>
<td>Increase passengers’ waiting time from being controlled which is considered as higher value of time</td>
</tr>
<tr>
<td>Less crowding on the critical station’s platform due to passengers being restricted to move onto platform</td>
<td>Reduce passengers’ dissatisfaction from being controlled</td>
</tr>
<tr>
<td>Less passengers in-vehicle time due to less train delays</td>
<td>More tasks added to station staff to control passengers</td>
</tr>
<tr>
<td>Less passengers accumulating at the next stations. due to less train delays</td>
<td>Increase a risk to overcontrol passengers leading to less passengers getting on trains, thus less passengers carried</td>
</tr>
<tr>
<td>Smaller number of rolling stocks required due to shorter journey time</td>
<td></td>
</tr>
<tr>
<td>Less train bunching effect from the following trains catch up with the delayed train</td>
<td></td>
</tr>
<tr>
<td>Higher service reliability due to smaller dwell time standard deviation</td>
<td></td>
</tr>
<tr>
<td>Higher reliability due to smaller dwell time standard deviation</td>
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</tr>
</tbody>
</table>
Chapter 8
Conclusion

The main contribution of this research is the development of the dwell time evaluation approach for high-passenger-volume stations. This research aims to use the proposed approach to evaluate the improvement of dwell time delays at high-passenger-volume stations. The research considers the improvement from the whole line perspective, not just at the station of interest. The research objectives have been fulfilled with the following results:

- The efficiency of the dwell times of stations on the line was benchmarked. Stations on the line were classified based on their dwell time efficiencies, and the characteristic that could lead to long dwell times was identified. Stations with specific characteristics (high passenger volume with bi-directional movement and trains arriving are additionally crowded) showed significantly longer dwell time, resulting in a lower dwell time efficiency score. The further analysis in this research would deal with this type of high-passenger-volume station.

- The factors affecting dwell times at the high-passenger-volume station were investigated using the actual operation data. Three passenger volume factors (boarders, alighters, and previous loads on trains) showed small positive correlations with dwell times. The reason that the data shows low correlations is due to the high variations in dwell times.

- The existing dwell time prediction models were tested and found to have poor fitting performance. London Underground's dwell time model and the regression model with the log of dwell time provided the best fit to the actual operation data with R-squared values of 0.23 and 0.26, respectively.

- A new concept for predicting dwell time was proposed, in which the estimation of dwell time is based on the probability of delay rather than the average or representative values. This concept offers greater accuracy with an R-squared value of 0.73 and is more suitable for high-passenger-volume stations where train delays have a significant impact on the whole line's service performance.
A bivariate dwell time delay function was developed, which enables the estimation of the probability of trains with a certain level of passenger volume being delayed by a certain amount of time.

The dwell time evaluation approach was developed by quantifying the impacts of dwell time delays using passenger-weighted journey time. The analytical model of dwell time impacts and the bivariate dwell time delay function were used to calculate the risk of dwell time delays.

The risk of dwell time delays was used to achieve the research aim of improving dwell time delays by providing optimal solutions. The dwell time delays could be improved by incorporating a sufficient dwell time margin into the schedule to absorb delays, as well as by maintaining an appropriate level of train crowding. The best-case scenario with the lowest risk of dwell time delays is when the dwell time margin is 20 seconds, and the load is maintained at 70% of the train's full capacity prior to arrival at the critical station.

The approach developed from this research makes several contributions to the current literature. Prior to this research, it was difficult to make predictions of dwell times in crowded situations. Earlier studies, such as Harris's research (Harris, 2005) on the London Underground's dwell time model (Weston and Maunder, 1989), had shown that predicting dwell times accurately in crowded situations was challenging. However, the new approach proposed in this research predicts the probability of dwell time delays, providing greater precision than existing point or average estimation methods. Moreover, the proposed approach takes the impact of passenger congestion on dwell time delays into account, which is critical for high-frequency services at high-passenger-volume stations. This research contributes to the existing line-level passenger flow management literature (such as Wang et al., 2015; Xu et al., 2016; Jiang et al., 2017; Li et al., 2017; Xu et al., 2018) by highlighting the importance of including dwell time delays in the line-level passenger flow model (LLFM). While some studies fit dwell time distributions and include a function as an input for other analyses (such as Yuan, Goverde and Hansen, 2010; Li et al., 2014; Lessan et al., 2018), they do not evaluate the impact of dwell time delays. This research makes a valuable contribution to the field by expanding the evaluation of dwell times to include both the probability and impact of dwell time delays. By integrating the proposed dwell time evaluation approach with the line-level passenger flow management, it is possible to assess the
risk of dwell time delays and obtain solutions for planning and management in high-
passenger-volume situations.

8.1 Applications of the evaluation methods

The main applications of the dwell time evaluation approach demonstrated in this research were to predetermine the appropriate passenger volume on trains and dwell time margins. This evaluation approach is suitable for planning that includes the dwell time delay in the analysis. When the evaluation approach considers all aspects, including demand and capacity, the probability of dwell time delay, and the consequences of dwell time delay on the whole line, it could also be used on other types of planning, such as service capacity planning, rolling stock planning, and staff planning, apart from the applications demonstrated in this research.

This dwell time delay approach is not limited to being used on the London Underground system or on the Victoria line. It can be applied to other systems by changing variables in the analytical models provided in Section 7.2.1. The selection of the scenarios to be tested in the model could be varied depending on the characteristics of the system being evaluated. Other systems may have different target frequencies. The lower target frequency could have more margins in the schedule. In addition, other variables or other parameters in the model, such as different lengths of run-out-run-in times, different levels of demand, different weights applied on the passenger journey time, and different train sizes, could be tested.

Bi-variate dwell time delay function developed in Chapter 6 can also be used as an input on other models or on other evaluation approaches apart from being used in a subsequent analysis in Chapter 7 (to calculate the risk of dwell time delays). In addition, the function can be developed using other passenger volume factors as independent variables. The bi-variate dwell time delay function is also expected to be applicable to other metros by calibrating the function's parameters and validating the function with their dataset.

Many metros' current performance indicators consider the impacts of delays and service reliability separately and have been unable to find a balance point between these two indicators. For example, using passenger weighted journey time alone to indicate the impacts or using the number of trains being delayed over the delay threshold alone
to measure the delays. The concept of integrating the consequences and the probability could be adopted as a performance indicator to evaluate services with uncertainty.

### 8.2 Limitations and further developments

This research achieves objectives as concluded at the beginning of this chapter and contributes to the new dwell time evaluation approach. However, there are some limitations on this research, which have been discussed earlier in the thesis. This section concludes all research limitations and provides suggestions for further developments on several aspects.

#### 8.2.1 Data availability

This research is data-driven and has full access to huge amounts of actual operation data. However, the actual dataset still lacks some types of passenger volume data, so this research has to make an estimation from other data (i.e., the estimation of the number of passengers boarding and the number of passengers alighting). In addition, train load data on the case study line is for the whole train; if train load is given for each car, passenger boarding distribution along the platform may be included in the dwell time analysis. Moreover, train actual operation data provides movement data for all trains; if the causes of delays on any train movements can be identified, the analysis may only take data on dwell time delays into account, which could give more accuracy.

#### 8.2.2 Evaluation method

In terms of the evaluation method, there are some assumptions that this research has made for the analysis. The assumptions were listed in Section 7.1. The crucial one that could be developed is the inclusion of delay recovery at any point in the system. When a train is delayed, the impacts will carry over to the following trains, and the following trains will try to recover at some point in order to catch up with the planned timetable. The suggested method for including delay recovery into the model is to set how fast trains can recover. The scenario with greater impacts should take longer to recover.

There are also limitations on using the passenger weighted journey time to measure the impacts of the delays. The passenger weighted journey time only considers impacts in terms of the time dimension. There might be impacts in other dimensions to which metro policies give importance, i.e., running as many trains as possible, minimising the number of trains delayed, minimising passenger control, reducing staff
workload, or minimising the number of rolling stocks being used. Further research could develop the analysis with these indicators.

The evaluation model includes multiple parameters (i.e., the weights on passenger weighted journey time, passenger demand, and the run-out-run-in time of the train). The analysis in Chapter 7 uses the current case study's parameter values to provide answers for the current situation. However, the results from the model are sensitive to changes in these parameters. Further research may conduct the sensitivity analysis by changing parameters in the model in Section 7.2.1.

In order to further develop the model, the current analytical model can be improved by developing better problem-solving approaches. The current approach to solving the problem employs the empirical method, which involves increasing one variable by a certain value and substituting it into the analytical model. If the model is improved, it should be able to solve more scenarios faster.

### 8.2.3 Further approach to control passengers

The new dwell time evaluation approach has been applied with a proactive line-level passenger control strategy to improve dwell time delays. The result obtained from the model suggests the optimum load before arriving at the critical station. The result does not include any control measures to achieve the suggested load. Appendix A demonstrates the line-level passenger flow model to allocate the number of passengers being controlled along stations on the line, which suggests how many passengers should be controlled at each station, and eventually the suggested load before arriving at the critical station could be obtained. However, there are no instructions regarding the actual passenger control measures that must be implemented to achieve the planned number of passengers boarding the trains. Actual control measures could be the subject of a future study.
References


Mather, R. (2003). Victoria Line Signal Diagrams. trainweb. Available at:


Transport for London. (2014). *Victoria line upgrade helps to deliver most frequent train service in UK*.


Appendix A

A model to allocate passenger flow control along stations on the line

This appendix demonstrates passenger flow allocation along stations on the line with the analytical model. The dwell time evaluation from Chapter 6 is used to present the service reliability of passenger allocation. Even this analytical model is not the main content of this research, it was presented in the 9th International Conference on Railway Operations Modelling and Analysis⁴ as mentioned in the impact statement. Part of the contents in this appendix is taken from the paper submitted to the conferences which have not been published yet.

This analytical model has been developed to show the application of line-level passenger flow management. The principle of this line-level passenger flow management is controlling passengers at the station where the long dwell time affecting the line service (Victoria station) and its upstream stations. This model focuses on the control of passengers before moving to the platform which directly limits the number of passengers boarding trains at each station and also leads to the reduction of the number of passengers on the train before arriving at the next station.

The results from the previous dwell time data analysis showed that high number of passengers on trains could affect the duration of the train dwell times, therefore passenger control at the upstream stations is deployed to reduce the number of passengers on trains. Figure A-1 illustrates the concept of line-level passenger flow control by demonstrating the limitation of passenger boarding at each station and showing how it changes the load on a train and finally when the train arrives at Victoria station it has a lower number of passengers on the trains.

Different designs of line-level passenger flow model for assigning passenger control strategies are possible depending on the objectives or performance indicators that the service would like to meet. The different objectives lead to the different settings of the model. System service performance can be evaluated in different aspects. London Underground Business Case Development Manual has indicated the evaluation in terms of financial, passenger time, service reliability, train capacity, passenger comfort, safety, etc.

An analytical model is developed to establish passenger flow management strategy. This preliminary model uses the demand survey data to estimate passenger volume at each station. In the previous dwell time analysis in Chapter 6, there is an evaluation of the service reliability for the different crowding levels on trains and a proposal for the control of passengers at Victoria’s upstream stations to reduce the number of passengers on trains before arriving at Victoria station. This appendix suggests the line-level passenger flow control strategy for different crowding levels on trains before arriving at Victoria station and compares the results with the service reliability that has been improved by controlling the crowding on these trains. The
model compared the given passenger control limit and assessed the service reliability at the specified load level for the current service frequency (36 trains per hour). The choice of the best scenario is based on the metro policy to trade between rate of control and train reliability. A lower rate of control will lead to lower service reliability.

The research focuses on the bottleneck from the extended dwell time at Victoria station, thus the model of the northbound service of the Victoria line from Brixton to Victoria station is constructed. Inputs of the model are the demand at each station of the northbound line from 8:00-9:00 AM from TfL’s demand dataset. The specified level of load on trains, the train capacity, and the balance of the boarding rate among stations are considered as the model’s constraints. The output of the model is a coordinated manner of passenger flow control rate at each station for the different specified levels of load on trains before getting to Victoria station.

The output of the model only provides the passenger flow control rate for each scenario. A higher rate of control will give less crowding on trains and lead to higher service reliability. This model will provide the performance for the different ranges of the crowding levels on trains which are divided into 6 ranges from the crowding level at 60% to 90% of the trains’ full capacity.

**Model inputs**

\[ Y_i = \text{Passenger arrival rate (Passengers per second) on the northbound service of Victoria line at station } i \text{ (the data is derived from London Underground’s survey data).} \]

The arrival rate is considered in deterministic or uniform distribution.

\[ H = \text{Train headway in seconds. This study considers the problem at the current scheduled train frequency (36 trains per hour). It ideally means that the trains should have 100 seconds headway.} \]

\[ D_i = Y_i \times H = \text{Demand to board a train on the northbound service of Victoria line at station } i \text{ is the arrival rate multiplied by train headway} \]

\[ A_i = \text{Passengers alighting rate in proportion to the train load (the data is derived from London Underground’s survey data)} \]
\textbf{Objective function}

The objective function of the model is to maximize the total number of passengers allowed to get to the platform (avoid controlling too many passengers).

\[ \text{Max } Z = \sum_i X_i \]  

(1)

Where: \( X_i \) = The decision variables which are the number of passengers allowed to get to the platform at station \( i \)

\textbf{Constraints}

(1) The number of passengers allowed to get to the platform at each station \( i \) must be lower than the demand.

\[ X_i \leq D_i \; \text{for all } i \]  

(2)

(2) The rate of passengers allowed to get to the platform at each upstream station compared to the demand should not be much different. (This is to avoid controlling too many passengers at one station).

\[ \text{Standard Deviation} \left( \frac{X_1}{D_1}, \frac{X_2}{D_2}, \frac{X_3}{D_3}, \frac{X_4}{D_4} \right) \leq \text{acceptable boarding ratio} \]  

(3)

(3) \( L_i \) = The number of passengers on trains (train load) after the boarding and alighting process at each station \( i \) is calculated from:

\[ L_i = L_{i-1} + X_i + (L_{i-1} \times A_i) \; \text{for all } i \]  

(4)

(4) The train load before arriving at Victoria station needs to be lower than the control level which is specified on each scenario.

\[ L_4 \leq \text{Specified Control Level} \]  

(5)

(5) The train load after the boarding and alighting process at Victoria station needs to be lower than the train capacity.

\[ L_5 \leq \text{Train Capacity} \]  

(6)
**Model outputs**

Rate of control is the total number of passengers being controlled at all stations (which can be calculated from the summation of demand minus passengers allowed to get to the platform for all stations) divided by the total demand.

\[
Rate \ of \ control = \frac{\sum_i (D_i - X_i)}{\sum_i D_i} \; ; \; for \; i = \{1,2,3,4,5\} \tag{7}
\]

The different levels of crowding on trains before arriving at Victoria station have been tested on the model. The model suggests passenger flow control per minute at each station to achieve the specified level of crowding on trains.

**Results**

The results from the model suggest passenger flow control per minute at each station and the overall rate of control for different ranges of load on trains, while the service reliability for each range of load was obtained from the probability distribution analysis in Chapter 6 which considers the likelihood of trains achieving dwell time within the target dwell time considering the current schedule. Both performances are shown on the results in Table A-1.

Table A-1: The suggested passenger control per minute for different load levels.

<table>
<thead>
<tr>
<th>Suggested Flow Control per Minute</th>
<th>Load on Trains (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>60-65</td>
</tr>
<tr>
<td>Brixton</td>
<td>15.65</td>
</tr>
<tr>
<td>Stockwell</td>
<td>54.39</td>
</tr>
<tr>
<td>Vauxhall</td>
<td>37.09</td>
</tr>
<tr>
<td>Pimlico</td>
<td>7.83</td>
</tr>
<tr>
<td>Victoria</td>
<td>0.00</td>
</tr>
<tr>
<td>Total Flow Control per Minute</td>
<td>114.96</td>
</tr>
<tr>
<td>Rate of Control</td>
<td>16%</td>
</tr>
</tbody>
</table>
With well-planned passenger flow control in coordination with the stations, the dwell time might be kept lower than the threshold which leads to higher service reliability.

Figure A-2 presents the increased trend of the service reliability when increasing the control level. The chart shows a dramatic increase of the service reliability from 35% to 57% while controlling only around 2% of the passengers at upstream stations (keeping the pre-load before arriving at Victoria station within 80% of the trains’ full capacity). This is a good choice for London Underground which might find it difficult to control passenger flow. However, if control of 11% of the passengers is possible, the service reliability could be increased to 72%.

Ideally, in a normal situation without any disruption, the results present that passengers boarding and alighting on trains up to Pimlico station (the station before Victoria station) are not more than 80% of the train’s full capacity (assuming a constant demand). However, there are variations in the demand or train disruptions in reality leading to trains with a pre-load of more than 80%. This situation will cause the dwell time to be longer than the threshold.

Figure A-2: The increased trend of the service reliability
In addition to the current demand level, Table A-2 presents the result when the demand is increased by 10%. This could reflect future demand or higher passenger volume due to train disruptions or events that might occur. When the demand is increased, the train could reach maximum capacity, so a control strategy is unavoidable. In the case of increased demand, the pre-planning flow control at the upstream stations is mandatory. Otherwise, all the control will be required at Victoria station and cause unpredictability for passengers and the whole line service. In the case of increasing demand, the service reliability worsens as there are a higher number of passengers demanding to board trains and a higher load on trains which makes the system more crowded and causes longer dwell times.

Table A-2: Passenger flow control with a 10% increase in passenger demand

<table>
<thead>
<tr>
<th>Suggested Flow Control per Minute</th>
<th>Load on Trains (%)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>60-65</td>
<td>65-70</td>
<td>70-75</td>
<td>75-80</td>
<td>80-85</td>
<td>85-90</td>
</tr>
<tr>
<td>Brixton</td>
<td>32.66</td>
<td>20.77</td>
<td>8.89</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Stockwell</td>
<td>75.52</td>
<td>63.48</td>
<td>51.38</td>
<td>32.28</td>
<td>4.78</td>
<td>0.00</td>
</tr>
<tr>
<td>Vauxhall</td>
<td>50.41</td>
<td>43.02</td>
<td>35.62</td>
<td>31.87</td>
<td>28.53</td>
<td>0.34</td>
</tr>
<tr>
<td>Pimlico</td>
<td>11.07</td>
<td>9.17</td>
<td>7.30</td>
<td>5.96</td>
<td>4.83</td>
<td>6.91</td>
</tr>
<tr>
<td>Victoria</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>10.60</td>
</tr>
<tr>
<td>Total Flow Control per Minute</td>
<td>169.67</td>
<td>136.43</td>
<td>103.19</td>
<td>70.11</td>
<td>38.14</td>
<td>17.85</td>
</tr>
<tr>
<td>Rate of Control</td>
<td>21%</td>
<td>17%</td>
<td>13%</td>
<td>9%</td>
<td>5%</td>
<td>2%</td>
</tr>
</tbody>
</table>