Analysing the efficiency of a temporal travel demand management strategy for an urban rail system

Phiwe Mnelisi Msomi
(Student number: 1098495)

School of Mechanical, Industrial and Aeronautical engineering

University of the Witwatersrand

Johannesburg, South Africa.

Supervisors: Andries Botha

A Research Project report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, in fulfilment of the requirements for the degree of Master of Science in Industrial Engineering.

09/09/2021

.PLAGIARISM DECLARATION

University of the Witwatersrand, Johannesburg

School of Mechanical, Industrial and Aeronautical Engineering

I, Mnelisi Phiwe Msomi (Student number: 1098495), am a student registered for the degree of Master of Science in Industrial Engineering in the academic year 2021.

- I am aware that plagiarism (the use of someone else's work without their permission
  and/or without acknowledging the original source) is wrong;
- I confirm that the work submitted for assessment for the above degree is my own unaided work except where I have explicitly indicated otherwise;
- I have followed the required conventions in referencing the thoughts and ideas of others;
- I understand that the University of the Witwatersrand may take disciplinary action against me if there is a belief that this is not my own unaided work or that I have failed to acknowledge the source of the ideas or words in my writing.

Signature: Date: 09/09/2021

ABSTRACT

The travel demand management strategies (TDM) urban rail agencies develop and implement are often not efficient at influencing the daily ridership patterns of commuters. The result of this is the large disparity of ridership during peak and non-peak periods, which lowers system efficiency for a given urban rail system. This paper uses the Gautrain urban rail system to analyse the various effects a temporal travel demand management strategy has on different types of commuters. In addition, an analysis was performed to understand the fare elasticities of different types of commuters. To perform the analyses, first, graphical data analysis was performed to note daily ridership patterns. Secondly, four sample sets were chosen for hypothesis testing analysis: (1) ridership before fare increase, (2) ridership after fare increase, (3) ridership during morning, (4) ridership during afternoon. Findings were as follows: most Gautrain users do not change their ridership patterns, regardless of the TDM strategy and fare increases. Certain users do change their ridership patterns, based on the TDM strategy, fare increases or both. This was found to be dependent on the various reasons people use the Gautrain for. It was recommended that the TDM strategy be developed to cater to specific types of commuter, this way the efficiency of the TDM strategy could be increased.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

TDM	Travel demand management
MRT	Mass rapid transit
BART	Bay Area Rapid Transit
GMA	Gautrain Management Agency
MTR	Mass transit railway
EMU	Electric multiple unit
AFC	Automatic fare collection
APC	Automatic passenger counting
O-D	Origin-Destination
DIC	Directional imbalance coefficient
SIC	Sectional imbalance coefficient
SP	Stated preference
MNL	Multinomial logit
MS	Microsoft
Q-Q	Quantile-quantile
CV	Coefficient of variance
df	Degrees of freedom
GPS	General passenger service
APS	Airport passenger service
DFDS	Distribution Feeder and Distribution Services

1. INTRODUCTION

For a lot of urban rail systems in various cities across the world, increases in ridership are outpacing capacity expansions (Ma, et al., 2011). This is inevitable given that population growth, economic activity and urbanisation are all on upward trajectories (Ma, et al., 2011). By focusing on travel demand management (TDM) initiatives, rail agencies are able to accommodate increases in ridership without performing any exorbitant capacity expansions on rail systems. There are several considerations that go into the design and implementation of TDM strategies. This chapter lays out the motivation, research questions and objectives of the research performed in this paper.

1.1. Research Background

Travel demand management (TDM) describes the strategies and policies aiming to achieve more efficient use of transportation resources (Van Audenhove, et al., 2014). Recent times have seen increased emphasis on travel demand management, particularly in urban rail systems (Bao, et al., 2020). A number of reasons have been explored based on this trend: (1) there has been increased travel demand in urban areas due to population and employment growth, (2) the overcrowding and excessively high utilisation of rail infrastructure poses threats to the sustainability of rail systems (Halvorsen, et al., 2016).

The challenge posed to urban rail agencies is: how can commuter travel behaviour be influenced such that, despite increasing ridership, the capacity of existing urban rail systems need not be expanded. Between 2004 and 2016, ridership on the San Francisco Bay Area Rapid Transit (BART) system increased by at least 40% (Greene-Roesel & Smith , 2019). Between 2010 and 2019, ridership on the Hong Kong Mass Rapid Transit (MTR) system increased by approximately 14% (MTR, 2019). Lastly, between 2013 and 2019, ridership on the Gautrain mass rapid transit system increased by roughly 27% (Agency, 2019). It is worth mentioning that several other notable rail transit systems in other parts of the world also experienced significant increases in ridership between the mentioned periods.

With the examples given previously, the commonality is that the ridership (or train service demand) increased yet there were no capacity expansions on the rail systems. Capacity expansions are often not a viable solution to address the increase in ridership. Capacity expansions are capital intensive and tend to be only considered as part of long-term strategic planning for rail agencies (Whelan & Johnson , 2004). For this reason, rail agencies resort to alternative approaches on how ridership can be influenced such that existing system capacity is used to maximum capability. This explains the emerging use of travel demand management with urban mass rapid transit (MRT) systems.

Attention will now be focused on Gautrain, the urban rail agency this research paper is based on. Gautrain is an urban rail system that operates in Gauteng province, South Africa. Appendix A shows how the business model canvas template was used to provide background of the Gautrain (Strategyzer, 2011). In order to achieve successful operations, it is important that Gautrain continues to deliver a high-quality train services to its passengers through the sustainable provision and use of its infrastructure. Currently the overwhelming demand for the train service, particularly during peak hours, has been identified as a challenge to Gautrain operations. The reason for this is that overcrowding at stations and trains negatively affect the comfortability, safety and security of the service which in turn deters passengers and potential passengers (Agency, 2019). In addition, overcrowding implies that the rail system is being utilised at an excessively high level. This is not ideal as it places strain on the rail system, which is costly.

Much like the other rail agencies, Gautrain has in-place a TDM strategy aimed at incentivising more commuters to use the train service during off-peak periods. However, preliminary analysis and reviewed literature indicate that the current

TDM strategy employed has several limitations. These limitations are significant because they potentially have non-ideal outcomes, for both the rail agency (Gautrain) and its passengers.

1.2. Problem statement and Motivation

The solution implemented by Gautrain to address the increased ridership during peak times is a temporal travel demand management strategy. This solution is designed to influence train service demand by applying fare adjustments to encourage a shift in commuter travel patterns and behaviours. To be specific, during non-peak periods, commuters are subjected to base fares for the various train trips they may use the train service for. However, during peak periods, commuters are subjected to surge fares for the various train trips they may use the train service for.

For the Gautrain, there are two peak periods: a morning peak period between 06h00 – 08h30, and an afternoon peak period between 15h30 – 18h00. It is during these periods that the rail system experiences very high passenger volumes in comparison to the passenger volumes experienced during non-peak periods. Therefore, it is understandable why surge fares are applied to peak periods and base fares are applied to non-peak periods. The rationale of this TDM strategy is that commuters will shift their travel patterns to use the train service during non-peak periods since it would be cost effective to do so.

As mentioned previously, the current solution has several limitations. Mainly, fare adjustments are solely temporal (function of the time-of-day). There is a multitude of other factors that need to be considered. Furthermore, this strategy is developed using a fixed set of assumptions of when the system is expected to be in a peak or a non-peak state. Not only does the current strategy have limited flexibility, it also imposes the risk of being ineffective in scenarios whereby the assumptions upon which it is designed are not being adhered to.

A scenario like this presents an opportunity to analyse the current travel demand management strategy and understand the impact it has on commuters and consequently, train service demand.

1.3. Research Question

a. What are the factors that inform train service demand for the Gautrain urban rail system?
b. What impact does fare increases have on train service demand?
c. How does a temporal travel demand management strategy affect the commuters of urban rail systems?

1.4. Research Objectives

The main objective of this research is to understand how a temporal travel demand management strategy influences the travel behaviour of passengers. Achieving this objective will depend on the following sub objectives:

a. Analyse ridership (train service demand) during off-peak & peak periods, before and after fare changes are implemented.
b. Evaluate the impact a temporal travel demand management strategy has on different train service commuters.

This chapter provides a background of the TDM and highlighted the importance of it for urban rail systems. Subsequently, the motivation, research questions and objectives of the research are introduced.

2. LITERATURE REVIEW

In this section, both theoretical and empirical contributions in literature are analysed concerning urban rail systems. In addition, TDM strategies and the approaches that have been used in the past for studies of this nature.

2.1. Definition of urban rail systems

Rapid transit systems are widely regarded as key proponents to the social and economic development of a given geographical region. By definition, a rapid transit system is a form of infrastructure or transportation resource that facilitates the speedy movement of people from origin to destination (Ma & Koutsopoulos, 2014). Based on this definition, it is conceivable that rapid transit systems are crucial for the integration of geographical regions, areas and districts etc. Following this logic, it is understandable why rapid transit systems are a cornerstone for social and economic development. Through the use of rapid transit systems, people are able to commute between regions for reasons that could be economically motivated, or socially motivated. Herein lies the strategic intent for government institutions to allocate resources into the provision and maintenance of such systems (Pelletier, et al., 2011).

There are various examples of rapid transit systems, these may include: buses, minibus taxis, trains and even private cars. This research focuses on trains, otherwise known as mass rapid transit systems (MRT). MRTs are a subset of rapid transit systems, however, with MRTs it is understood that system capabilities allow for the mass transportation of people simultaneously (Tang & Cheung, 2014). This is the differentiator of mass rapid transit systems compared to ordinary rapid transit systems. Having defined rapid transit systems and mass rapid transit systems, the definition of an urban rail system becomes straightforward. Urban rail systems are rail transit systems that facilitate the mass transportation of people between urban areas (Jiang, et al., 2017). Based on the literature reviewed, the terms ‘mass rapid transit systems’ and ‘urban rail systems’ are often used interchangeably.

Urban rail systems have generally been considered a requisite to allow for the efficient movement of people between densely populated areas, regions and cities. Urban rail systems have several comparative advantages over the other existing forms of rapid transit systems. Travel via urban rail systems is cost effective. Urban rail systems operate at a large scale and commuters benefit from the economies of scale that are leveraged (Fu & Gu, 2018). Urban rail systems operate exclusively – infrastructure provided is allocated solely for the metro. This allows for urban rail systems to be operated on a right-of-way basis. This has positive implications for commuters and rail agencies providing the service. Mainly, the train services provided are reliable given that schedules are standardised, and the train services are less susceptible to external factors (e.g. traffic congestions, accidents, weather conditions) that may introduce variability to the system (Feng, et al., 2010).

The advantages that urban rail systems have over other transit systems cannot be accepted at face value; this would be misleading given that there are several disadvantages associated with such systems. For commuters, the main one would be that urban rail systems generally lack flexibility; this applies to routes travelled, train schedules and fare structures (Dend & Xu, 2015). It is understandable that the routes travelled are dependent on whether rail infrastructure is present at various regions and locations. Secondly, given that urban rail systems are designed for mass transportation, schedules cannot be adjusted to individual requirements. Lastly, the complex cost structure that is associated with providing train services makes it infeasible to have a flexible fare structure imposed to commuters (Dend & Xu, 2015).

For rail agencies, the key disadvantage is that operating at low capacity or for short distances is unsustainable (Dend & Xu, 2015). There is a minimum threshold for the associated operating costs of providing an urban rail service, per unit distance and per passenger, that must be achieved for the operation to be financially viable.

Furthermore, infrastructure limitations mean that little can be done to scale down these systems for low capacity and short distance operations. Ordinarily, this viewpoint is sufficient when defining the key disadvantage of urban rail systems ─ recent literature begs to differ and indicates further assertions on this.

Much like there being a minimum threshold for capacity and distance that must be achieved for the operation to be financially viable, there is also a maximum threshold that, if exceeded, the operation becomes financially infeasible (Krueger, 1999). This presents itself as a disadvantage that ties back to the point that urban rail systems have limited configurability and scalability. In summary, there is an ideal range for both distance and capacity that ensures the sustainable operation of an urban rail system. A study by Graham on economies of scale and economies of distance for rail systems elaborates on this phenomenon (Graham, et al., 2003).

Focus will now be placed on understanding the demographics of commuters, the end users of urban rail systems. In a customer survey performed by the San Francisco Bay Area Rapid Transit (BART) in 2016, the significant findings were that: 70% of BART riders were aged 25-44, approximately 37% of riders came from high income households, and 66% of riders are employed (Greene-Roesel & Smith , 2019). In a customer survey performed by the Gautrian Management Agency (GMA), findings were that: 75% of survey participants were aged 18-49, 65% of survey participants were employed, and that a significant number of Gautrain riders have a living standard measure of 7-10 which implies that they are from middle to high income households (Agency, 2019). Rider demographics for the New York city subway metro and Hong Kong MTR indicated similar percentage splits.

Understanding the demographics of the people who use urban rail systems is important as this has a direct relationship on travel patterns and ultimately, ridership. Commuter travel characteristics and patterns for urban rail systems are covered in the next section.

In this section, the importance of rapid transit systems was discussed as it pertains to government institution and the public. Urban rail systems were defined, and advantages & disadvantages were discussed compared to other transit systems. And lastly, information on the user demographics of reputable urban rail agencies was discussed, briefly. These are all important considerations for travel demand management and form the basis of the research conducted.

2.2. Commuter travel characteristics for urban rail systems

This section focuses on reviewing existing literature on travel characteristics for urban rail systems in detail. Evidently, travel characteristics are informed by the different users of the rail systems. The first segment researchers seek to analyse with the demographics is the employment status of urban rail system users (Jiao, et al., 2017). Based on this demographic alone, information can be obtained or assumed on the expected frequency of travel, travel times, entry & exit stations and age groups of riders.

Modern approaches also take interest in the income level and customer satisfaction measures of riders. This is done to obtain insights on the affordability of riders and to understand more on what drives their behaviours (Zhang, et al., 2014). Such information is key for travel demand management.

A study by Halvorsen, based on users of the Hong Kong MTR, defined six specific user groups for urban rail train services. The groups were: (1) commuters, (2) casual users, (3) intermittent users, (4) short term users, (5) occasional cross-border travellers and (6) cross-border commuters (Halvorsen, et al., 2016). These six user groups are well studied and have been applied to many other urban rail systems. The six user groups defined from the Hong Kong MTR are extensive, thus, they have also been applied to the Gautrain Management Agency, the rail agency this research is based on. The last two user groups, occasional cross-border travellers and cross-border commuters were omitted for this research because the Gautrain system does not incorporate any border region commute for its passengers, it is an urban rail system.

Commuters are riders who are the heaviest users of a rail service and travel most frequently. They were described as people who take their trips mostly during morning and afternoon peak periods. In addition, commuters were described as riders whose travel patterns are most consistent and replicated for weekday commute compared to the other groups. Halvorsen's analysis on peak period ridership characteristics made further developments on this. The study demonstrates that morning and afternoon peak periods are comprised of commuters who aim to adhere to business day hours, which are usually between 8h00 – 17h00. Understandably, this user group is comprised mostly of students and employed people.

Casual users are riders who use train services less frequently, to travel relatively long trips. Casual users are described as people who utilise train services in conjunction with other modes of transportation. The motives behind their travel are varied hence their travel patterns are varied too. Users from this group may utilise train services on selected weekdays or weekends, and their travel times typically span across an entire day. This user group was assumed to be comprised of: unemployed people, employed people who have flexible schedules and people who are traveling for leisure. This was mainly deduced from the high variability of travel times and frequencies of users from this group.

Intermittent users are described as riders who primarily rely on other means of transportation but do, occasionally, make use of train services. They are users who travel moderate distance trips. Intermittent users generally account for a small portion of the overall ridership, hence information on these users is limited. A result of this is that little is known on their reasons for commute, their travel patterns and common travel times. Travel frequency and origin-destination data was the only information obtained from these users. This allowed for conclusions to be made that intermittent users rely mostly on other modes of transportation and that they commute moderate distances. In another study, Ma puts forward the notion that riders who utilise train service on an intermittent basis, especially during peak periods, are likely to be people incapable of using train services frequently (Ma & Koutsopoulos, 2014). The limitations could be imposed by affordability, access to train stations etc.

The short-term users are characterised by short range trips, over a short period. Data on this group showed that their travel times span across the entire day; less travel takes place during morning and afternoon peak periods. Based on this information, it is assumed that this user group is comprised of tourists who use the urban rail system for its convenience, to explore a given urban area. While this assumption is substantiated, it must also be considered that short-term users could also be the general public. Short term users could be locals experimenting and evaluating urban rail systems for personal use.

In this section, the user groups for urban rail systems were defined. The characteristics of each user group were discussed and how it relates to the expected travel patterns of the respective users. A fundamental understanding of this information is a pre-requisite for research on travel demand management because it contextualises the behaviours of urban rail system users.

2.3. Ridership for urban rail systems

This section is a review of empirical data on the ridership of several urban rail systems that have been studied in the past. Ridership refers to the number of passengers in a transit system. Focus is placed on understanding ridership as a function of day-of-week, time-of-day, peak vs non-peak periods and fare structure. It is understandable that the ridership is closely related to the commuter characteristics covered in section 2.2.

We start off by reviewing ridership by day-of-week. In section 2.2 it was established that *commuters* are the heaviest (account for roughly 55% of overall ridership) users of an urban rail system and that these are typically people commuting to their places of employment (Chan & Miranda-Moreno, 2013). Assuming majority of users conform to standard business days (Monday-Friday), it is expected that daily ridership figures during weekdays will be higher than on weekends. Daily ridership refers to the total trips taken on a given rail system, daily.

Data on the New York subway showed the average daily ridership (table 1) to be roughly 5,5 million passengers during weekdays (Monday – Friday). Ridership on weekends, Saturday and Sunday, was roughly 3,1 million passengers and 2,5 million passengers, respectively. Ridership during weekends represented approximately 45% - 55% of the weekday ridership.

Table 1: Summary of daily subway ridership for the New York subway transit system between 2016 - 2019 *(MTA, 2019)*.

Year	Average Weekday	Average Saturday	Average Sunday
2016	5,655,755	3,202,388	2,555,814
2017	5,580,845	3,156,673	2,525,481
2018	5,437,586	3,046,289	2,392,658
2019	5,493,875	3,087,043	2,407,152

Ridership data on the Washington Area Metro showed the average daily ridership to be on roughly 616 200 passengers during weekdays, 253 000 passengers during Saturdays, and 171 000 passengers during Sundays (figure 1). For the Washington Area Metro, ridership during weekends represented approximately 27% - 41% of the weekday ridership.

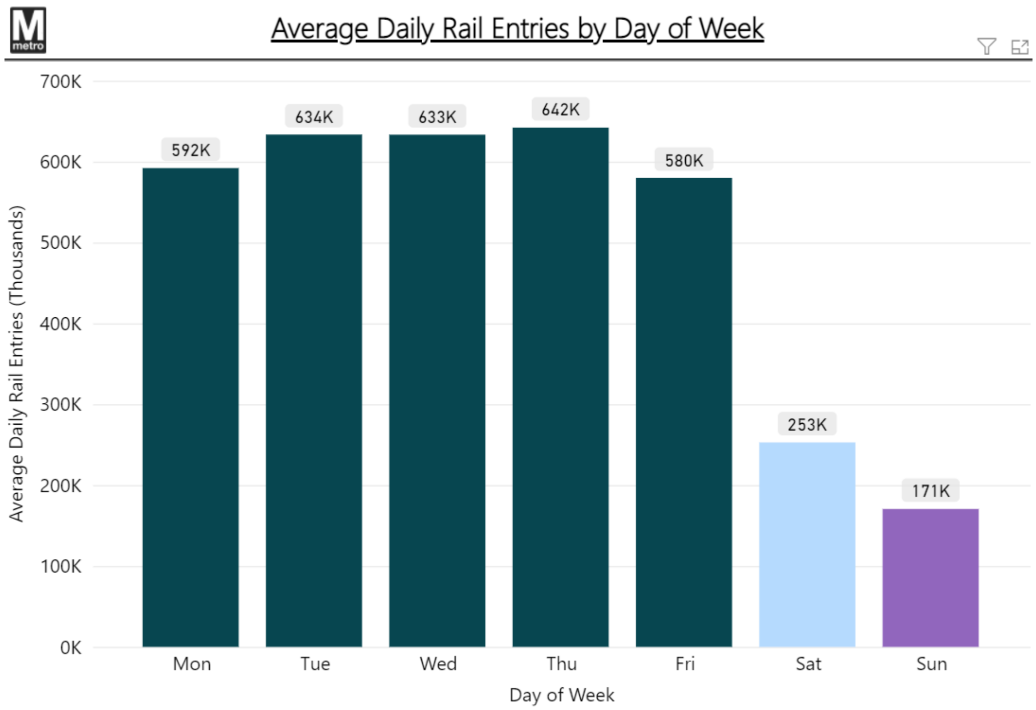


Figure 1: Average daily ridership on the Washington Area Metro between 2016 – 2019 *(WMATA, 2020)*

Lastly, ridership data on the Chicago Transit Authority showed the average daily ridership to be on roughly 733 000 passengers during weekdays, 431 000 passengers during Saturdays, and 320 000 passengers during Sundays (table 2). For the Chicago Transit Authority, ridership during weekends represented approximately 44% - 58% of the weekday ridership.

Table 2: Summary of daily subway ridership for the Chicago Transit Authority between 2016 - 2019 *(CTA, 2020)*

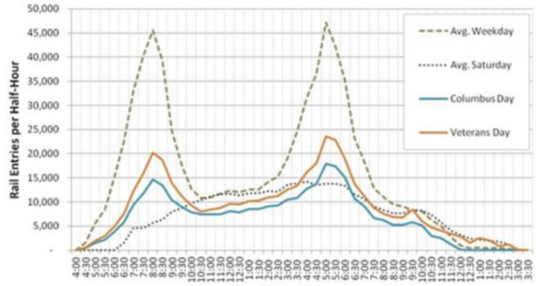
Year	Average Weekday	Average Saturday	Average Sunday
2016	759,866	466,335	347,658
2017	740,026	439,630	328,421
2018	728,643	422,950	312,029
2019	708,154	397,346	296,997

Ridership data from tables 1,2 and figure confirm the rationale discussed in section 2.2: ridership during weekdays is higher than on weekends. The hypothesised reason for this is that majority of *commuters* traverse to their places of employment and back to their places of residence on weekdays. In the three discussed urban rail systems, it can be seen that weekend ridership represents a fraction of weekday ridership.

Travel demand management strategies employed on urban rail systems are generally centred on influencing the travel patterns of riders during weekdays. The strategies are usually less imposing on riders during weekends. It is apparent that the reason for this is that weekday ridership is much higher than weekend ridership (Ma & Koutsopoulos, 2014). It is during weekdays whereby urban rail systems are strained due to over utilisation (Fu & Gu, 2018). This is a key consideration for this research; the Gautrain is an urban rail system in Gauteng, whereby standard business days are also Monday to Friday.

Weekday ridership is dominated by *commuters,* riders traversing between home and their places of employment. In addition, business hours for employed people in most parts of the world are understood to be 8h00 – 17h00. This explains the weekday ridership patterns in figure 2a and 3a. A market survey performed on urban rail system users confirmed why ridership generally surges between 06h00 – 09h00 and 15h30 – 18h30. Ridership surges between these time periods as a result of people using the metro to go to work in the morning, then return home in late afternoon (Gan, et al., 2020).

Although this is the well-accepted reasoning for this ridership pattern; it is applied to other transit systems as well. The study by Gan demonstrates that although this reasoning generally hold true, it must be exercised with caution. It must also be considered that across different parts of the world employee shift systems are different – some employees work night shift, others, day shift. This means that there are likely certain users who contribute to the weekday ridership appearing this way because they travel to work in the late afternoon, and return home in the morning.



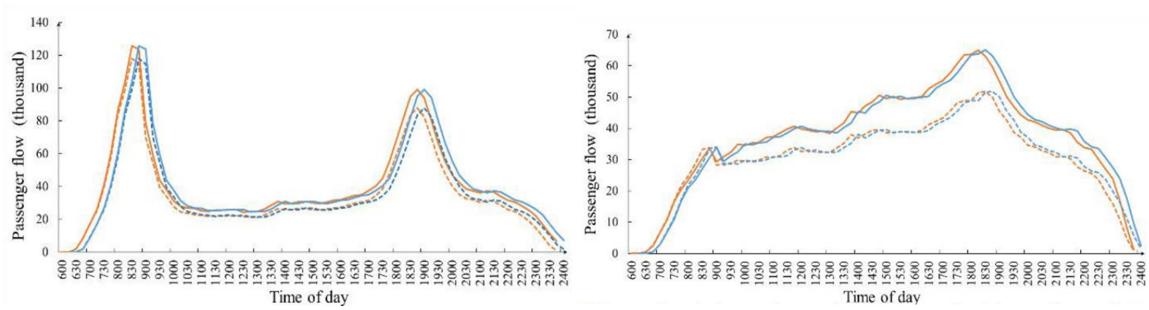
(a) Weekday ridership pattern

(b) Saturday ridership pattern

(c) Sunday ridership pattern

Figure 2: Average ridership patterns for weekdays and weekends for the Washington Area Metro between 2008 – 2012 *(WMATA, 2020)*

The ridership patterns on figures 2a and 3a for weekday ridership are similar: ridership surges in the early morning and late afternoon, at other times throughout the day it is relatively low and steady. There are also some slight differences to note as well between the two figures. In figure 2a, the surge in ridership in the morning period is very similar to the surge in ridership during the late afternoon surge period. In figure 3a, the surge in ridership in the morning period is higher than the surge in ridership during the late afternoon period. Critical discussions from previous studies explain that these differences in ridership patterns are related to the bespoke travel demand management strategies (TDM) rail agencies decide to impose on users (Gan, et al., 2020). Sections 2.5 and 2.6 provide explanation on this. These critical discussions are acknowledged, however an open-mind to explore the other related potential influencing factors must be applied.



(a) Weekday ridership pattern (b) Weekend ridership pattern

Figure 3: Shenzen metro average ridership patterns for weekdays and weekends during 2019 *(Yang, et al., 2018)*

Ridership patterns during weekends are not characterised by aggressive surges, unlike weekday ridership patterns. Ridership during weekends is better distributed throughout the course of the day. Weekend travel is dominated by *casual, intermittent* and *short-term* users (Halvorsen, et al., 2016). As mentioned previously, these user groups are typically people who are travelling for leisure purposes, or people who generally have flexibility with their daily schedules since weekends are not considered standard business days.

A comparison often performed on urban rail systems is the analysis of weekday and weekend ridership patterns is the peak ridership, respectively. Peak ridership is the point (time of day) at which ridership was the highest throughout the day. As seen from figures 2 and 3, peak ridership is much higher on weekdays than on weekends. This observation generally holds true and is accepted as standard for urban rail systems (Ben-Akiva & Lerman, 1985). Furthermore, as previously discussed, ridership during weekdays is much higher than on weekends. These two points substantiate the focus of TDM strategies mainly being geared at influencing ridership behaviour during weekdays opposed to weekends.

In addition, previous research takes interest in understanding how much the peak ridership deviates from the average daily ridership, for weekday and weekends. Kerh and Ting derived an expression to calculate this, terming it ‘peak co-efficient’.

Peak co-efficient is a measure of fluctuation of ridership throughout the course of a day (Kerh & Ting, 2005). Extensive studies on various urban rail systems show that ridership fluctuation during weekday is normally higher than on weekends. This point further provides context on why TDM strategies and frameworks are designed to be more imposing during weekdays. Section 2.4 is a review of more literature on this but from the perspective of urban rail system capacity.

A key part of this discussion is peak periods. This relates to the methods used to define peak periods, and the analyses performed during peak periods. For urban rail systems, peak periods refer to periods in which ridership, and effectively the utilisation of the system increases dramatically (Krueger, 1999).These periods are typically characterised by the overcrowding of riders in stations and train coaches. These periods are not ideal for riders. Studies show that overcrowding results in the deterioration of service quality, safety and security of the train service (Preston, et al., 2017).

It has been established that ridership surges at the start and end of typical business hours during weekdays (8h00 and 17h00). The next points of interest that urban rail system managers are usually tasked with is defining the time intervals that are considered peak, and the ones that are not considered peak. System performance managers of the Taipei Rapid Transit Corporation stipulate 7h30 – 09h00 as the morning peak period and 17h00 – 19h30 as their afternoon peak period (figure 4) (Lin & Shin, 2007) . For this particular system, it is during these time intervals whereby the cumulative ridership between these time intervals represents a significant amount of the total daily ridership.

Literature indicates that although the time intervals rail agencies define for their peak and non-peak periods sometimes differ, the commonality is that peak periods are defined to be periods in which cumulative ridership represents roughly 60% - 80% of the daily ridership (Chan & Miranda-Moreno, 2013). Based on this assertion, literary findings further confirm that it is mostly *commuters* travel during peak periods (Lin & Shin, 2007). And it is usually the *casual, intermittent and short-term* users who travel during non-peak periods, especially during midday and at night (Ma & Koutsopoulos, 2014).

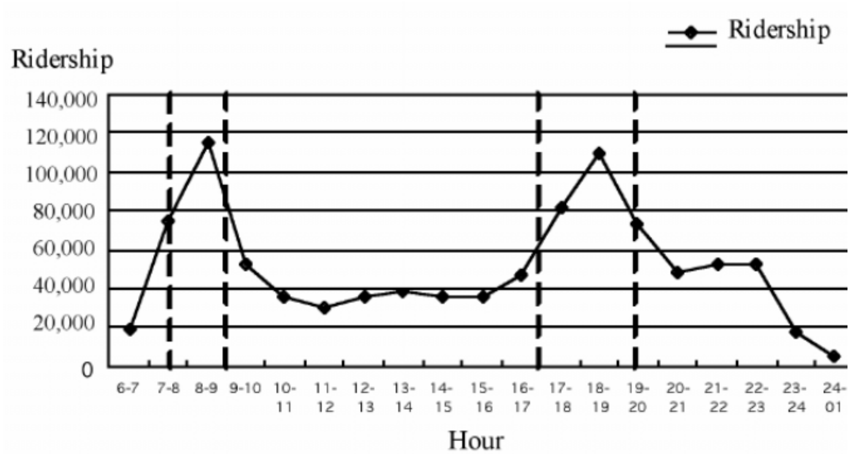


Figure 4: Ridership pattern on Taipei metro on a typical weekday *(Lin & Shin, 2007)*

To summarise the section, empirical ridership data from urban rail systems was reviewed. The data showed that ridership during weekdays is typically greater than ridership on weekends. This confirmed the commuter characteristics on urban rail systems discussed in section 2.2. The data also compared daily ridership patterns on weekdays and weekends. The concept of peak and non-peak periods was covered, and how it relates to ridership patterns. This concept will be discussed in tandem with the following sections of the literature review.

2.4. The supply of transportation resources for urban rail systems

This section focuses on the understanding train service supply. This relates to system capacity. Specifically, the capacity of train stations, train coaches, the scheduling and the utilisation of trains.

Train service supply forms an integral part of the literature that is reviewed for travel demand management (TDM). It is arguably the main driver that made rail agencies decide to explore TDM strategies to begin with. In section 2.1 it was established that, for sustainability, urban rail systems must be operated at ideal capacity and trip distances. If system utilisation is low and trip distances are short, urban rail systems typically become non-profitable to operate. And conversely, when system utilisation and trip distances are exorbitant, urban rail systems become unsustainable to operate due to deteriorated service levels and excessive strain on infrastructure. Considering this, and the weekday ridership patterns discussed in section 2.3, it can be deduced that train service demand fluctuations pose several challenges to urban rail agencies.

During weekdays, train service demand is low during the early hours of the morning (refer to figure 2, 3, and 4). Train service demand subsequently surges; this gives rise to the first peak that is experienced by most systems, the morning peak. This is generally followed by a non-peak period between 9h00 – 15h00 for most urban rail systems. This is normally a period in which train service demand is significantly lower than what it was at peak, and more importantly, this is when train service demand stabilises. Past literature often describes this period as 'steady state' (Lam & Zhou, 2000). Following this period, train service demand generally surges once more for the afternoon peak period then it gradually falls until it there is no longer any demand.

Weekday ridership patterns have several implications on urban rail systems. During peak periods, demand for train services are immense. This implies that, in order to meet this immense demand, system capacity must be high as well. During non-peak periods demand for train services are often low and stable relative to peak periods. This means that the system capacity required to meet the demand is low and can be constant. Given that peak and non-peak periods have contrasting system capacity requirements, rail agencies must be flexible to ensure that sustainable operations are achieved for both peak and non-peak periods (Sun & Schonfeld, 2016).

There are several approaches rail agencies employ to adjust system capacity based on train service demand requirements. The simplest approach is to modify the infrastructure of the trains (Sun & Schonfeld, 2016). Configurations between locomotives and coaches are adjusted; more coaches are attached to locomotives to increase train capacity, or less coaches are attached to locomotives to decrease train capacity. During peak periods, train configurations are longer, resulting in increased capacity. During non-peak periods, train configurations are shorter, resulting in decreased capacity. Although this is a simple, logical approach, studies have demonstrated that infrastructure limitations and constraints pose a lot of challenges when train configurations are being adjusted (Yang & Tang, 2018).This approach is often labour and time intensive (Cascetta & Coppola, 2016). It is notable that the advent of electric multiple unit (EMU) passenger trains has enabled adjusting train configurations to have less technical limitations thereby allowing for significantly reduced process times (Mwambeleko & Kulworawanichpong, 2019).

The approach that has been adopted in modern times involves adjusting system capacity by adjusting train service schedules to meet peak and non-peak period operation requirements, respectively (Cascetta & Coppola, 2016). During peak periods, more trains are introduced into the system and interarrival times between trains are shortened which thereby increases system capacity. During non-peak periods, less trains operate in the system, interarrival times between trains are longer which thereby decreases system capacity. With the rise of advance scheduling software, this approach has become the preferred option.

For urban rail systems where disparity between peak period and non-peak period train service demand is large, the two approaches are often utilised simultaneously. As an example, during peak periods the Taipei metro typically has longer train configurations and shorter interarrival times between trains (Wen & Lan, 2010). During non-peak periods train configurations are shorter and interarrival times between trains are longer. This approach is widely used in urban rail systems for managing system performance throughout the course of a day. There are several parameters rail agencies use to measure performance on rail systems. Some parameters are focused on measuring efficiency with which systems are being operated, some are focused on measuring system utilisation and others are focused on measuring system changes within a given time period etc (Ma & Koutsopoulos, 2014). The measurement and analysis of certain parameters allow rail agencies to make informed decisions on how to improve operations to benefit riders and the rail systems. The commonly used parameters and metrics are discussed below.

The first parameter is passenger flow. As standard, modern day urban rail systems are equipped with automatic fare collection (AFC) and automatic passenger counting (APC) infrastructure that allow riders to utilise train services (Green, et al., 2005). For riders, this infrastructure is savvy as it allows for instant boarding and payment for train services utilised. For rail agencies, this infrastructure allows for the measurement of passenger flow at various train stations, trains, rail lines etc. Passenger flow is a count of the riders who utilise a rail system at a given point in time, much like ridership. The infrastructure also provides information on the origins and destinations, also known as ‘O-D’, of individual passengers (Zhao, et al., 2007).

Peak hour coefficient refers to the proportion of passenger flow that is concentrated in one hour in a day, to the total passenger flow in a day (Wei, et al., 2019). The peak hour coefficient of daily average passenger flow is used to reflect the crowding degree of passenger flow at a point in time. Given that urban rail systems are characterised by peak and non-peak periods of passenger flow, it is understandable why such a parameter is important, particularly during weekdays where fluctuations of train service demand are large.

$$C_i = \frac{F_i}{F_t}(i = 0,1,2,\ldots 23) \quad (1)$$

In equation (1), C_i is peak hour coefficient, F_i is one hour passenger at i o'clock, F_t is the passenger flow of one day, and i is the time, from 0h00 to 23h00 (Wei, et al., 2019)

As mentioned previously, some parameters focus on measuring system performance on selected parts of system infrastructure. Passenger flow intensity is a parameter that reflects the operational efficiency and compression capacity of rail lines found in a rail system (Wei, et al., 2019). This parameter is obtained by a ratio of passenger flow and the mileage of the rail lines found in the system.

$$S_i = \frac{F_j}{L_j}(j = 1,2,3\ldots total\ \#\ of\ rail\ lines) \quad (2)$$

In equation (2), S_j is passenger flow intensity, F_j is passenger flow at the rail line j, L_j is the length of the rail line j, and j is the rail line whose intensity is being calculated in the rail system (Wei, et al., 2019).

Directional imbalance coefficient (DIC), $\mathcal{E}_j$ is the ratio of two times of the maximum period passenger flow on a given line, j to the sum of the upstream maximum period passenger flow F_{jp}^{max} and the downstream maximum period passenger flow F_{jx}^{max} in the period of *t* (Li, et al., 2016). This value represents the balance of passenger flow in the upstream and downstream direction of a line. A large value of DIC, implies that passenger flow is more concentrated in one direction. This coefficient is crucial to analyse during peak periods whereby there tends to a large number of riders travelling in the same direction; to and from urban areas and central business districts, and places of residence.

$$\mathcal{E}_j = \frac{2*\max(F_{jp}^{max}, F_{jx}^{max})}{F_{jp}^{max} + F_{jx}^{max}} \quad (3)$$

Section imbalance coefficient (SIC), δ_j is the ratio of the product of the maximum one-way section passenger flow of a rail line and the number of rail line sections to the sum of all section passenger flow in over a period of *t* (Li, et al., 2016). The value represents the passenger flow distribution of sections in a rail line. A large value of SIC implies that passenger flow is more concentrated in a certain section of a rail line. This coefficient is important when analysing which stations on a given rail line have a significant impact on the passenger flow and utilisation of an urban rail system.

$$\delta_j = \frac{F_j^{max} * k_j}{\sum_k F_j^k} \tag{4}$$

To recap this section, the concept of train service supply was discussed. Train service demand and ridership patterns were discussed once more but this time, in the context of rail system supply and how the two relate. The approaches employed in urban rail systems to manage peak and non-peak operations were reviewed. It was also established that weekday operations pose more challenges to rail agencies opposed to weekend operations due to ridership patterns discussed. Parameters used to measure the system performance of rail systems were discussed.

2.5. The design of travel demand management to urban rail systems

In the past, travel demand management (TDM) has been defined as the strategies and policies aiming to achieve more efficient use of transportation resources (Garling & Schutema, 2007). For urban rail systems in particular, TDM has been defined as: strategies that increase system efficiency by altering demand patterns, rather than increasing the *supply* the of service (Ma & Koutsopoulos, 2019). The latter definition is used for this discussion moving forward.

Government institutions have a mandate to provide transportation resources to the public as this has been proven to generate economic value, and that urban rail systems are a means through which this mandate is fulfilled. Simply put, it is desirable that train service demand is high on urban rail systems; that urban rail systems are utilised as much as possible, by as many commuters as possible. The dilemma is: the disparity of train service demand between peak and non-peak periods (during weekdays) result in low system efficiency, which puts at risk the sustainability of operations for urban rail systems (Ma & Koutsopoulos, 2014). This is the fundamental reason rail agencies employ TDM strategies.

During peak periods train service demand, system utilisation and crowding all increase drastically. Oftentimes, increasing train service supply is not enough to manage the surge in ridership experienced during peak periods: overcrowding still occurs, service levels deteriorate, and system infrastructure is over utilised (Li, et al., 2016). During non-peak periods train service demand, system utilisation and crowding degree are low and very tolerable. This is the impetus for employing TDM strategies on urban rail systems. By influencing daily train service demand to be more evenly distributed and have less fluctuations, better system efficiency can be achieved (Ben-Akiva & Lerman, 1985). Studies have even demonstrated that, if designed and employed effectively, TDM allows for increased overall ridership capacity for urban rail systems (AEI, 2020).

Several different types of TDM strategies have been applied to urban rail systems to influence commuter behaviour, and thereby influence train service demand. These will be discussed shortly. For now, it is important we establish the rationale with which TDM strategies are developed to influence train service demand. For urban rail systems, TDM strategies are conventionally developed based on two principles: incentivise a shift in commuter behaviour that is accompanied by a ‘reward’, or incentivise a shift in commuter behaviour through penalising undesirable behaviour (Bhattacharjee, et al., 1997).

2.5.1. Differential pricing frameworks

Differential pricing is a prevalent TDM strategy that has been implemented extensively in urban rail systems, globally. Differential pricing is when rail agencies devise a fare structure for its train services such that the fares commuters are subjected to a function of specified variables (Qin, et al., 2019). The variables could be temporal whereby riders are subjected to base (or discounted) fares when travelling during non-peak periods and are subjected to surge fares when travelling during peak periods. The variable could be spatial whereby riders are subjected to base (or discounted) fares when their O-D are on a rail line with low utilisation. Conversely, riders could be subjected to surge fares when their O-D are on a rail line with high utilisation; Qin's work explains the different variables.

Train service fares are generally priced via the cost-plus pricing method (Voith , 1997). The associated costs of delivering train services are tallied, a reasonable mark-up is added to the costs, which then produces the fares commuters are subjected to (Voith , 1997). In the context of urban rail systems, these are referred to as base fares. Discounted fares are typically when rail agencies decrease or completely eliminate mark-up costs from the base fares that riders are normally subjected to (Paulley, et al., 2006). Surge fares are when rail agencies increase the mark-up costs that they normally include for base fares (Paulley, et al., 2006). When developing TDM strategies, rail agencies tend to leverage between the two abovementioned fare types.

The Washington Area Metro applies surge fares during its peak periods which are 06h00 – 09h30 and 15h00 – 19h00 during weekdays. During these periods riders pay a 15% - 27% surge on base fares, depending on their origin-destination (O-D) trips (WMATA, 2020). During non-peak periods, riders of The Washington Area Metro pay base fares – there are no discount fares offered to riders. In the past, the implementation of surge fares on transit systems has been scrutinised and politicised given that rail agencies are government institutions (Halvorsen, et al., 2016). In these instances, discount structure have been useful; the Hong Kong MTR is a good example of how this approach was once applied. For a brief period, riders of the Hong Kong MTR paid base fares when travelling during peak periods and discounted fares when travelling off-peak periods.

The two approaches mentioned are similar in that differential pricing is applied to influence train service demand. The differences are that the former approach generates more revenue for the rail agency and is subject to scrutiny whereas the latter generates less revenue but is often better received by the public (Ma & Koutsopoulos, 2019). A study by Wen and Lan on the Taipei metro compared the benefits and trade-offs of discounting, base and surge fare structures. The study was aimed at investigating the effects of temporally differential fares on ridership. For the study, stated-preference (SP) experiments were performed then multinomial logit (MNL) and nested logit models were employed to depict the changes in riders' behaviours. SP experiments and MNL models are an approach that involves capturing the hypothetical preferences and decisions stated by persons participants of a given experiment (Louviere & Timmermans, 1990). The preferences and decisions are then used as inputs to multinomial logit models to simulate outcomes of future events (Louviere & Timmermans, 1990).

For their study, Wen and Lan performed the SP experiments as shown in table 3. Riders of the Taipei metro who participated in the study were required to state their preferences between peak surcharge or off-peak discount differential pricing scheme. Based on the attributes chosen by riders for: metro fare, train frequency, and degree of crowding, the MNL models developed compute the expected shifts in travel behaviour and sometimes, shifts in mode of transportation. Note that, in table 3, from Wen & Lan's research, CV refers to base metro fares.

Table 3: Attributes and levels set in the SP experiments performed on Taipei metro riders *(Wen & Lan, 2010)*

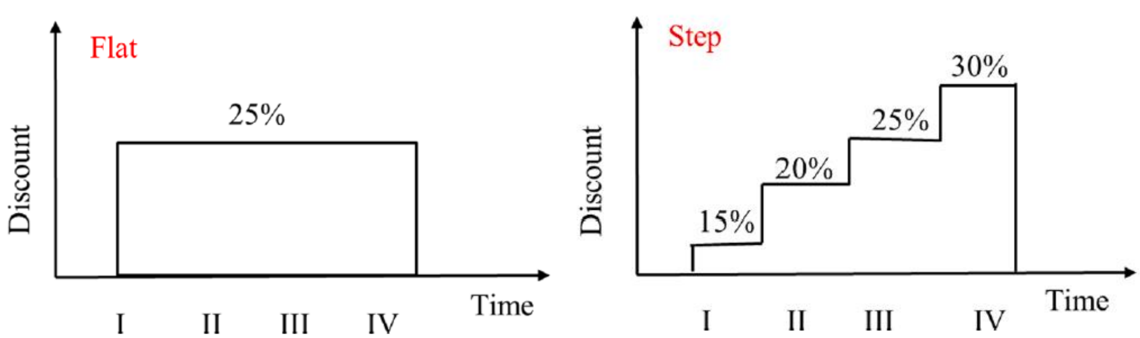
Differential pricing scheme	Period	Metro fare	Train frequency	Degree of crowding
Peak surcharge	Peak hours	CV[a] × 1.25 CV × 1.50 CV × 1.75	every 2 min every 4 min every 6 min	Same as now[b]
	Off-peak	CV	every 6 min every 8 min every 10 min	Somewhat crowded, Not crowded
Off-peak discount	Peak hours	CV	every 2 min every 4 min every 6 min	Same as now
	Off-peak	CV × 0.75 CV × 0.50 CV × 0.25	every 6 min every 8 min every 10 min	Somewhat crowded, Not crowded

MNL models have been used extensively in the development of TDM frameworks to predict expected changes in ridership and train service demand. The limitations of using MNL models are well explored as well (Ashford & Benchemam, 1987). Given the nature and objectives of the research performed for this paper, SP experiments and MNL models were not used.

It is understandable that the discounting and surcharge structures employed in TDM frameworks are crucial for the success and effectiveness of the TDM strategy; they are key components that determine ridership response. Ideally, differential pricing structures should be developed such that, the discounting or surcharging in place motivates a shift in rider behaviour and effectively, train service demand patterns (Zhang, et al., 2014). In addition, it must be capable of motivating commuters who rely on other transportation modes to switch to urban rail systems (Zhang, et al., 2014). The non-ideal outcome of a differential pricing structure is one that, due to the discounting or surcharging in place, results in riders effectively changing their mode of transportation from urban rail. This would represent a loss in overall ridership and revenue for urban rail. These considerations tie-in with the concept of fare elasticity (Halvorsen, et al., 2016).

A study by Ma and Koutsopoulos compared two basic discount structures applicable to urban rail systems to influence ridership (Ma & Koutsopoulos, 2019). As seen from figure 5, the flat discount scheme is one whereby a fixed discount is offered to riders over a given period of time. The step discount scheme is one whereby the discount offered to riders is either stepped up (or down) as a function of time, depending on the desired behaviour riders are being influenced on. These types of structures have also been applied and studied for surcharge schemes.

Conceptually, the step discount scheme is more sophisticated which means it is likely to be more effective at influencing train service demand patterns. However, in reality there are more factors to consider. As the sophistication of the of the differential pricing structure increases, the complexity of implementing the structure increases too (Halvorsen, et al., 2016). Rail agencies avoid complicated structures because they are less understandable to riders (Halvorsen, et al., 2016). This presents risks of the structure being ineffective



(a) Flat discount (b) Step discount

Figure 5: Flat and stepped discount schemes (I, II, III, IV represent 15-minutely time intervals within a one-hour period) (Ma & Koutsopoulos, 2019)

As mentioned previously, fare elasticity is crucial consideration for any TDM framework that employs differential pricing. Fare elasticity refers to the degree of sensitivity train service demand is characterised by (Hensher, 1998). Put differently, fare elasticity gives an indication of how sensitive urban rail system users are to fares they are subjected to. Curtin derived a formula, through performing regression analyses on before-and-after results of several transit systems that implemented fare changes (McCollom & Pratt, 2004). Given the extensive use of the formula and the reliable results it has produced, it has become accepted in literature as the '0.30 Common rule' formula for estimating ridership changes due to fare changes.

$$Y = 0.80 + 0.30X \tag{5}$$

Where Y is the percent loss in ridership as compared to the prior (before) ridership, and X is the percent increase in fare as compared to the prior (before) fare.

2.5.2. Promotion-based travel demand management frameworks

Promotion-based TDM strategies for urban rail systems are designed to influence ridership through means that are usually not directly related to the fare structures users are subjected to (Halvorsen, et al., 2016). Similar to differential pricing structures, promotion-based TDM strategies are used to incentivise reductions in ridership during peak periods, thereby decreasing disparity of peak and non-peak period train service demand. The key distinction is that promotion-based TDM frameworks qualitatively focus on variables that determine ridership patterns and the incentive structures to offer riders to influence them (Ma & Koutsopoulos, 2019). Promotion-based TDM strategies are modern and have not been implemented extensively hence literature on these types of strategies is limited.

Promotion-based strategies in transit systems are notorious for being inefficient in shifting ridership away from peak periods to off-peak periods. Ma and Koutsopoulos showed that promotion-based TDM strategies are sometimes inefficient because a significant number of rail system users benefit from such strategies without having to change their travel behaviour (Ma & Koutsopoulos, 2019). For this reason, promotion-based strategies require enhanced understanding of the spatial and demographic characteristics of users for efficient results. This was demonstrated through the classification of four main user groups on the Hong Kong MTR, that were each affected in different ways by a promotion-based TDM strategy during peak and non-peak periods. The key conclusions of the study were that promotion-based TDM strategies are limited in incentivising certain user groups to change their behaviours (Ma & Koutsopoulos, 2019). This research method (classifying riders according to user groups) was crucial for the research conducted in this paper, on the Gautrain rail system.

The successful six-month programme performed by the San Francisco Bay Area Rapid Transit, BART Perks, testing their promotion-based TDM strategy exemplifies the important factors that need to be accounted for to efficiently shift ridership patterns. The programme managed to shift 10% of train service demand from peak periods to non-peak periods, which is significantly more than the shifts reported from other promotion-based strategies applied to urban rail systems in the past (Greene-Roesel & Smith , 2019).

The BART Perks programme was structured as follows: programme participants were awarded points based on periods throughout the day they travelled, and with the use of a status structure participants could be further classified and 'promoted' based on their shifts in travel behaviour (table 6 and 7). It is important to scrutinise the structure chosen by BART Perks for awarding points to users. The points or cash earned by riders was 'stepped' up or down to incentivise desired behaviours from users; this resembles the rationale discussed in section 2.5.1 on flat vs. stepped discounting structures. Points awarded were redeemable to be transferred to popular consumer rewards programmes (e.g. Amazon, iTunes, Walmart etc.) and cash rewards were paid out monthly to users.

Table 4: Perks programme points rules

	BONUS HOUR 6:30 TO 7:30 A.M.	PEAK HOUR 7:30 TO 8:30 A.M.	BONUS HOUR 8:30 TO 9:30 A.M.	ALL OTHER TIMES
POINTS EARNED	3,4,5 or 6 points/mile* (depending on status)	1 point per mile*	3,4,5 or 6 points/mile* (depending on status)	1 point per mile*

Table 5: BART Perks programme status rules

STATUS	BRONZE	SILVER	GOLD	PLATINUM
BONUS HOUR POINT MULTIPLIER	3 points/mile*	4 points/mile*	5 points/mile*	6 points/mile*
MAXIMUM REWARD (IN GAME PLAY)	$10	$20	$50	$100
NUMBER OF BONUS HOUR TRIPS REQUIRED FOR THIS STATUS	0	2/week, for at least 2 weeks	3/week for at least two weeks	4/week for at least 2 weeks

Figure 6 shows the shift in ridership patterns during morning and afternoon peak periods before and after the launch of the BART Perks programme. This once again highlights the efficiency and success of the programme.

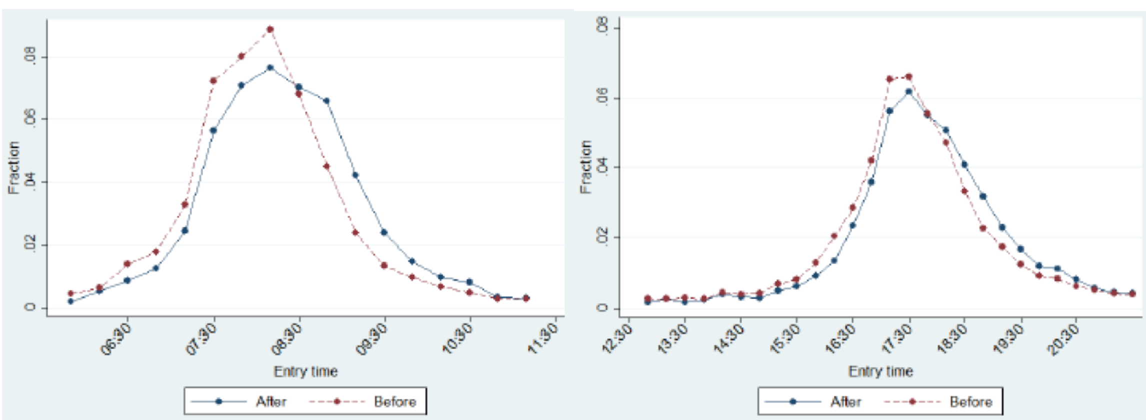


Figure 6: Ridership patterns (during weekdays) before and during BART Perks programme

In summary, the success of the BART Perks programme was attributed to: (i) market survey performed to understand user demographics for peak periods, (ii) design of points and cash rewards structure, (iii) transparency and accessibility of information to programme participants (iv) evaluation approach of the programme (Greene-Roesel & Smith , 2019). The program's effectiveness was evaluated using two methods: statistical analysis of smartcard data (daily ridership and ridership pattern shifts) and (2) survey data collected after completion of the programme. These methods were used as part of the research method employed for this paper (section 2.6).

The limitations of BART Perks were that it was not sophisticated enough to consider the imbalances of ridership between the different rail in the system (Greene-Roesel & Smith , 2019). In addition, the strategy was not rigorously designed for various trip O-D users have when using BART. This meant that certain groups of riders who used BART to commute long trips stood to gain from the Perks framework, even during peak periods, which was not ideal. Ma and Koutsopoulos proposed a more complex framework that does aim to solves this, in theory. By framing the strategy as an integer optimisation problem, they were able to derive objective functions that considered various permutations of O-D pairs riders would travel and time periods riders were expected to be in a rail system (Ma & Koutsopoulos, 2019).

2.6. Efficiency of TDM strategies to urban rail systems

The efficiency of a TDM strategy is primarily measured by how well the strategy reduces ridership disparity and fluctuations between peak and non-peak periods, thereby improving system efficiency of the urban rail system (Taylor, et al., 1997). An additional consideration that pertains to efficiency is the level of sophistication of the strategy: how well does the strategy target specific user groups to *shift* their commute patterns (Taylor, et al., 1997). Emphasis is placed on ‘shift’ because the ideal outcome of the TDM strategy is one that maintains (or increases) daily ridership in a manner that achieves improved system efficiency (Bao, et al., 2020). Understandably, this is attainable if daily ridership is well distributed throughout the course of day rather than being high at certain periods of the day and low for other periods of the day.

Whether commuters decide to shift their commute patterns or stop utilising an urban rail system, due to an in-place TDM strategy is dependent on a range of internal and external variables to the urban rail system. Studies performed in the past have used a system dynamics approach to define and analyse such variables (figure 7). The system dynamics approach emphasizes the interrelations and feedback ‘loops’ that exist between variables such as train service demand and train service supply (Wang, et al., 2018). This is an advanced approach that can be used when analysing the efficiency of a TDM strategy of an urban rail system.

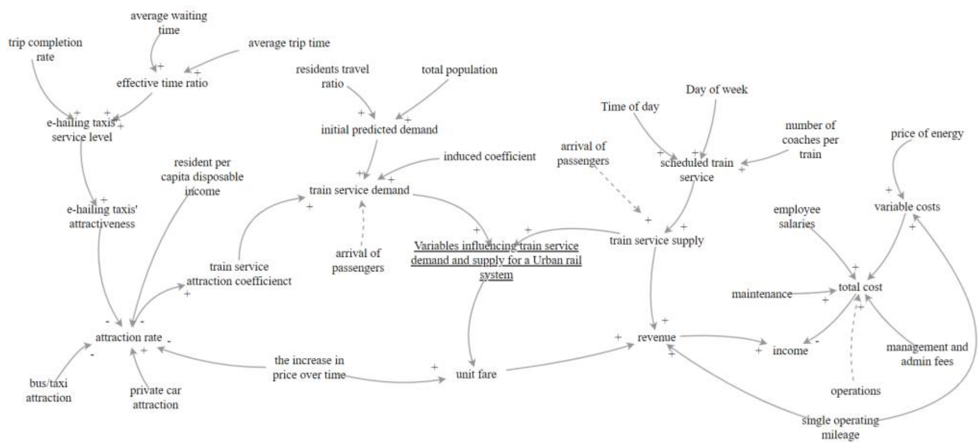


Figure 7: Cause and effect relationship chart for variables that influence demand and supply of an urban rail system *(adapted from Wang, et al., 2018)*

More commonly used approaches to evaluate TDM strategy efficiency include: graphically analysing changes in daily ridership patterns, sensitivity analyses, MNL models (section 2.5.1), hypothesis testing, etc. As depicted in figure 6 from the BART Perks programme, the shifts in ridership patterns can be seen graphically; after the introduction of the TDM strategy, ridership became slightly better distributed and the maximum ridership point reduced.

Sensitivity analyses are performed to understand the extent to which passengers change their commute patterns based on the train service fares they are subjected to (Ma, et al., 2011). They are particularly relevant when evaluating TDM strategies that use differential pricing structures (table 6). Oftentimes, passengers show less elasticity during peak periods because these are assumed to be periods in which they are commuting for professional reasons (e.g. work or school). Hence, changes in fares are less likely to affect train service demand significantly. During off-peak periods, passengers show more elastic behaviour because it is assumed that the reasons for commute are not professional. Hence, changes in fares are more likely to affect train service demand because, during off-peak periods, passengers are expected to have more flexibility with regards to their times of travel and transport modes.

Table 6: Peak and off-peak period fare elasticity of passengers on different cities and transit modes *(Ma, et al., 2011)*

City / Transit Mode	Peak	Off-Peak	Source
London / Bus	–0.27	–0.37	Rendle, Mack and Fairhurst (1978)
London / HRT	–0.10	–0.25	Rendle, Mack and Fairhurst (1978)
New York / HRT	–0.04	–0.11	Mayworm, Lago and McEnroe (1980) from Lassow (1968)
Stevenage, England / Bus	–0.27	–0.87	Smith and McIntosh (1974)

Lastly, the hypothesis testing approach has been used in the past to compare the various changes in ridership and train service demand that *may* have been as a result of a TDM strategy (Werner, et al., 2016). The 'changes' of interest may be defined according to quantitative metrics (e.g. average daily ridership, peak period ridership, level of crowding etc.) or qualitative metrics (e.g. service quality). It all depends on the areas of interest of the persons performing the study. This paper made use of graphical and hypothesis testing approaches (section 4).

In summary, the efficiency of an urban rail system TDM strategy relates to understanding and, where possible, quantifying how well train service demand is in influenced to increase system efficiency. The efficiency can be analysed in different ways which have varying levels of complexity. Ultimately, the approach used to analyse the efficiency is determined by the area of interest one is focused on, and data available for analysis. Research performed in this paper made use of graphical and hypothesis testing approaches.

3. ANALYSIS

This chapter aims to contextualise the research performed for this paper by providing detailed information on the Gautrain. This section also reviews previous analyses performed on the Gautrain and how information produced was used for the study performed for this paper.

3.1. Gautrain train service supply

Gautrain is an urban rail system that operates in the Gauteng province. The Gautrain network comprises ten train stations that integrate the northern, eastern and southern metropolitan areas of the Gauteng province. Three bi-directional rail lines are operated on the Gautrain network; each line is graphically represented in figure 8. The North-South line (red) is comprised of the following stations: Hatfield, Pretoria, Centurion, Midrand, Marlboro, Sandton, Rosebank and Park. The East-West line (blue) is comprised of the following stations: Rhodesfield, Marlboro and Sandton. The airport passenger line (yellow) is dedicated for passengers travelling to or from the OR Tambo International airport and it is comprised of the following stations: OR Tambo, Rhodesfield, Marlboro and Sandton.

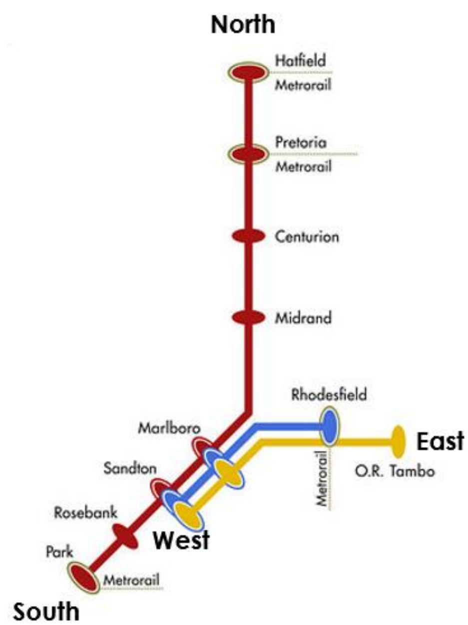


Figure 8: Gautrain rail network (GMA, 2019)

The three lines converge at the Marlboro and Sandton stations. This convergence interconnects the various urban areas from the northern, eastern and southern regions of the Gauteng province. Train services provided allow passenger O-D pairs to be along the same lines (e.g. travel from Pretoria to Rosebank) and across different lines (e.g. travel from Rhodesfield to Park or O.R. Tambo to Centurion). Passengers travelling across different lines are required to use the two interchange stations (Marlboro and Sandton) to switch from one line to the next.

Gautrain operates two train configurations depending on train service supply requirements: 4 car trains and 8 car trains. Four car trains have a capacity of approximately 460 passengers and are mostly utilised during non-peak periods where train service demand is relatively low. Gautrain operates from 04h45 – 21h00. Eight car trains have a capacity of approximately 900 passengers and are mostly utilised during peak periods where train service demand is very high. Train car configurations can be viewed as the primary lever used by the Gautrain Management Agency (GMA) to manage fluctuations is ridership.

The second lever is the scheduling of trains for the supply of train services. The interarrival times for trains are as follows: 10 minutes during peak periods, 20 minutes during non-peak periods and 30 minutes during weekends. Gautrain train schedules are available to all current and potential passengers online and in Gautrain stations and trains at https://www.gautrainalerts.co.za/timetables/

3.2. Gautrain train service demand

Gautrain stations are equipped with automatic fare collection (AFC) and automatic passenger counting (APC) 'gates' that allow users to access the Gautrain system and pay fares swiftly with a simple tap of their Gautrain smartcards. The gates are situated at entry and exit points throughout the Gautrain network, before passengers embark and disembark trains at each of the stations. Smart cards issued to users have unique user identification barcodes. This allows for analyses to not be limited to general ridership behaviour, but to specific user behaviour. Origin-Destination (O-D), travel times, trip durations, fares paid are examples of some of the rider information that can be derived from the AFC and APC gates.

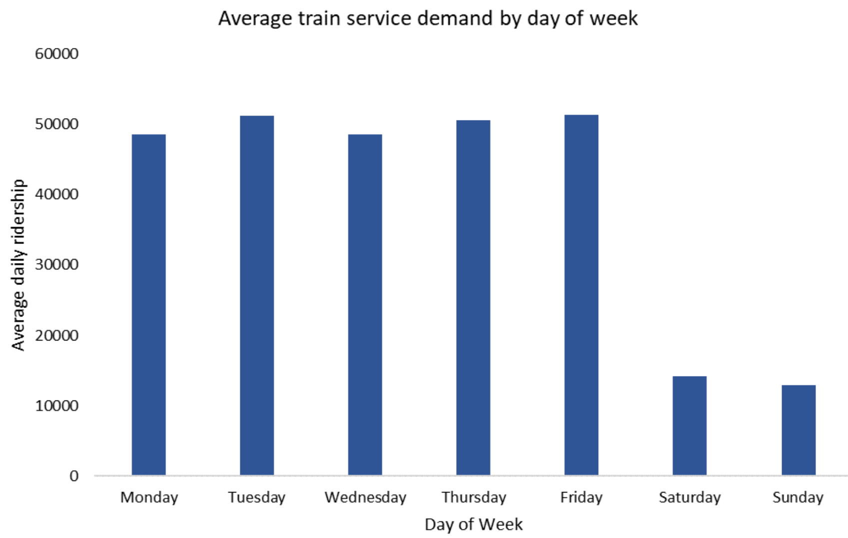


Figure 9: Average daily ridership on the Gautrain (GMA, 2019)

Figure 9 shows that train service demand for the Gautrain is in accordance with expectations from literature – ridership is significantly higher on weekdays than on weekends. Figure 10 shows that train service demand patterns are also in accordance with expectations from reviewed literature. There are two peak periods during weekdays which are in the morning and afternoon, and the ridership during peak periods is much greater than the ridership during non-peak. During weekends there are no peak periods, ridership climbs and falls at a steady rate.

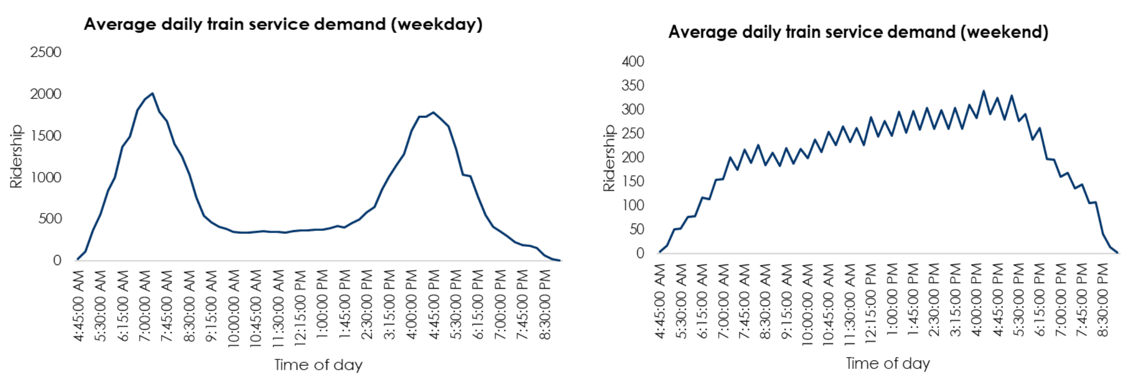


Figure 10: Train service demand patterns on the Gautrain (GMA, 2019)

Given the ridership patterns, it is conceivable that GMA is able to manage weekend operates with ease and high system efficiency. The challenges GMA faces are mostly related to weekday operations. The mitigation strategies GMA has in place (e.g. adjusting train configurations and train interarrival times, TDM framework) are not sufficient to achieve desired system efficiency levels on the Gautrain. Oftentimes overcrowding occurs at stations, terminals and trains, service levels deteriorate, and infrastructure is strained due to excessive utilisation during peak periods (Agency, 2019). In addition, the very low ridership and utilisation levels during off-peak periods jeopardise the profitability of the Gautrain during those periods. Thus, the TDM strategy Gautrain has in place only applies to weekdays.

A study performed in 2019 on the Gautrain aimed at understanding what influences train service demand identified a multitude of factors that need to be considered (table 7). Research performed in this paper made use of some of the factors identified, namely: fare elasticity, travel time and train service levels.

Table 7: Factors influencing train service demand on the Gautrain *(GMA, 2019)*

Group	Factors
Socio-economic	Population
	Economic growth
Internal train system	Fares (elasticity)
	Travel time
	Train service levels
	Capacity
Other transportation systems	Fuel price
	Parking fees
	Toll prices
	Traffic congestion on urban roads
	Service levels on other public transit systems

The key outcome of the study was a model that calculated the fare elasticity of Gautrain users. The fare elasticity was calculated to be -0.44. This allowed for scenarios to be evaluated on how increases or decreases in fares would be expected to impact train service demand.

3.2. Gautrain travel demand management strategy

Gautrain employs a temporal, differential pricing TDM strategy on its users. As mentioned previously, the TDM strategy only applies during weekdays. In addition, the TDM strategy is not applied to airport passenger service users – fares are fixed for these users. Figure 11 shows the fare structures that apply during peak and off-peak periods. Peak periods are 06h00 – 08h30 and 15h30 – 18h00, the remaining periods are considered off-peak.

Peak Fares

Pay-As-You-Go Single Train Fares

Hatfield		R 28	R 36	R 57	R 67	R 72	R 75	R 81	R 75	R 192
Pretoria	R 28		R 32	R 45	R 62	R 67	R 72	R 75	R 72	R 192
Centurion	R 36	R 32		R 37	R 45	R 58	R 61	R 67	R 65	R 192
Midrand	R 57	R 45	R 37		R 32	R 37	R 42	R 45	R 43	R 178
Marlboro	R 67	R 62	R 45	R 32		R 28	R 31	R 37	R 32	R 165
Sandton	R 72	R 67	R 58	R 37	R 28		R 28	R 31	R 41	R 165
Rosebank	R 75	R 72	R 61	R 42	R 31	R 28		R 28	R 43	R 178
Park	R 81	R 75	R 67	R 45	R 37	R 31	R 28		R 45	R 178
Rhodesfield	R 75	R 72	R 65	R 43	R 32	R 41	R 43	R 45		R 165
OR Tambo	R 192	R 192	R 192	R 178	R 165	R 165	R 178	R 178	R 165	
	Hatfield	Pretoria	Centurion	Midrand	Marlboro	Sandton	Rosebank	Park	Rhodesfield	OR Tambo

Note: Valid between 06h00 and 08h30 and between 15h30 and 18h00 on weekdays, based on time of entry. These fares also apply on weekends and public holidays.

Off- Peak Fares

Pay-As-You-Go Single Train Fares

Hatfield		R 22	R 28	R 45	R 53	R 57	R 60	R 64	R 60	R 192
Pretoria	R 22		R 25	R 36	R 49	R 53	R 57	R 60	R 57	R 192
Centurion	R 28	R 25		R 29	R 36	R 46	R 48	R 53	R 52	R 192
Midrand	R 45	R 36	R 29		R 25	R 29	R 33	R 36	R 34	R 178
Marlboro	R 53	R 49	R 36	R 25		R 22	R 24	R 29	R 25	R 165
Sandton	R 57	R 53	R 46	R 29	R 22		R 22	R 24	R 32	R 165
Rosebank	R 60	R 57	R 48	R 33	R 24	R 22		R 22	R 34	R 178
Park	R 64	R 60	R 53	R 36	R 29	R 24	R 22		R 36	R 178
Rhodesfield	R 60	R 57	R 52	R 34	R 25	R 32	R 34	R 36		R 165
OR Tambo	R 192	R 192	R 192	R 178	R 165	R 165	R 178	R 178	R 165	
	Hatfield	Pretoria	Centurion	Midrand	Marlboro	Sandton	Rosebank	Park	Rhodesfield	OR Tambo

Figure 11: Gautrain differential pricing TDM strategy

Analysis of the differential pricing structure shows that: peak period fares are 20 – 27% more than off-peak period fares. This strategy is temporal, meaning that the differential pricing structure is solely a function of time of day. This presents limitations and possible areas of improvement on the effectiveness of the strategy in shifting ridership patterns. From section 2.5 it was established that there are multiple variables (e.g. spatial, O-D pair, fare elasticity etc.) that must be considered in the design of an effective TDM strategy.

An extensive market survey was performed in 2017 aimed at understanding the demographics of current Gautrain users and prospective Gautrain users. Findings from survey were deemed sensitive by the GMA thus have not been included in this paper. The key, high-level findings from survey participants were as follows: 60% of users have a living standard measure (LSM) of 10, users between the ages of 18 – 49 account for 75% of ridership, and majority (roughly 80%) of users are employed (Agency, 2019). The survey also extracted key information on the determinants of user behaviours as it pertains to travelling times, travel distances (O-D), service level expectations etc. This information is crucial for travel demand management. Findings from the survey were used to correlate some of the findings produced in this research paper.

In summary, there has been multiple, separate studies performed on the Gautrain, quantitative and qualitative. The previous studies performed have mostly focused on analysis of Gautrain capacity, revenue and overall train service demand using descriptive statistical methods. Research performed in this study, for this paper, focuses more on the travel demand management strategy Gautrain has in place and how train service demand is influenced by it. In addition, this research makes use of inferential statistical methods (e.g. hypothesis testing) for analysis and to produce findings.

4. RESEARCH METHOD

This chapter provides a detailed description of the research methods used by the researcher to answer the research questions and objectives stipulated. It must be noted that this section makes use of certain sections of the literature that was reviewed in section 2.

Before embarking on the details of the research method and techniques employed in this research, the overview of the research process must be presented. This aids with understanding the rationale followed by the researcher. Figure 12 shows the research flow. The process blocks are enumerated for ease of reference.

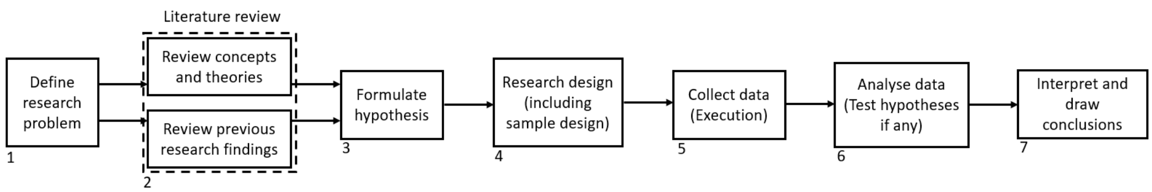


Figure 12: Research flow *(Kothari, 2004)*

4.1. Defining the research problem

The research problem (or opportunity) for the research conducted relates to understanding relationships that exist between train service demand, fare changes and the TDM strategy on the Gautrain. The problem is: daily ridership patterns on the Gautrain deteriorate system efficiency. As discussed in section 3, it is crucial that GMA understands factors that influence ridership on the system as this has implications on the sustainability of the Gautrain. Literature reviewed indicated that urban rail system sustainability can be analysed from two aspects: train service demand (e.g. daily ridership, ridership patterns etc.) and train service supply (e.g. train configuration, schedules, system capacity etc.). Research performed for this paper focused on the train service demand aspect. In addition, a preview of empirical literature informed the researcher to utilise quantitative methods to conduct the research.

4.2. Literature review

Upon formulating the research problem, an extensive literature review was performed on relevant topics of the study. Literature reviewed came from three sources, namely: previously performed studies on urban rail systems of other cities across the world, theoretical and conceptual research performed by researchers in the past, and studies & initiatives performed by the GMA. Most of the literature reviewed was focused on train service demand, fare structure changes and TDM, analysed using quantitative methods. Literature review indicated the established quantitative methodologies commonly used to address research problems related to that of this study: multinomial regression modelling, hypothesis testing, system dynamics. Prior evaluation of research objectives and data availability on the Gautrain informed the decision to use hypothesis testing methodology. The research method was also reviewed in section 2.

4.3. Formulate hypothesis

Given the reviewed literature and extensive engagement with GMA stakeholders, two working hypotheses were developed. Hypothesis 1 was formulated based on studies performed on urban rail systems from other cities across the world that indicate that increases in train service fares are commonly accompanied by decreases in ridership. Hypothesis 1 serves to test whether the Gautrain conforms to this assertion. For hypothesis 1, the two variables of interest are train service fares and ridership. It is being hypothesised that changes in ridership can be correlated with fare changes implemented on the system.

Hypothesis 1: *An increase in Gautrain train service fares does not result in a change in overall ridership.*

Hypothesis 2 was formulated based on a review of TDM initiatives performed on other urban rail systems and conceptual frameworks developed related to TDM for urban rail systems. Section 2.5 established the inefficiencies of temporal TDM strategies. Considering this, the researcher was tentatively biased that Gautrain's temporal TDM strategy is not efficient at shifting ridership patterns. Efficiency is defined as how well Gautrain's TDM strategy is at shifting commuter behaviour such that daily ridership during weekdays has less fluctuations. For hypothesis 2, the variables of interest are the TDM strategy GMA currently has implemented and ridership during peak & non-peak periods. Hypothesis 2 is specific to weekdays given that the TDM strategy has in place only applies on weekdays.

Hypothesis 2: *Gautrain's temporal travel demand management strategy is not efficient at shifting daily ridership from peak periods to off-peak periods during weekdays.*

4.4. Research design

Research conducted to test and explore the hypotheses formulated entailed: (1) performing statistical analyses on ridership data sets prior and after fare increase was implemented (2) clustering data based on spatial & temporal characteristics and performing statistical analyses on ridership data sets (within the same frames of reference). This approach classifies the research as experimental, specifically, quasi-experimental (Kothari, 2004). It is quasi-experimental because the ridership data sets to be collected and analysed are chosen from existing groups and are intentionally chosen by the researcher. Whereas purely experimental designs normally assign a control group which is used to benchmark the results of the experiment. In addition, for experimental designs groups are normally assigned randomly.

Smart card data of entries and exits of Gautrain users was the primary source of data utilised for the research. For the research, data from 01/01/2019 – 31/12/2019 was collected and analysed using MS Excel. Due to the large size of the data (more than 1,5 million data entries) it was required that the data be managed as databases using MS Access before MS Excel could be used for data processing. In addition, PowerBI was used to create flexible and adaptable graphical visuals of the data sets the researcher was interested in previewing before performing in-depth analysis on MS Excel.

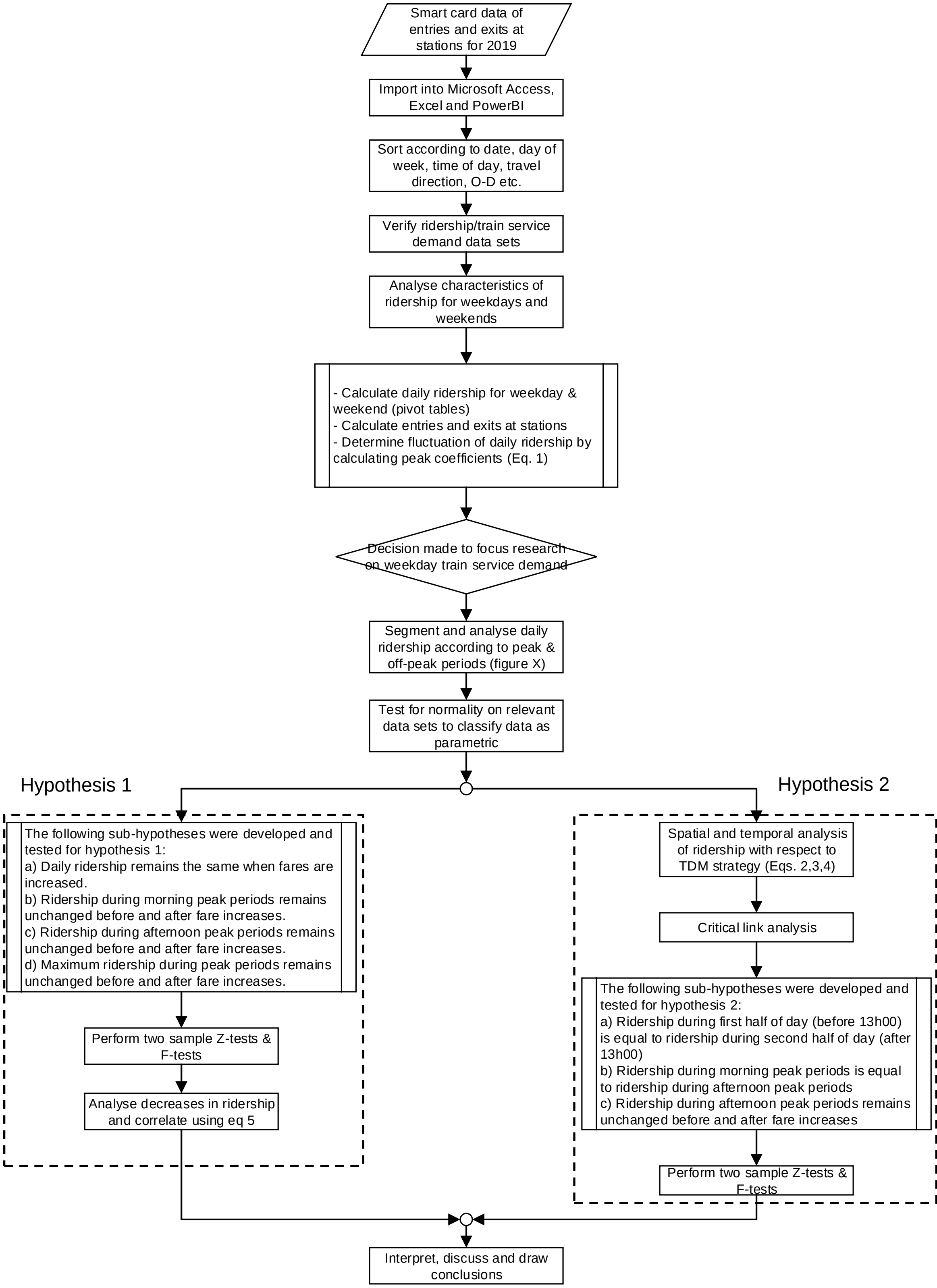


Figure 13: Summary of research

As mentioned in section 3.2, smartcard data contains information on user travel dates & times, O-Ds and estimated trip durations. Thus, data sets were sorted categorically, column by column, in the same order (table 10). Data that informs on the number of riders who used the system over a given period (e.g. dates, weeks, days, times etc.) classifies as discrete data. This data represents a ‘count’ of the parameter/s the researcher was interested in – it is represented integer values. Data that informs the origin and destination (O-D) stations of riders is categorical since data is categorised based on the different O-D pairs that riders commute. Once tallied up based on relevant categories the data can be analysed as discrete data to perform relevant statistical analyses. MS Excel ‘pivot table’ and ‘power query’ features enabled the researcher to transform the data into the required formats and perform descriptive statistical analyses on the data.

Data verification was crucial for analysis. The Gautrain system is susceptible to irregular events that affect train service demand and ridership. In 2019 the system experienced the following events, viz: (1) strikes by Gautrain station and train operators that halted the system (2) musical festivals and concerts that result in a surge of train service demand (3) power supply disruptions that slow down the operations of the system (4) public holidays whereby significantly less passengers commuted to work (Agency, 2019). Data that was affected by these events were not included as part of the analyses as they were outliers.

Once the outliers were removed, data analysis could be performed. The aim of the analysis was to quantify and understand ridership characteristics of weekdays and weekends. Section 3.2 discussed the key differences between weekday and weekend ridership figures and daily ridership patterns. It was also established that given that weekend ridership and ridership patterns are significantly less than on weekday, the research would focus on weekday ridership. In addition, Gautrain’s TDM strategy only applies to weekdays. Figure 13 shows the research methods used for the study. Where relevant, process blocks indicate (in parentheses) which equations were used to analyse data sets.

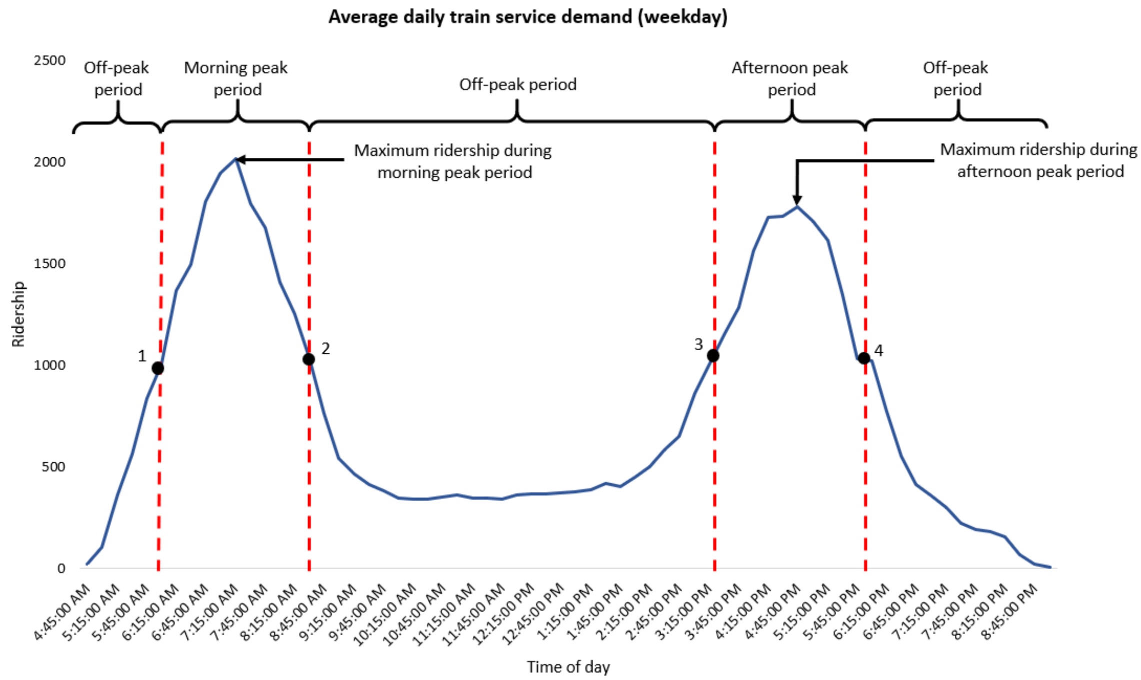


Figure 14: Segmentation of ridership patterns

Figure 14 shows how the daily ridership patterns data was segmented for analysis. Morning peak period ridership is obtained by integrating the area under the ridership line (blue), starting at point 1 and ending at point 2. Similarly, afternoon peak period ridership is obtained by integrating the area under the ridership line, starting at point 3 and ending at point 4. Lastly, off-peak period ridership is obtained by integrating the area under the ridership line between point 2 and point 3 MS Excel's built in integrate and summation functions were used to perform these calculations. As shown on figure 13, maximum ridership refers to the points at which ridership is highest. Points 1,2,3 and 4 are important for the research as they represent the 'shoulders' of the TDM strategy because these are points whereby the TDM strategy becomes active or become inactive (Jiang, et al., 2017).

4.4.1. Sampling

At this juncture, it is important to discuss the sample design for the research. As mentioned previously, the research considered 2019 data. Data from 2019 was chosen because it was the most recent data that could be acquired for a complete year. The data had an excess of 1,4 million entries; this was deemed sufficient for the data. In addition, 2019 data was chosen because in June 2019 a fare increase was applied to the train service fares. This meant that data before and after June 2019 could be sampled separately to test hypothesis 1.

The hypotheses and sub-hypotheses shown figure 13 were tested using two sample z-tests and f-tests. Data from 2019 was collected completely and in-full to create samples to perform hypothesis tests. Therefore, the elements of chance in the hypothesis tests performed were significantly reduced – very high accuracy was obtained (Kothari, 2004). The caveat to performing hypothesis testing on very large sample data is that assessing elements of bias in the tests is not easy to do (Kothari, 2004). Tables 8 and 9 show the samples chosen for analysis. The research design is quasi-experimental hence deliberate sampling design was employed (Kothari, 2004). This implies that the researcher chose samples in a purposive manner; there was no element of probability in the samples chosen.

Table 8: Sample groups chosen to perform statistical tests for sub-hypotheses developed to address hypothesis 1

Null hypotheses being tested:	Sample 1	Sample 2
a) Daily ridership remains the same when fares are increased.	Daily ridership (Feb – May)	Daily ridership (Jun – Nov)
b) Daily ridership during morning peak periods remains unchanged before and after fare increases.	Ridership during morning peak period (Feb – May)	Ridership during morning peak period (Jun – Nov)

c) Daily ridership during afternoon peak periods remains unchanged before and after fare increases.	Ridership during afternoon peak period (Feb – May)	Ridership during afternoon peak period (Jun – Nov)
d) Maximum ridership during morning peak periods remains unchanged before and after fare increases.	Maximum ridership during morning peak (Feb – May)	Maximum ridership during morning peak (Jun – Nov)
e) Maximum ridership during afternoon peak periods remains unchanged before and after fare increases.	Maximum ridership during afternoon peak (Jun – Nov)	Maximum ridership during afternoon peak (Jun – Nov)

Sample 1 comprised of daily ridership between February and May (before fares were increased). During these months daily ridership and ridership patterns were consistent and deemed homogenous. The month of January was subjected to high variability given that it is normally a month in which Gautrain users are in recess and not using the Gautrain regularly. The number of observations in sample 1 was 82 because there was a total of 82 weekdays between February and May. Sample 2 comprised of daily ridership between June and Nov (after fares were increased). The month of December was excluded for the same reasons mentioned for the month of January. The number of observations in sample 2 was 125 because there was a total of 125 weekdays between June and November.

Table 9: Sample groups chosen to perform statistical tests for sub-hypotheses developed to address hypothesis 2

Null hypothesis being tested:	Sample 3	Sample 4
a) Daily ridership during first half of day is equal to ridership during second half of day (testing if people	Ridership between 04h45 – 13h00	Ridership between 13h00 – 21h00

use the Gautrain to traverse to-and-from work)		
b) Daily ridership during morning peak period is equal to ridership during afternoon peak period	Ridership during morning peak period (06h00 – 08h30)	Ridership during afternoon peak period (15h30 – 18h00)
c) Maximum ridership during morning peak period is equal to maximum ridership during afternoon peak period	Maximum ridership during morning peak	Maximum ridership during afternoon peak

Samples 3 and 4 comprised of daily ridership throughout the year (February and November). For sub-hypotheses *a* – *c*, both samples had 207 observations as this was the total number of weekdays between February and November. The key difference between sample 3 and 4 for: sample 3 is comprised of ridership data that relates to morning travel, sample 4 is comprised of ridership data that relates to afternoon travel.

In addition to statistical tests, various analyses were performed to answer hypothesis 2. This is detailed in section 4.6.

4.4.2. Instrumentation

The smart card infrastructure found at Gautrain stations constitutes the one of the instruments used for the research. To access and egress the Gautrain system passengers are required to 'beep' their Gautrain cards at various points of entry/exit. These points of entry and exit are equipped with modern APC and AFC technology records user entries into a repositories, databases and servers etc. Vast amounts of historical data was recoverable however, given hardware and software limitations it was decided that 2019 would be sufficient for the research. By design, data collected by APC and AFC technology captures variables on Gautrain users such as: O-D, number of riders, time of travel etc. This was sufficient for the research as it focused on temporal and spatial analyses on Gautrain's TDM strategy.

4.5. Data collection procedure

The research performed required the researcher acquire sensitive information and data on Gautrain's train service demand (ridership), and studies & initiatives performed on the Gautrain by the GMA and consultancies. For this to happen, the researcher committed to non-disclosure agreements of certain information. Furthermore, ethical clearance was granted by the Witwatersrand School of Mechanical, Industrial and Aeronautical (MIA) engineering to allow the researcher to obtain and use information from the GMA for the research.

Gautrain system infrastructure automatically counts riders, records the dates and times at which they travel and O-D they travel. In this scenario, the Gautrian AFC and APC systems that record smart card data entries are the means through which data was collected. This is convenient for the researcher. The research being quasi-experimental, the researcher was simply required to make assignments to existing groups or datasets and compare. For example, in this case, datasets were chosen as: ridership during morning peak period before fare increase vs. ridership during morning peak period after fare increase, ridership during morning peak vs. ridership during afternoon etc. The distinction is that data sets collected to test hypothesis 1 were classified to perform *between groups* tests of comparison whereas data sets collected to test hypothesis 2 were classified to perform *within groups* tests of comparison (Kothari, 2004).

The analysis tools that were used for the research were as follows:
MS Visio – process mapping software used to develop research flow/method.
MS Excel – software was used to perform a range of tasks, such as: data cleaning, descriptive & inferential analysis, and other add-in features (Solver, Power Query, Data Analysis, Pivot table etc.)

MS Acess – manage large ridership data by creating data sets prior to performing analysis on MS Excel.

PowerBi – create dashboards and instant visuals of parameters researcher was focused on.

4.6. Analyse data

Before hypothesis testing could be performed on samples, it was pertinent to distinguish if sample sets being analysed were parametric or non-parametric. This is a key exercise as it relates to the validity of the hypothesis tests performed and how they are interpreted by the researcher (Chan, 2003). Firstly, data sets are graphically visualised using histograms to inspect the shape & spread of the data to determine if the data sets were normally distributed. This can only classify as preliminary inspection of normality since it is purely dependent on visual inspection and intuition whether or not the data sets are normally distributed. Secondly, quantile-quantile (Q-Q) plots were used to determine if data sets were normally distributed. This approach entails comparing a given data set against a standard normal distribution (theoretical distribution), quantile by quantile (Wang & Bushman, 1998).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \quad (6)$$

Equation 6 is the standard normal distribution expression, $f(x)$ is the probability density function, σ is sample standard deviation, μ is sample mean.

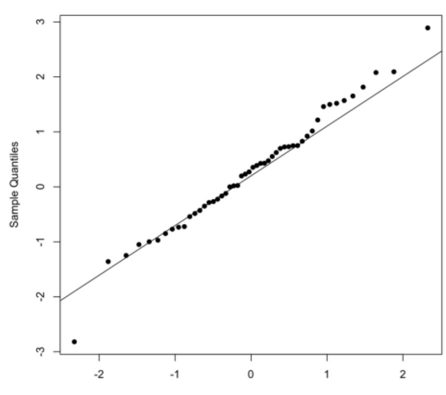


Figure 15: Q-Q plot comparing theoretical quantiles (standard normal distribution) against sample quantiles *(Wang & Bushman, 1998)*

Figure 15 shows what a Q-Q plot typically looks like when sample data is normality distributed – the scatter plot produced by the theoretical and sample quantiles is in the form of a straight line. For the research performed in this paper, all sample sets were normally distributed (refer to Appendix F). This informed the researcher to use parametric statistical tests on the data (e.g. F-test, Z-tests, Co-efficient of variance etc.)

Two sample z-tests were performed on the null hypotheses listed in tables 8 and 9 to compare the means between sample sets. Alternative hypotheses that accompanied the null hypotheses shown in tables 8 and 9 are not shown, for brevity. In principle, the alternative hypotheses were established as contrasts of the null hypotheses. For example, the null hypothesis '*daily ridership remains the same when fares are increased'* is accompanied by the alternative hypothesis '*daily ridership does not remain the same when fares are increased'*. The two expressions below demonstrate the difference between how the null and alternative hypotheses were formulated. H_0 is the null hypothesis, H_1 is the alternative hypothesis, μ_1 is the mean of sample 1 under analysis, μ_2 is the mean of sample 2 under analysis. As per convention, the significance level, α, was chosen to be 0.05 for all tests performed (Campbell & Gardner, 1988).

$$H_0: \mu_1 = \mu_2 \qquad\qquad H_a: \mu_1 \neq \mu_2$$

F-tests were performed on the null hypotheses listed in tables 8 and 9 to compare the variances between sample sets. The research was interested in the variances of sample sets because this enabled for inferences to be made on spread, which further allows for inferences to be made on ridership behaviours. Similar to the z-tests, the alternative hypotheses for the f-tests were established as contrasts of the null hypotheses. H_0 is the null hypothesis, H_1 is the alternative hypothesis, σ_1^2 is the variance of sample 1, σ_2^2 is the variance of sample 2. It must be noted that the f-tests performed were one-tailed tests. This means that if the null hypothesis is rejected, it can be concluded which of the two samples has a higher variance than the other. As per convention, the significance level, α, was chosen to be 0.05 for all tests performed.

$$H_0: \sigma_1^2 = \sigma_2^2 \qquad\qquad H_a: \sigma_1^2 \neq \sigma_2^2$$

Figure 16 shows the step-by-step procedure followed when the z-tests and t-tests were performed on sample sets. The researcher made use MS Excel built-in statistical packages to perform the tests, hence emphasis was not placed on the statistical theory that governs these tests but rather, the interpretation of the results produced by the tests. Equations 7 and 8 show how z and f test statistics were computed.

$$z_{test} = \frac{(\bar{x}_1 - \bar{x}_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \tag{7}$$

$$f_{test} = \frac{\sigma_1^2}{\sigma_2^2} \tag{8}$$

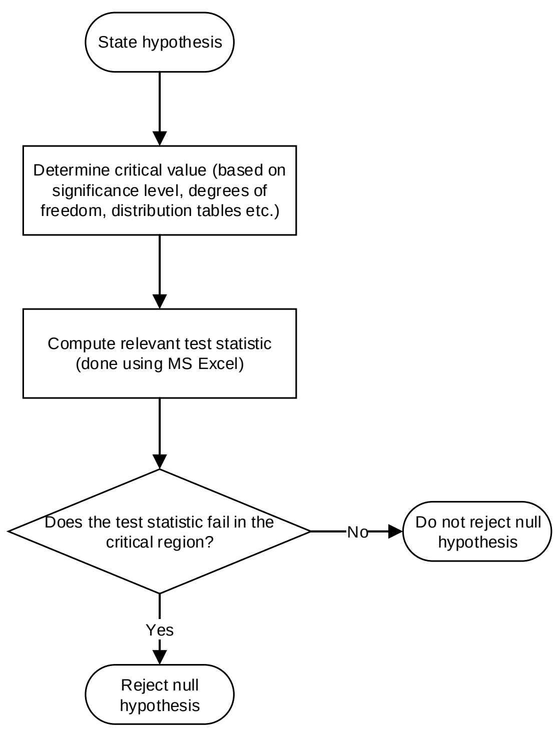


Figure 16: Hypothesis testing approach followed for z-tests and f-tests *(Campbell & Gardner, 1988)*

Co-efficient of variance (CV) calculations were performed on certain sample sets where it was necessary. This allowed the researcher to quantify the magnitude of variance between sample sets, in a manner that accounts for the differences in sample sizes. This aided allowed the researcher to make inferences with validity.

$$CV = \frac{\sigma}{\mu} \tag{9}$$

Spatial and temporal analyses performed were focused on ridership patterns, flow directions and ridership between stations (or sections). This analysis was done critically with respects to Gautrain's temporal travel demand management strategy. Simply put, the researcher focused on understanding how different users were impacted by the TDM strategy as it pertains to the fares paid, time of day travelled, and O-D stations travelled from. Equations 2, 3 and 4 were supplementary for the analysis.

4.7. Interpret and draw conclusions

The research design is quasi-experimental, and the sampling design is purposive. This means that the researcher used existing observations (ridership, Gautrain TDM strategy etc.) from history to conduct research on working hypotheses 1 and 2. Therefore there are limitations to the way results can be interpreted and how conclusions of the research can be drawn. For example, hypothesis tests might have indicated that ridership decreases when fare increases are applied on the Gautrain. There could be several external or internal reasons for this, namely: employment growth in Gauteng regions might have been declining hence ridership on the Gautrain gradually declines, Gautrain users switching to other modes of transportation (e.g. e-hailing), price of fuel and tolls etc. Conclusions for such research designs need to be made with caution (Agency, 2019).

The researcher interpreted and drew conclusions based on results produced from hypothesis tests and spatial & temporal analysis. Findings from qualitative studies prior on the Gautrain were used to correlate some of the findings produced in the research. Given the extensive analysis performed, recommendations of the possible ways in which the Gautrain TDM strategy could be improved to ensure improved system efficiency was provided.

5. RESULTS

In this chapter, key results (primitive and processed) are presented as a series of concise tables and graphs. Complete sets of primitive data could not be included in this report as the data was too large. The results presented in this section can be segmented into two main sections: (1) results obtained from spatial & temporal analysis of ridership with respect to Gautrain's TDM strategy (2) results obtained from hypothesis testing. But first, general ridership and train service demand analysis of the Gautrain must be established. Supplementary findings from studies performed on the Gautrain and literature from other research conducted in the past aided the researcher with understanding the characteristics of the train service demand.

5.1. Gautrain ridership

Table 10 shows an excerpt of the format in which ridership parameters are captured and stored by automatic passenger counting (APC) systems at entry and exit points of Gautrain stations. There was an excess of 1,4 million rider entries for the data hence it is not possible to show in complete form. The 'From' and 'To' columns refer to the stations riders travelled from and to, also known as origin-destination (O-D) from literature. For simplicity, Gautrain uses a O-D naming convention for the various trips riders commute on the system. For example, 'Pretoria-Sandton', refers to riders who travelled from Pretoria to Sandton. Therefore, an example of how table 10 can be interpreted is as follows: on 1 January, 5 riders travelled from Pretoria to Sandton between 04h45 – 05h00, 14 riders travelled from Pretoria to Sandton between 05h00 – 05h15 etc. Direction refers to the travel direction of the riders in question (figure 8).

Table 10: Ridership entries as registered by the APC system on Gautrain stations (2019)

Date	From	To	Direction	Time of travel & # of riders			
				04h45	05h00	…	21h00
1 Jan	Pretoria	Sandton	N-S	5	14		3
1 Jan	Hatfield	Centurion	N-S	4	22		2
1 Jan	Park	Midrand	S-N	3	9		7
1 Jan	Marlboro	Rhodesfield	W-E	6	13		4
2 Jan	Hatfield	Midrand	N-S	1	8		3
2 Jan	Centurion	Rhodesfield	N-E	4	14		1
2 Jan	Rhodesfield	Midrand	E-N	7	15		6
3 Jan	Park	Rosebank	S-N	2	10		4
3 Jan	Park	Marlboro	S-N	3	21		3
3 Jan	Sandton	Rhodesfield	W-E	6	24		8
3 Jan	Pretoria	Sandton	N-S	9	17		2
…							
31 Dec	Rhodesfield	Hatfield	E-N	7	10		1

After performing various transformations on the data, all results pertaining to ridership and train service demand were analysed. The research made use of 2019 data and focus was placed on weekday ridership. In the appendix, weekend ridership analysis can be found, as a means for comparison and reference. In addition, in certain instances ridership data on passengers who commuted to or from OR Tambo International airport was excluded. Preliminary findings done in a separate study indicated the following: (1) airport passengers typically do not commute using the Gautrain daily hence their ridership characteristics cannot be predicted very well (2) Gautrain's TDM strategy is not implemented on airport-related travel.

5.2. Spatial analysis of Gautrain ridership

Figure 17 shows that most Gautrain passengers (approximately 80%) use the Gautrain system commuting from Sandton, Park, Centurion, Hatfield and Midrand stations.

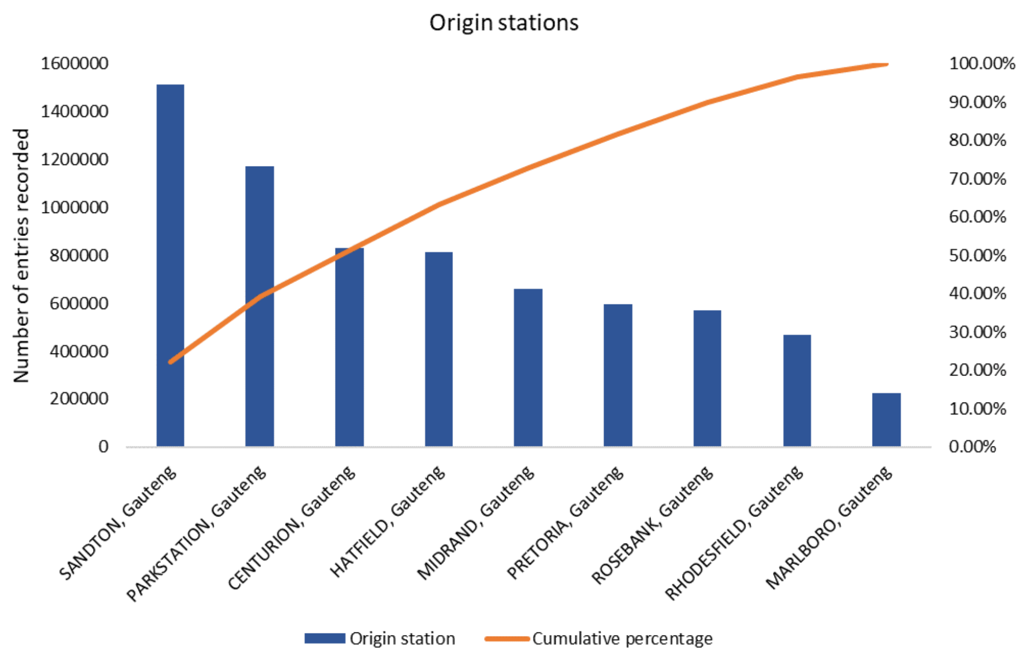


Figure 17: Stations passengers commuted from (origin stations)

Similarly, figure 18 shows that approximately 80% of Gautrain passengers use the system commuting to Sandton, Park, Centurion, Hatfield and Midrand. Comparison of the entries recorded at origin and destination stations indicates that there is roughly an equal number of 'origin' entries and 'destination' entries at each of the stations on the Gautrain rail network. It is conceivable that for daily commute (to places of employment, study or otherwise), passengers use the Gautrain twice: firstly to commute from home to work or school, then secondly to commute from work or school to home. Hence there is a consistent number of passenger entries at origin and destination stations

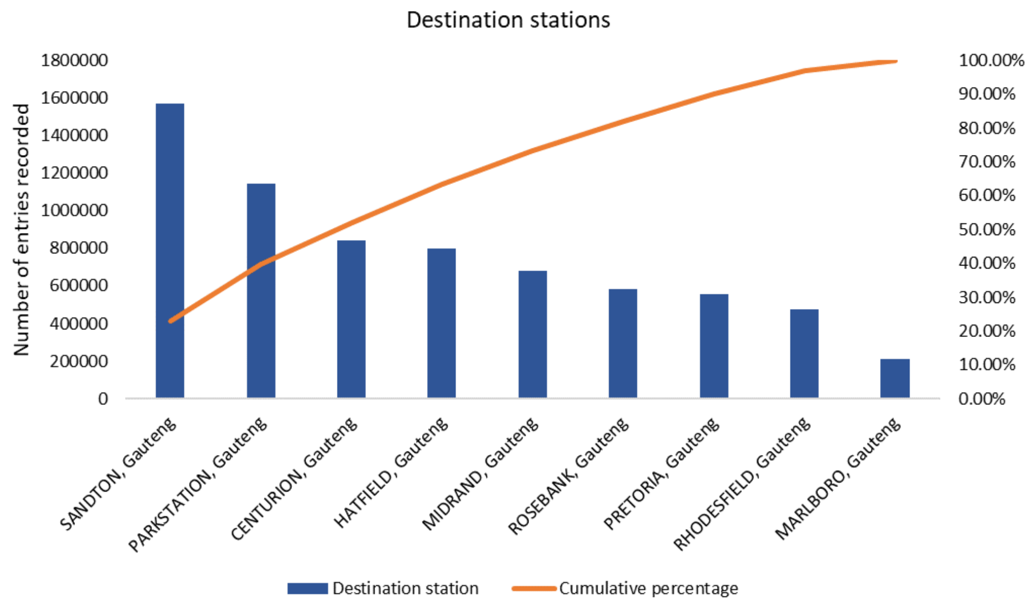


Figure 18:Stations passengers commuted to (destination stations)

Figure 19 shows a pareto chart for the trips Gautrain users travelled. Figures 17 and 18 showed that ridership is comprises mostly of passengers travelling between Sandton, Park, Centurion, Hatfield and Midrand. Therefore, it is plausible that origin-destination permutations will mostly comprise of passengers who travelled from or to these common stations, as shown in figure 19.

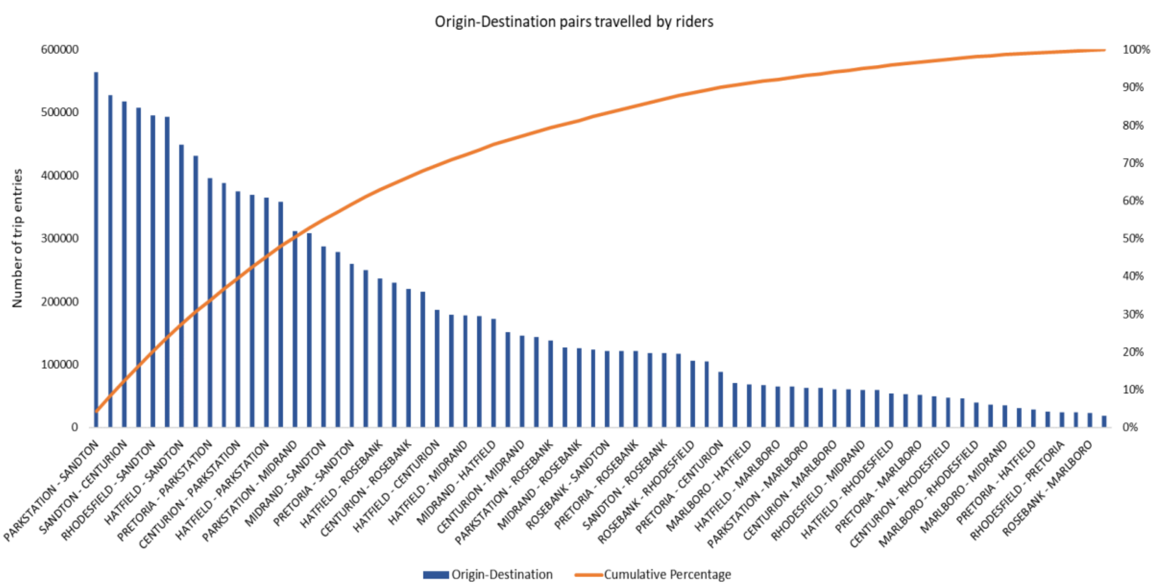


Figure 19: Origin-Destination pairs commuted

Figures 17, 18, and 19 provide spatial information; these figures analyse ridership as it pertains to the different stations riders commute between. Although this is valuable information, there are limitations to its usefulness in the context of TDM.

5.3. Temporal analysis of Gautrain ridership

The following analyses provide temporal information that was used when analysing the efficiency of Gautrain's TDM strategy. Figure 20 shows the peak hour coefficients that were computed based on the daily ridership pattern shown in figure 14. Peak hour coefficient describes the proportion of ridership that occurs within an hour, compared to the total ridership that occurs on the system (Gautrain operates between 04h45 – 21h00). By summing ridership during peak periods (6am – 8 am and 3pm – 6pm), it was computed that ridership during these periods accounts for 68% of total daily ridership. This conforms with literature that was reviewed on other urban rail systems (section 2.3). For reference purposes peak hour coefficient for weekend ridership was computed as well (appendix).

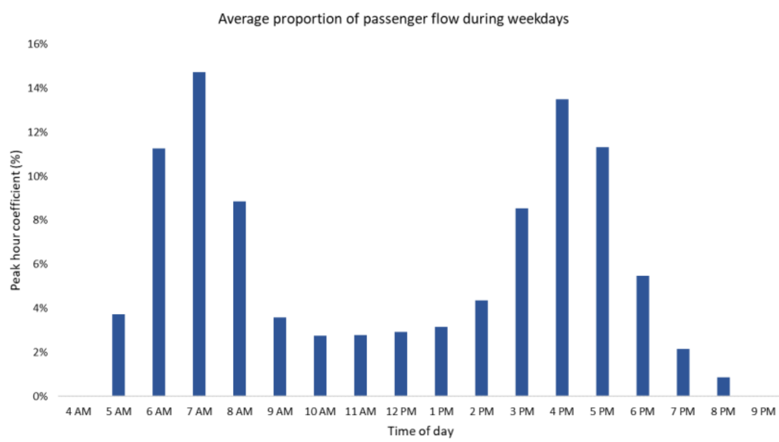
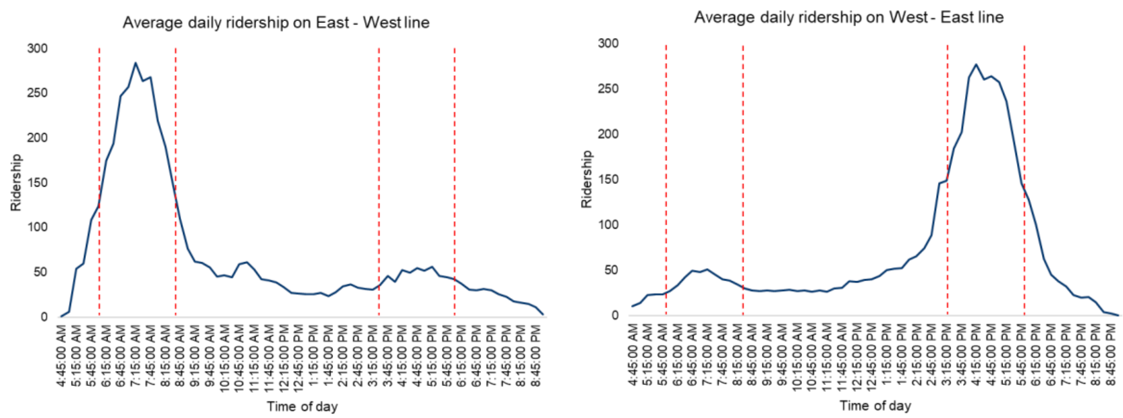


Figure 20: Peak hour coefficient for daily ridership pattern

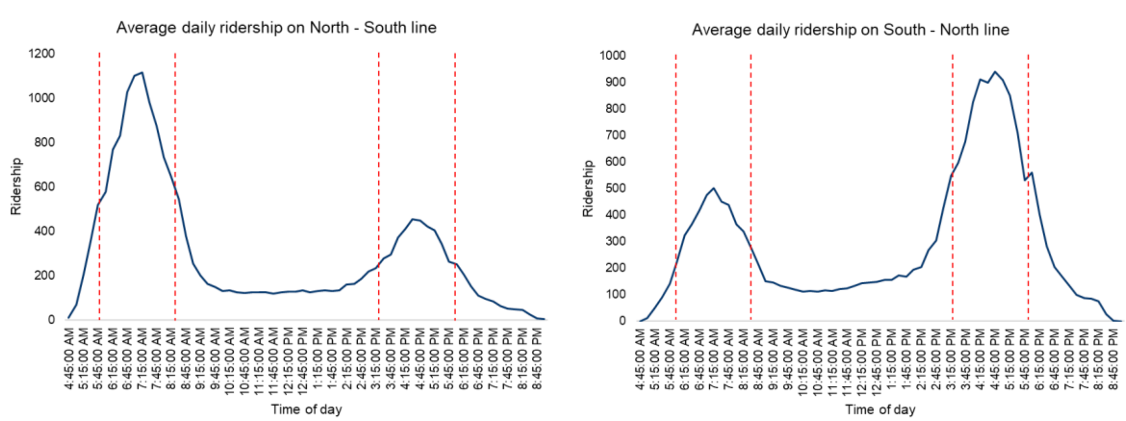
Figure 21 and 22 shows daily ridership according to specific Gautrain rail lines and directions. The dashed, red, vertical lines indicate the peak and off-peak periods on the figures. This analysis was pertinant for the research as it decodes the ridership patterns shown in figure 14 which shows combined daily ridership patterns on all of the rail lines and travel directions. From figure 21a, it was computed that 48.6% of daily ridership on the East-West line takes place during the morning peak period. The remainder is evenly spreadout through the off-peak periods and afternoon peak period. From figure 21b, it was computed that 49.6% of daily ridership on the West-East line takes place during the afternoon peak period. The remainder is evenly spreadout through the off-peak periods and morning peak period.



(a) East-West direction (b) West-East direction

Figure 21: Daily ridership on East-West rail lines

From figure 22a, it was computed that ridership during morning peak period and afternoon peak period represents 44.5% and 19.0%, respectively, of daily ridership on the North-South line. From figure 22b, it was computed that ridership during morning peak period and afternoon peak period represents 20.2% and 40.6%, respectively, of daily ridership on the South-North line.



(a) North-South direction (b) South-North direction

Figure 22: Daily ridership on North-South rail lines

For figures 23-26, focus was placed on using the ridership patterns at each of the rail lines and rail directions (figure 21 and 22) to construct user travel patterns of passengers from each of the four regions the Gautrain network spans over. The assumption was made that passengers typically commute in the ‘forward’ direction to work or school between 04h45 – 13h00, and commute in the ‘backward’ direction when returning home between 13h00 – 21h00. This represents an equal split in the total daily operating times of the Gautrain. This assumption was verified with GMA based on previous studies and information obtained on passengers.

Given the assumptions made, figure 23 shows that the ridership of passengers commuting from northern regions surges and drops at a significantly higher gradient for morning peak period compared to afternoon peak period. This gives rise to the average maximum ridership during morning peak period (±1100 passengers) being greater than the average maximum ridership during afternoon peak period (±950 passengers). In addition, during morning peak period ridership surges and drops with no *kinks* at the shoulders of the TDM strategy. During afternoon peak period there are significant *kinks* in ridership at the shoulders of the TDM strategy, particularly just after 18h00 when fares are adjusted.

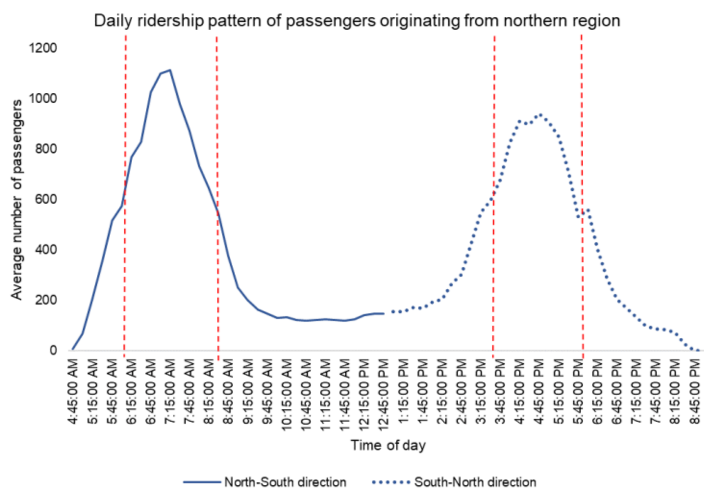


Figure 23: Daily commute pattern for passengers originating from northern regions

Figure 24 shows that the ridership of passengers commuting from southern regions surges and drops at a higher gradient for morning peak period compared to afternoon peak period. This gives rise to the average maximum ridership during morning peak period (±500 passengers) being greater than the average maximum ridership during afternoon peak period (±450 passengers). The *kinks* at the shoulders of the TDM strategy are less significant here both during morning and afternoon peak periods.

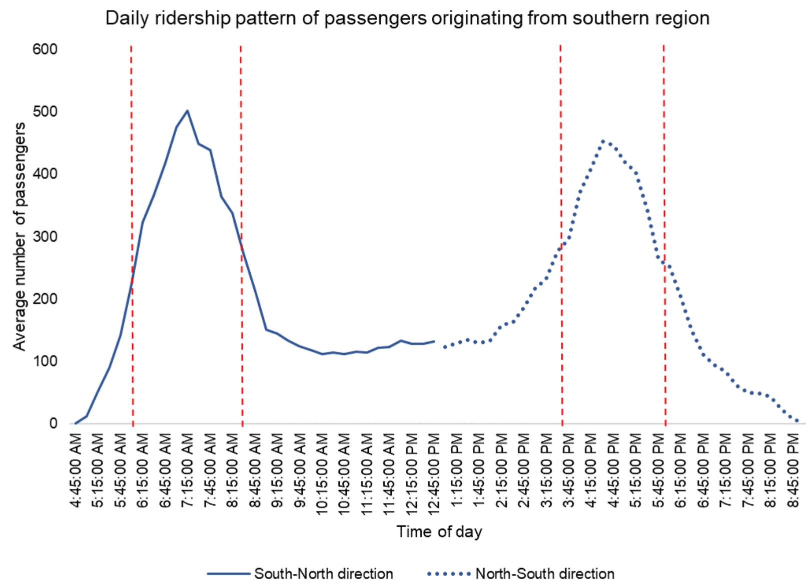


Figure 24: Daily commute pattern for passengers originating from southern regions

Figure 25 shows that the ridership of passengers commuting from eastern regions (mainly Rhodesfield) surges and drops at a significantly higher gradient for morning peak period compared to afternoon peak period. This gives rise to the average maximum ridership during morning peak period (±275 passengers) being greater than the average maximum ridership during afternoon peak period (±230 passengers). For this ridership pattern, there was one significant *kink* at the 15h30 shoulder of the TDM strategy.

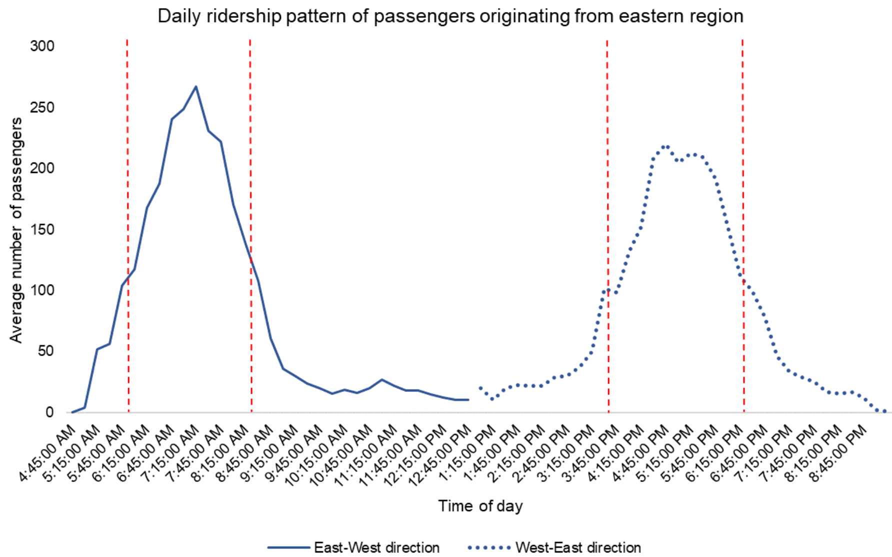


Figure 25: Daily commute pattern for passengers originating from eastern regions

Figure 26 shows a ridership pattern that is vastly different compared to the ones previously discussed. Notable differences are: there are significantly less passengers that commute from the western region (640 total daily passengers), ridership during morning and afternoon peak does not account for most of daily ridership. In addition, for ridership for passengers commuting from western regions does not stabilise at all throughout the day, it remains erratic. The reasons for this behaviour are discussed in section 6.

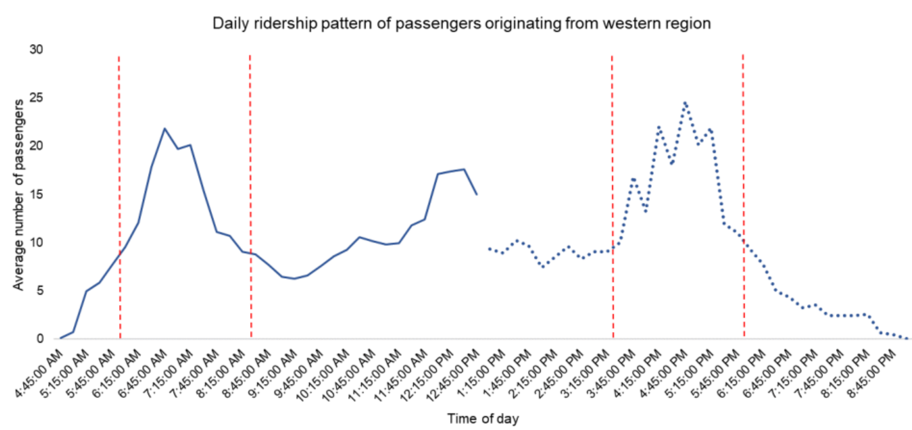


Figure 26: Daily commute pattern for passengers originating from western regions

Figures 27-30 show the flow of passengers, station-by-station, from when trains begin trips to when trains finish trips. This analysis was only performed on rail lines and rail directions which experienced high ridership during peak times. This analysis provides insights that allowed the researcher to evaluate the efficiency of the Gautrain's current TDM strategy. On figures 27-30, *passenger entries* are the number of passengers who embark the Gautrain, *passenger exits* are the number of passengers who egress the Gautrain, at each of the respective stations. *Cumulative passenger difference* refers to the difference of the number of passenges who embark and egress the Gautrain, at each of the stations. Therefore cumulative passenger difference can be used to analyse average ridership levels of trains, station-by-station, from when trains begin to when trains finish trips, over a specified period of time. This analysis focused on peak period time intervals.

Figure 27 shows that, according to the gradient of cumulative passenger difference, the highest increase in ridership on trains commuting north-south (during morning peak period) occurs at the Centurion station. This is just before trains head to the Midrand station. The highest decrease in ridership on these trains occurs at the Sandton station, just before trains head to Rosebank station.

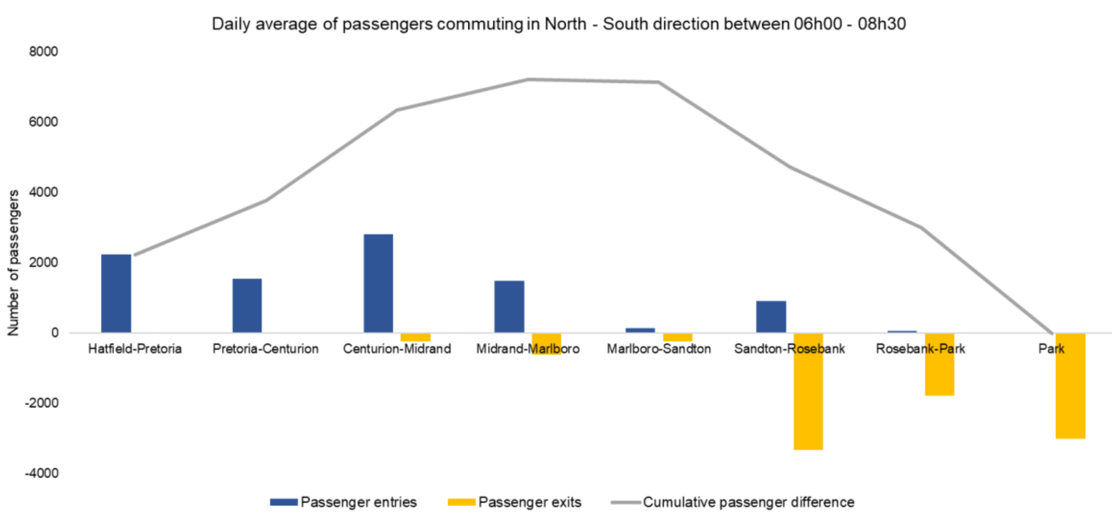


Figure 27: Cumulative ridership on trains from Hatfield to Park during morning peak period

Figure 28 shows that, according to the gradient of cumulative passenger difference, the highest increase in ridership on trains commuting sout-north (during afternoon peak period) occurs at the Park station. This is just before trains head to the Rosebank station. The highest decrease in ridership on these trains occurs at the Centurion station, just before trains head to Pretoria station.

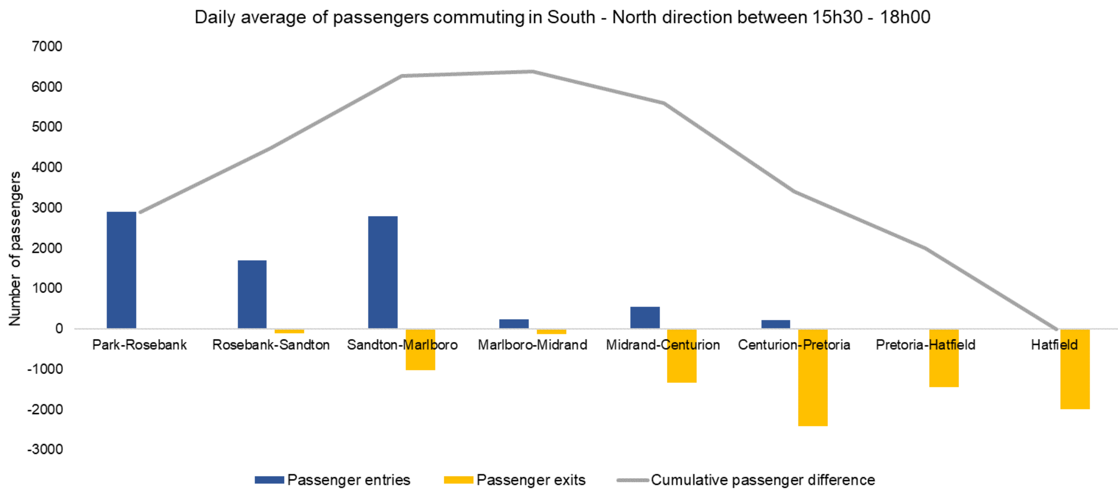


Figure 28: Cumulative ridership on trains from Park to Hatfield during afternoon peak period

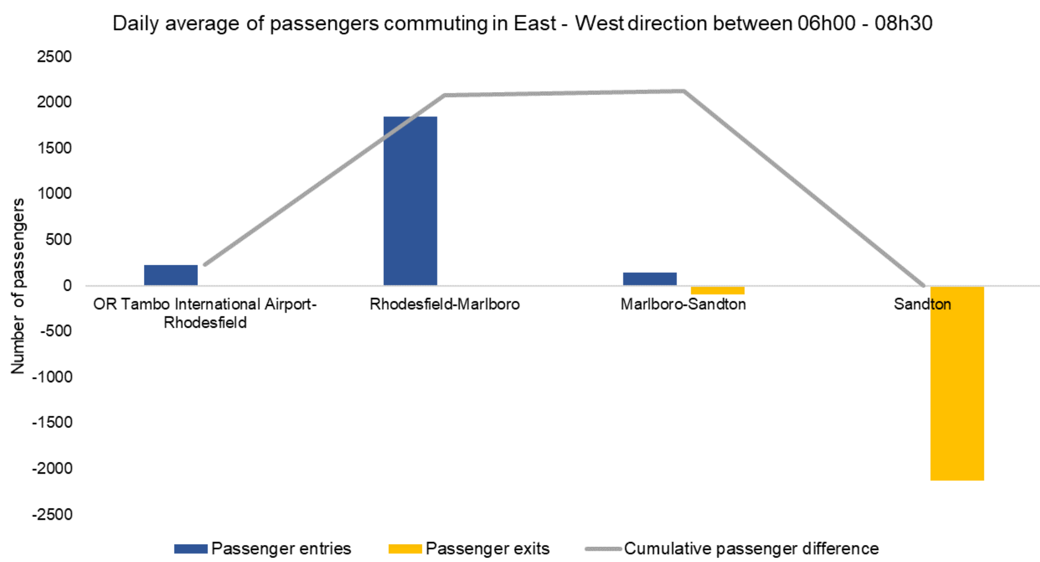


Figure 29: Cumulative ridership on trains from OR Tambo Int. airport to Sandton during morning peak period

Figure 29 shows that, according to the gradient of cumulative passenger difference, the highest increase in ridership on trains commuting east-west (during morning peak period) occurs at the Rhodesfield station. This is just before trains head to the Marlboro station. The highest decrease in ridership on these trains occurs at the Sandton station, just before trains head to Rosebank station.

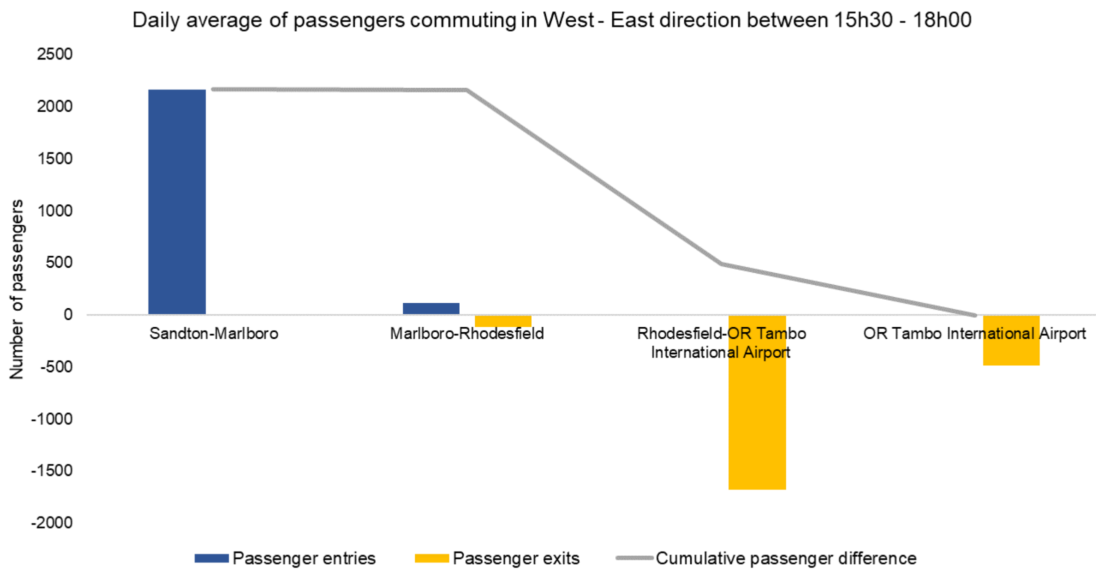


Figure 30: Cumulative ridership on trains from Sandton to OR Tambo Int. airport during afternoon peak period

Figure 30 shows that, according to the gradient of cumulative passenger difference, the highest increase in ridership on trains commuting west-east (during afternoon peak period) occurs at the Sandton station. This is just before trains head to the Marlboro station. The highest decrease in ridership on these trains occurs at the Rhodesfield station, just before trains head to OR Tambo airport station.

5.4. Hypothesis testing and statistical analysis

At this juncture, results obtained from hypothesis testing and other statistical methods (z-tests, f-tests, coefficient of variance etc.) are presented. The statistical approaches were used to analyse differences and similarities between sample sets whereby graphical analyses were not feasible to do. Hypothesis testing was mostly used to produce findings relating to temporal ridership characteristics of passengers opposed to spatial characteristics. Hypothesis tests were performed at a significance level, α, of 95%, as suggested from literature.

5.4.1 Results addressing working hypothesis 1: *An increase in Gautrain train service fares does not result in a change in overall ridership.*

The null and alternative hypothesis for the z-test on table 11 were as follows:

H_0: mean ridership before fare increase = mean ridership after fare increase

H_a: mean ridership before fare increase ≠ mean ridership after fare increase

Table 11: Results of t-test and f-test for the hypothesis that daily ridership remains the same before and after a fare increase is applied

	Daily ridership before fare increase	Daily ridership after fare increase
Mean, μ	50698.77	48420.25
Std. deviation, σ	1576	1830.8
Sample size, n	data collected over 82 days	data collected over 125 days
z-test statistic	9.54	
Critical z-value	1.64	
df	82	125
f-test statistic	1.35	
Critical f-value	1.41	
z-test outcome	$z_{test} > z_{crit}$	
f-test outcome	$f_{test} < f_{crit}$	
CV	3.11	3.78

Table 11 outcomes can be interpreted as follows:

z-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the means of the ridership before and after fare increase is applied.

f-test: At a significance level of 95%, do not reject H_0, it cannot be concluded that the variance of ridership before and after fare increase is applied is equal.

The null and alternative hypothesis for the z-test on table 12 were as follows:

H_0: mean ridership during morning peak period before fare increase = mean ridership during morning peak period after fare increase

H_a: mean ridership during morning peak period before fare increase ≠ mean ridership during morning peak period after fare increase

Table 12: Results of t-test and f-test for the hypothesis that ridership during morning peak period remains the same before and after a fare increase is applied

	Ridership during morning peak period (before fare increase)	Ridership during morning peak period (after fare increase)
Mean, μ	16813.01	15934.70
Std. deviation, σ	805.02	845.75
Sample size, n	data collected over 82 days	data collected over 125 days
z-test statistic	7.50	
Critical z-value	1.96	
df	81	125
f-test statistic	1.10	
Critical f-value	1.41	
z-test outcome	$z_{test} > z_{crit}$	
f-test outcome	$f_{test} < f_{crit}$	
CV	4.79	5.31

Table 12 outcomes can be interpreted as follows:

z-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the means of the ridership before and after fare increase is applied during morning peak periods.

f-test: At a significance level of 95%, do not reject H_0, it cannot be concluded that the variance of ridership before and after fare increase is applied is equal.

The null and alternative hypothesis for the z-test on table 13 were as follows:

H_0: mean ridership during afternoon peak period before fare increase = mean ridership during afternoon peak period after fare increase

H_a: mean ridership during afternoon peak period before fare increase ≠ mean ridership during afternoon peak period after fare increase

Table 13: Results of t-test and f-test for the hypothesis that ridership during afternoon peak period remains the same before and after a fare increase is applied

	Ridership during afternoon peak period (before fare increase)	Ridership during afternoon peak period (after fare increase)
Mean, μ	15322.40	14576.85
Std. deviation, σ	531.55	605.49
Sample size, n	data collected over 82 days	data collected over 125 days
z-test statistic	9.30	
Critical z-value	1.96	
df	81	125
f-test statistic	1.29	
Critical f-value	0.11	
z-test outcome	$z_{test} > z_{crit}$	
f-test outcome	$f_{test} > f_{crit}$	
CV	3.47	4.15

Table 13 outcomes can be interpreted as follows:

z-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the means of the ridership during afternoon peak periods, before and after fare increases are applied.

f-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the variance of ridership during afternoon peak periods, before and after fare increases are applied.

The null and alternative hypothesis for the z-test on table 14 were as follows:

H_0: mean max. ridership during morning peak period before fare increase = mean max. ridership during morning peak period after fare increase

H_a: mean max. ridership during morning peak period before fare increase ≠ mean max. ridership during morning peak period after fare increase

Table 14: Results of t-test and f-test for the hypothesis that maximum ridership during morning peak period remains the same before and after a fare increase is applied

	Maximum ridership during morning peak period (before fare increase)	Maximum ridership during morning peak period (after fare increase)
Mean, μ	2241.679012	2132.976
Std. deviation, σ	109.66	104.88
Sample size, n	data collected over 82 days	data collected over 125 days
z-test statistic	7.07	
Critical z-value	1.96	
df	81	125
f-test statistic	1.09	
Critical f-value	1.39	
z-test outcome	$z_{test} > z_{crit}$	
f-test outcome	$f_{test} < f_{crit}$	
CV	4.89	4.92

Table 14 outcomes can be interpreted as follows:

z-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the max. ridership before and after fare increase is applied during morning peak periods.

F-test: At a significance level of 95%, do not reject H_0, it cannot be concluded that the variance of max. ridership before and after fare increase is applied is equal during morning periods.

The null and alternative hypothesis for the z-test on table 15 were as follows:

H_0: mean max. ridership during afternoon peak period before fare increase = mean max. ridership during afternoon peak period after fare increase

H_a: mean max. ridership during afternoon peak period before fare increase ≠ mean max. ridership during afternoon peak period after fare increase

Table 15: Results of t-test and f-test for the hypothesis that maximum ridership during afternoon peak period remains the same before and after a fare increase is applied

	Maximum ridership during afternoon peak period (before fare increase)	Maximum ridership during afternoon peak period (after fare increase)
Mean, μ	2020.16	1935.15
Std. deviation, σ	86.79	86.28
Sample size, n	data collected over 82 days	data collected over 125 days
z-test statistic	6.88	
Critical z-value	1.965	
df	81	125
f-test statistic	1.01	
Critical f-value	1.39	
z-test outcome	$z_{test} > z_{crit}$	
f-test outcome	$f_{test} < f_{crit}$	
CV	4.30	4.46

Table 15 outcomes can be interpreted as follows:

z-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the maximum ridership before and after fare increase is applied during afternoon peak periods

f-test: At a significance level of 95%, do not reject H_0, it cannot be concluded that the variance of maximum ridership before and after fare increase is applied is equal during afternoon periods.

5.4.2. Results addressing working hypothesis 2: *Gautrain's temporal travel demand management strategy is not efficient at shifting daily ridership from peak periods to off-peak periods during weekdays.*

The null and alternative hypothesis for the z-test on table 16 were as follows:

H_0: mean ridership during first half of the day = mean ridership during second half of the day

H_a: mean ridership during first half of the day ≠ mean ridership during second half of the day

Table 16: Results of z-test and f-test for the hypothesis that ridership during first half of the day is equal to ridership during second half of the day

	Ridership during first of the day (04h45 – 13h00)	Ridership during second half of the day (13h00 – 21h00)
Mean, μ	24901.107	24422.84
Std. deviation, σ	1224.83	1132.34
Sample size, n	data collected over 205 days	data collected over 205 days
z-test statistic	4.11	
Critical z-value	1.96	
df	204	204
f-test statistic	1.17	
Critical f-value	1.26	
z-test outcome	$z_{test} > z_{crit}$	
f-test outcome	$f_{test} < f_{crit}$	
CV	4.55	5.02

Table 16 outcomes can be interpreted as follows:

z-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the means of the ridership during first and second half of the day.

f-test: At a significance level of 95%, do not reject H_0, it cannot be concluded that the variance of ridership during first half of the day is equal to second half of the day.

The null and alternative hypothesis for the z-test on table 17 were as follows:

H_0: mean ridership during morning peak period = mean ridership during morning peak period

H_a: mean ridership during morning peak period ≠ mean ridership during morning peak period

Table 17: Results of z-test and f-test for the hypothesis that ridership during morning peak period is equal to ridership during afternoon peak period

	Ridership during morning peak period	Ridership during afternoon peak period
Mean, μ	16275.94	14858.17
Std. deviation, σ	934.88	902.36
Sample size, n	data collected over 205 days	data collected over 205 days
z-test statistic	15.62	
Critical z-value	1.64	
df	204	204
f-test statistic	1.79	
Critical f-value	1.26	
z-test outcome	$z_{test} > z_{crit}$	
f-test outcome	$f_{test} > f_{crit}$	
CV	5.74	6.07

Table 17 outcomes can be interpreted as follows:

z-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the means of the ridership during morning and afternoon peak periods

f-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the variance of ridership during morning and afternoon peak periods.

For table 18, just the f-test was done to compare sample variances, there was no need to compare sample means (z-test) since graphically analysis clearly showed that maximum ridership during morning peak is greater than maximum ridership during afternoon peak period.

The null and alternative hypothesis for the f-test on table 18 were as follows:

H_0: variance for max. ridership during morning peak period = variance for max. ridership during afternoon peak period

H_a: variance for max. ridership during morning peak period ≠ variance for max. ridership during afternoon peak period

Table 18: Results of f-test for the hypothesis that maximum ridership during morning peak period is equal to maximum ridership during afternoon peak period

	Maximum ridership during morning peak period	Maximum ridership during afternoon peak periods
Mean, μ	2176.05	1967.23
Std. deviation, σ	118.7	114.26
Sample size, n	data collected over 205 days	data collected over 205 days
df	204	204
f-test statistic	1.47	
Critical f-value	1.26	
f-test outcome	$f_{test} > f_{crit}$	
CV	5.45	5.80

Table 18 outcomes can be interpreted as follows:

f-test: At a significance level of 95%, reject H_0, there is a statistically significant difference in the variance of max. ridership during morning and afternoon peak periods.

6. DISCUSSION

Once all of the data was processed, results were analysed in order to draw conclusions that fulfil the questions and objectives of the research. The discussion is presented with a similar structure as the previous section in order to aid understanding and facilitate logical flow. Focus is placed on results obtained on the temporal ridership analysis and hypothesis testing as these sections are most relevant for when evaluating the efficiency of Gautrain's TDM strategy.

6.1. Temporal analysis of Gautrain ridership

As established previously, the research conducted focuses on analysing the efficiency of Gautrain's temporal TDM strategy. In this context, *efficiency* refers to how suitable the strategy is for shifting commuter behaviour such that there are less disparities in ridership during peak and non-peak periods. It was already established that achieving this would result in improved system efficiency on the Gautrain, thereby realising value for both the GMA and Gautrain users.

Section 3.2 established that Gautrain's TDM strategy is temporal and makes use differential fare structures during peak and non-peak periods. This implies that during peak periods (06h00 – 08h30 and 15h30 – 18h00) commuters are subjected to surge fares, and during other periods of the day commuters are subjected to base fares. There are several limitations to this approach of incentivising shifts in passenger behaviour.

Figure 20 shows that a total of 68% of daily ridership occurs during morning and afternoon peak periods. Hence it understandable that the TDM strategy aims to shift ridership from these peak periods to the non-peak periods. The effect would be less train service demand during peak periods, less crowding and lower maximum ridership during morning & afternoon peak periods. This would improve service level quality for riders and allow GMA to scale down train service supply during peak periods, thereby achieving better system efficiency of the Gautrain.

However, the significant shortcoming of such a TDM strategy is that it is not bespoke enough to consider daily ridership patterns, by line, by travel direction and O-D pair. This results in such TDM strategy, according to literature, having limited efficiency at shifting commuter travel patterns.

Figures 21 and 22 assist in demonstrating the assertions from literature. Figures 21and 22 show a breakdown of the daily ridership pattern shown in figure 20, by rail line and travel direction. The figures demonstrate that there are significant directional imbalances of passenger flow on rail lines throughout the day. For instance, during morning peak period there is excessive ridership on the East-West and North-South rail lines. Whereas there is much less ridership on the opposing directions (West-East and South-North) of the corresponding rail lines. The same is observed for the afternoon peak period. There is excessive ridership on the West-East and South-North lines during this period and passenger flow in the opposing directions of each of these lines is much less.

DIC on the East-West and West-East rail lines during morning peak period, $\mathcal{E}_{E-W,06h00-08h30}$, is 1.70. This value is greater than the common values often indicated in literature that are usually in the range of 1.15 – 1.57. This DIC value indicates that over-crowding occurs in the on the East-West direction during the morning peak period. $\mathcal{E}_{E-W,15h30-18h00}$ is 1.67. This DIC value indicates that over-crowding occurs on the West-East direction during the afternoon peak period.

DIC on the North-South and South-North rail lines during morning peak period, $\mathcal{E}_{N-S,06h00-08h30}$, is 1.38. This DIC value indicates that over-crowding occurs in the on the North-East direction during the morning peak period. $\mathcal{E}_{N-S,15h30-18h00}$ is 1.35. This DIC value indicates that over-crowding occurs on the South-North direction during the afternoon peak period.

The following can be said regarding the DIC values: (1) DIC values for morning and afternoon peak periods are very similar on the respective rail lines. (2) the East-West and West-East rail lines have greater imbalances than the North-South and South-North lines. On the first point, the DIC values being similar for morning and afternoon periods allows us to make the assertion that it is roughly the same passengers who use the Gautrain in the morning and in the afternoon. The similar ridership patterns during morning and afternoon further supports this. It was based on this logic that daily ridership patterns for specific segments of passengers were developed (figures 23 – 26).

One the second point, the imbalances in ridership relate to the level of development and economic activity in the different regions covered by the Gautrain network. A significant proportion of Gautrain users commute to areas like Sandton and Park, for work. A smaller proportion commutes to northern regions like Centurion and Hatfield. Hence there is high passenger flow in the morning of riders traversing to these regions, then in the afternoon passenger flow occurs in the opposite direction when people are returning home.

The directional imbalances expose several limitations of the TDM strategy. Firstly, there is a segment of passengers who travel during off-peak periods. These passengers travel during periods whereby train service demand is low, system utilisation is low and are subjected to base fares ─ rightfully so. For the purposes of this discussion, this segment of passengers will be referred to as ‘class 1’. Class 1 passengers are not affected by the TDM strategy; no shift in commute behaviour is required from them.

Class 2 passengers can be described as passengers who commute during peak periods on rail line with low ridership during those peak periods. Figure 24 and 26 show class 2 passengers. Unfortunately, class 2 passengers are subjected to surge fares even though the rail lines they commute on during peak periods have low utilisation and no crowding during those periods. This highlights an inefficiency of the temporal TDM strategy because subjecting class 2 passengers to surge fares is not justifiable.

Class 3 passengers describes passengers who commute during peak periods and on rail lines with high ridership during those periods. Figure 23 and 25 show class 3 passengers. Class 3 passengers are subjected to surge fares and rightfully so because their ridership patterns lead to overcrowding, over utilisation and a deterioration of system efficiency of the Gautrain. Therefore, the TDM strategy is correct in incentivising a shift in the ridership patterns of these passengers.

At this juncture, the discussion continues to focus on temporal analysis of ridership however; results from the spatial analysis are used to support the discussion. Figure 27-30 demonstrate the inflow & outflow of passengers at each of the stations and the cumulative passenger in the Gautrain system during peak periods. This analysis was only done on rail lines (& directions) that had high ridership during peak periods, viz: North-South line during morning peak period, South-North line during afternoon peak period, East-West line during morning peak period, and West-East line during afternoon peak period.

Analysing cumulative ridership as trains traverse from one station to the next is pertinent when analysing the efficiency of a TDM strategy. The efficiency of TDM strategies refers to how well the strategy is designed to influence a shift in commuter behaviour of the correct segments of passengers. Figure 26 shows that ridership on trains increases from when trains begin trip at Hatfield, to when trains get to Midrand. At the Marlboro station ridership on the trains decreases until trains are empty, at Park. Maximum ridership and utilisation on trains occur at the Midrand station, before trains head to Marlboro. According to literature, Midrand-Marlboro is defined as the critical link (or section) of the North-South line during the morning peak period.

Passengers who enter the Gautrain at stations before the critical link (Hatfield, Pretoria, Centurion, Midrand), and remain in the Gautrain as it traverses through the critical link are described as Class 4 passengers. Class 4 passengers are the most significant contributors to overcrowding and over-utilization of the Gautrain system. A sophisticated TDM strategy would be one that focuses on shifting the commute patterns and times of class 4 passengers.

From Hatfield to Midrand stations there is mostly an inflow of passengers into trains however, the small percentage of passengers who egress the Gautrain at Pretoria, Centurion and Midrand stations cannot be disregarded. These are passengers who egress the Gautrain before trains reach the critical link (Midrand-Marlboro), hence they do not contribute to the overcrowding, high utilisation and deterioration of system efficiency of the Gautrain. These are class 5 passengers. The passengers who enter the Gautrain at stations after the critical link (Marlboro, Sandton and Rosebank) also do not contribute to overcrowding, regardless of where they egress. This is because by the time they enter and egress the Gautrain, cumulative ridership is declining and past its peak point (critical link). These passengers are also class 5 passengers. Class 5 passengers, unfortunately, are also subjected to surge fares even though there would no gain to them shifting their commute patterns and times.

The same reasoning was applied to determine the critical links on: East-West line during morning peak period (Rhodesfield-Marlboro), South-North line during afternoon peak period (Marlboro-Midrand), and West-East line during afternoon peak period (Sandton-Marlboro).

6.2. Working hypothesis 1: *An increase in Gautrain train service fares does not result in a change in overall ridership.*

Working hypothesis 1 is aimed at investigating the effects increasing train service fares has on ridership. It is indicative of how sensitive Gautrain users are to fares;

do users continue to use the Gautrain despite increased fares, or do they switch to other modes of transportation (e.g. e-hailing, private car etc.)?

The research acknowledges that a plethora of stimuli may affect ridership and train service demand levels on the Gautrain. Ridership levels may be influenced by key external factors such as economic growth in Gauteng regions, prices of fuel & tolls, competition (e.g. e-hailing services, carpooling etc.). Therefore, caution was exercised when correlating ridership with fare changes. This was achieved by the formulation sub-hypotheses (section 5.4.1) that allowed for the analysis of in-depth ridership statistics to produce reliable results.

Table 11 shows that after the fare increase was applied (at the beginning of June), daily ridership decreased from 50698 passengers to 48420 passengers per day. This is a 4.5% decrease in daily ridership. Information provided by GMA indicate that fares were increased by 5.9%, in June 2019. Therefore, using Curtin's formula (equation 5), it is computed that given a 5.9% increase in fares, ridership is expected to decrease by 2.57%. However, in this instance ridership decreased by 4.5%, almost double the estimated percentage. This indicates that Gautrain users are much more sensitive to fare increases than what Curtin's formula estimates. A reason for this disparity could be that Curtin's formula was developed and mostly tested on urban rail systems situated in developed countries, with much bigger economies. It is plausible that the socio-economic factors of developed vs. developing (e.g. South Africa) are fundamentally different.

Alternatively, the drop in ridership could be split into two components that potential reason why the drop in ridership is much greater than expected. The first component for the drop in ridership is attributed to the fare increase that was implemented. The first component of ridership decline is attributed to passengers who, by all means, can no longer afford to use the Gautrain as their daily mode of urban commute and resort to other modes of transportation. The second component of ridership decline is passengers who, despite the fare increase, can still afford to use the Gautrain but decided to switch to alternatives regardless, possible due to dissatisfaction of the fare structure. The efficiency of the TDM strategy is crucial in this regard. Section 6.1 demonstrates that the current TDM strategy affects the different classes of passengers in various ways, and some classes of passengers end up being subjected to exorbitant fares unfairly plainly due to the TDM strategy not being bespoke enough.

Results of the z-test indicated that indeed there is a significant difference in daily ridership before and after fare increases are applied. This is a reasonable and acceptable outcome given the explanation provided on fare elasticity and passenger classes. F-test outcome was that it cannot be concluded that the variances of daily ridership (before and after fare increase) are statistically different. However, CV after fare increase is greater than CV before fare increase. This implies that, given the chosen samples, there is potentially more variation in daily ridership figures after fare increase is applied. Analysis of daily ridership for the months of June and July showed that there were high variations of ridership. It is reasonable that promptly after fare increases are applied, daily ridership will vary because certain users would be in an experimental phase of evaluating whether or not they can afford to use the Gautrian. From July onwards, daily ridership stabilises because by then users (of all passenger classes) have likely accepted fare increases and consciously decided to continue using the Gautrain for commute.

Table 12 shows that mean ridership during morning peak period drops by 5.22%. Z-test outcomes further support this drop in ridership by confirming that there is a statistically significant difference in the means of the two sample sets. Note that once more, the drop in ridership (5.22%) is much greater than the expected drop of 2.57%. Analysis showed that, proportionately, it was mostly class 2 passengers whose ridership dropped during morning period peak period after fares were increased. This supports the notion that passengers of this class are less likely to accept fare increases and pay surge fares considering that they are already getting hard done by the TDM strategy. This highlights an inefficiency of the TDM strategy. Ridership of class 1 and 3 passengers dropped (approx. 5%). This was concerning because it indicated that after the fare increase, users did not shift their commute times to non-peak periods, in the hopes to be economical. Some passengers stopped using the Gautrain altogether, during morning peak period. This is not ideal; a drop in ridership goes against the mandate of the GMA.

The f-test outcome was that it could not be concluded that variance of ridership during morning peak period was statistically different, before and after fare increase was applied. This indicates that although ridership declines, a vast majority of users who continued to use the Gautrain during morning peak periods. Hence commute patterns are likely to be similar to what they were before fare increases were applied, which results in there not being enough statistically significant evidence to demonstrate that the variances are different, before and after fare increases. CV shows that there is likely more variation after fare increase is applied. This is attributed to the transient ridership patterns of users responding to the fare increase.

Drop in mean afternoon peak period after fare increase was applied was 4.87% (table 18). For afternoon peak period, z-test and f-test outcomes were similar to those in table 15. The interpretation is similar as well: Gautrain users generally did not shift their commute times to off-peak periods. Some passengers simply stopped using the system during the afternoon peak period.

Tables 13 and 14 show that, as expected, maximum ridership during morning and afternoon peak periods is less after fares are increased. This is because overall ridership after fares were increased dropped. The drop in maximum ridership was 4.8% (roughly 110 passengers), during morning and afternoon peak periods. This decline in ridership is not large enough for train service supply to scaled down. Therefore, this implies that after the fare increase was applied, ridership dropped and Gautrain could not capitalise on this decline in ridership by possibly scaling down supply and reducing operating costs. This deems the benefits of the fare increase to be solely financial.

F-test outcomes on tables 13 and 14 show that it cannot be concluded that the variances of max. ridership before and after the fare increase are equal. In addition, the CV’s for before and after fare increases were applied in both tables are strikingly similar. Aggregated time series data for the sample sets were analysed and it was observed that the times at which maximum ridership occurs remains the same, before and after fare increases were applied. During morning peak period maximum ridership occurs at 07h15. During afternoon peak period maximum ridership occurs at 17h00. This information does not reveals a lot about Gautrain users and the factors that drive their decision-making. For peak period travel patterns to be this congruent before and after fare increase was applied, it implies that fares are not the main determinant of the commute times and periods passengers decide to travel in. It is likely driven by factors relating to the flexibility of their weekday schedules, which is ultimately determined by places of employment or school.

6.3. Working hypothesis 2: *Gautrain’s temporal travel demand management strategy is not efficient at shifting daily ridership from peak periods to off-peak periods during weekdays.*

Working hypothesis 2 is aimed at investigating different commute characteristics of riders of the Gautrain. Results analysed give indications of the various reasons why users may or not decide to use the Gautrain, and secondly, why users travel at certain periods of the day. This way the TDM strategy could be analysed based on how efficient it is to Gautrain users, bearing in mind their commute characteristics.

By analysing ridership for weekday versus weekend, basic characteristics of Gautrain users can be understood (Table 21). Of course, mean daily ridership during weekdays (49331 passengers) is greater than the mean daily ridership during weekends (10145 passengers). This was expected given the literature reviewed. The statistics of interest here is the variance between the two sample sets. F-test outcome shows that there is a statistically significant difference between of daily ridership between weekdays and weekends. Following this, CV for weekday and weekend were computed to be 4.20 and 14.37, respectively. This means that ridership on the Gautrain on weekdays happens with great consistency whereas on weekends it is varies significantly.

It is plausible that weekday ridership is more consistent because majority of *commuters* use the Gautrain for work and school purposes during weekdays (refer to section 2.2). The reasons why ridership on weekends varies more is because weekend commute is mostly for informal, leisure trips. In addition, weekend commute is mostly characterised by *casual* and *intermittent* riders; a market survey performed on Gautrain passengers confirmed these assertions (Agency, 2019).

We now shift our focus back to weekday ridership. Firstly, table 16 shows that mean ridership during the second half of the day is less than mean ridership first half of the day. This means that more passengers use the Gautrain when traversing in the *forward* direction, when commuting to work, school etc. Slightly less passengers use the Gautrain to go back home, implying that they probably use other modes of transportation to get back home. The possible reasons for this will be discussed shortly.

Secondly, the f-test outcome showed that it cannot be concluded that ridership during first half and second half of the day are different. This indicates that although there are differences in the number of people who use the Gautrain during first and second half of the days, it is likely that is the same people who use the Gautrain during first half and second half of the day, respectively. Hence the z-test confirmed that the means for the two data sets are different, but the f-test failed to confirm that the variances are equal. CV for second half of the day is 5.02, it is greater than the CV of 4.55 for first half of the day. Although the f-test was inconclusive, CV allows for the interpretation that, considering the sample sets chosen, ridership during second half of the day has more variability compared to ridership during first half of the day.

One of the competitive advantages Gautrain has over other means of transportation is that is a rapid transit system that is not susceptible to traffic congestions or external disturbances. It must be noted that using the Gautrain generally costs more than using other modes of transportation because it is a premium train service (hypertext, 2019). The results from table 16 possibly mean that, during the first half of the day, passengers have got strict time schedules to adhere to, hence higher ridership. Then during the second half of the day, people’s schedules are relaxed and flexible, hence some passengers decide to not use the Gautrain to commute back home. This is a plausible interpretation considering that during mornings people are rushing to get to work or school at designated times. During afternoons there is less rigidity on the times at which people may leave work or school – as long as people do not leave sooner than permissible. It is likely that some passengers decide to use more affordable, convenient or flexible transportation modes when travelling back home. Plus, certain people run errands after work or school.

Table 17 shows that ridership during morning peak period is greater than ridership during afternoon peak period – there is a 9% difference, which is significant. In addition, z-test and f-test outcomes showed that there are statistically significant differences for mean (μ) and variance (σ^2) between the two data sets. Furthermore, CV for afternoon peak period was greater than for the morning peak period. Results from table 17 can be interpreted in a similar fashion as those from table 16; during mornings people commute to get to work at rigid, designated times, and during afternoons people are flexible on the times they travel home.

However, it must be discussed that CV’s on table 17 are considerably greater than those on table 16. This means that relatively, there is greater variation of passengers who travel during peak periods, when the TDM strategy surge fares are applicable. This is understandable as section 6.2 established that: (1) passengers are sensitive to train service fares (2) the current TDM strategy is not suitable to certain classes of passengers. Therefore, when feasible, certain passengers avoid travel during peak periods to avoid being subjected to the surge fares imposed by the TDM strategy during these periods. From a TDM efficiency point of view, indeed it is desirable that passengers avoid travel during peak periods. However, the concern with the analysed ridership patterns is that a significant proportion of passengers (roughly 9%) decide to not use the Gautrain altogether, where possible. This exemplifies a TDM strategy whose efficiency has opportunity for improvement.

Graphical analysis of peak period ridership patterns provides valuable information. In South Africa, the business hours for institutions is generally 08h00 – 16h30. Therefore, it is expected that Gautrain ridership is high during these periods (figure 19). Figure 14 shows that during morning peak period, ridership increases sharply, reaches maximum ridership point, then decreases sharply. There are no ‘kinks’ in ridership at the shoulders of the temporal TDM strategy (points 1 and 2). However, during afternoon peak period there are ‘kinks’ in ridership at the shoulders of the TDM strategy (points 3 and 4). There is a spike of passengers who travel just before surge fares are applied (15h30), then there is another spike of passengers who travel just after surge fares have stopped (18h00). It is plausible that these are fare sensitive passengers who are willing to adjust their travel times in order to avoid being subjected to surge fares. Figures 23-25 demonstrate just how significant these ‘kinks’ in ridership are.

Kinks being present during afternoon and not morning peak period confirms the claim that passengers generally have more flexibility during afternoon peak periods. During afternoon peak periods some passengers' travel times are shifted to off peak periods, others do not use the Gautrain altogether, and lastly, majority do use the Gautrain to travel back home.

In summary, Gautrain users are sensitive to fare increases – daily ridership decreased (more than expected) after the increase of train service fares. Granted, majority of Gautrain users continued to use the Gautrain for daily commute, but their travel patterns shifted likely due to the increase of fares. Class 1 passenger segment increased, meaning that after fare increase was applied some users shifted their travel times to avoid surge fares. Understandably, the percentage differences for classes 2-5 are all negative because of the significant number of passengers who shift their travel to off-peak period, thereby becoming class 1 passengers.

Interestingly, there is very minimal change in class 4 passengers. Class 4 passengers are the prime target of the users whose behaviour the TDM strategy is supposed to shift. The lack of change from class 4 passengers possibly indicates that these are individuals who are less sensitive to fare increase. This could be because they (class 4 passengers) have not got any viable alternatives that are better than the Gautrain, hence they continue using the Gautrain, during peak periods, peak rail directions and cause overcrowding etc.

Table 19: Summary of impact of fare increase on different passenger classes

Class	Proportion of daily ridership before fare increase (in %)	Proportion of daily ridership after fare increase (in %)	Percentage difference
Class 1	39.06	40.03	+0.97
Class 2	15.67	15.55	-0.12
Class 3	40.22	39.95	-0.27
Class 4	35.45	35.42	-0.03
Class 5	7.60	7.31	-0.29

Based on percentage differences, the classes of passengers behave differently during morning and afternoon peak periods. Percentage differences in table 20 are much greater than those in table 19, for the respective classes of passengers. This means that Gautrain users are more likely to shift or change their ridership behaviour due to temporal reasons opposed to financial ones. As established before, during morning peak periods passengers are not very responsive to the TDM strategy; there are no kinks at TDM strategy shoulders and ridership patterns are consistent, day by day. Whereas during afternoon peak periods passengers are very responsive to the TDM strategy; there are kinks at the shoulders of the TDM strategy and ridership patterns are less consistent, day by day.

There are tangibles shifts in ridership during afternoon peak period. The proportions of class 2 passengers remain roughly the same (0.1% difference). Class 2 passengers are subjected to surge fares, on low utilisation rail lines or travel directions. Table 19 & 20 suggest that they do not mind this (paying surge fares). Proportionately, there are less class 3,4 and 5 passengers during afternoon peak period. Class 3,4 and 5 passengers are those who travel during peak periods, on high utilisation rail lines or travel directions. Table 19 & 20 suggests that more class 3, 4 and 5 passengers shift their ridership behaviour because: (1) some are avoiding being subjected to surge fares, (2) others might be avoiding using an overcrowded system with reduced service levels.

Table 20: Summary of difference of ridership behaviour for morning vs. afternoon peak period

Class	Proportion of ridership during morning peak period (in %)	Proportion of ridership during afternoon peak period (in %)	Percentage difference
Class 2	25.66	25.76	+0.1
Class 3	67.48	64.43	-3.05
Class 4	59.15	57.18	-1.97
Class 5	13.57	10.90	-2.67

7. CONCLUSIONS AND RECOMMENDATIONS

The purpose of this chapter is to critically summarise the research conducted, within the context of the research questions and objectives defined. The section also outlines recommendations the GMA should consider with regards to train service fare structures and travel demand management

7.1. Research question, objectives and key findings

- The fundamental determinant of train service demand is day of week; weekday or weekend. Weekdays are characterised by high, consistent daily ridership Weekends have low daily ridership with high variability. During weekdays, more people use the Gautrain possibly because it is reliable, this is imperative for people generally commuting for professional reasons (work, school or otherwise). During weekends, less people use the Gautrain possibly because the reason for travel is leisure hence, they do not necessarily need to use a system that is as reliable as the Gautrain.

- As mentioned, the *reason* for travel is a key consideration for daily ridership as mentioned in the previous bullet point. This is also the case when analysing train service demand patterns throughout the day. During mornings, there is greater impetus for people to make it to work or school timeously than during afternoons. Hence ridership during morning peak periods is higher than during afternoon peak period. During morning there is a significant, rigid commonality that exists between passengers: making it to work or school by a given specified time (usually 08h00). During afternoon, there fewer commonalities that exist between passengers: for various reasons some passengers remain at work or school longer before commuting home, some passengers run errands afterwork, other passengers do not use the Gautrain when commuting home.

- Train service demand drops (slightly) when train service fares are increased. Daily ridership patterns remain the same before and after fare increase. Upon implementation of fare increase there is a number of passengers who show more elasticity than others; daily ridership for the first few months after the increase are transient, then become consistent. Over approximately two months, passengers evaluate whether they can still afford to use the Gautrain given the increased fares. Some can no longer afford and decide to stop using the Gautrain. Other passengers can still afford (conditionally) to use the Gautrain, but to do so, they shift their ridership times to off-peak periods (when feasible) to save money. Lastly, there are those passengers who do not change or shift their commute patterns, they are accepting of the fares and crowding during peak periods.

- Given the bullet point discussed above, it can be said that the increasing of train service fares is also a form of TDM strategy since there is evidence of passengers changing and shifting their travel patterns in response to the fare increase. The caveat to is that it is a form of TDM strategy that has no positive incentives to all passengers, GMA is the beneficiary of it because it increases revenue. The passengers who do change their travel patterns do so to minimise negative financial impact of the fare increase.

- For the most part, the temporal TDM strategy Gautrain has in placed targets the correct proportion of passengers during peak periods (refer to table 15 and 19). This is indication of the strategy being correctly designed, from a temporal point of view. However, the TDM strategy is not efficient at promoting a significant number of people to shift their travel times such that the disparities between peak period and non-peak periods are not high and that system efficiency is not deteriorated. The lack of efficiency of the TDM strategy is a reflection that there is great potential for the TDM strategy be improved in terms of structuring incentives that will drive Gautrain passengers to shift their ridership patterns.

7.2. Limitations of the research

- The decline in ridership upon the increase of train service fares may be attributed to external factors that the research did not analyse. The state of the economy is correlated with the economic activity, employment levels, inflations and commute of citizens of a given region. The changes in ridership might have been influenced by such factors. It cannot be concluded that ridership dropped solely because train service fares were increase.
- Ridership is also influenced by the different alternative transportation modes commuters weigh the Gautrain against when commuting. Depending on the price of fuel and tolls, it is sometimes more affordable for commuters to commute by private car, carpooling or e-hailing services. The research did not analyse these competition dynamics and how Gautrain ridership is affected by them.
- The research analysed tallied up smartcard data collected up APS systems, not user specific smartcard data…therefore….
- The study was focused on researching the TDM strategy as a means to achieve system efficiency during peak and non-peak periods. This was done by analysing train service demand (or ridership). An alternative approach that could bring about key findings is analysing train service supply (e.g. scheduling of trains, configurations of trains, route optimisation)
- Analysis of ridership data from before and after GMA developed and implemented the TDM strategy would have produced the best results in terms of understanding how daily ridership patterns are influenced by the TDM strategy. Ridership data from before GMA implemented a TDM strategy is data from 2012 and prior years. This data could not be obtained by the researcher.

- Most of the analyses performed for the research excluded passengers traversing to and from OR Tambo airport. This was done because the commute characteristics of these passengers was erratic, even during weekdays. In addition, Gautrain's TDM strategy does apply to passengers travelling from and to the airport.

7.3. Recommendations

The following future developments can be made on Gautrain's TDM strategy:

- The differential pricing structure GMA has in place classifies as *flat*; the difference between base and surge fares is constant for peak and non-peak periods. (refer to section 2.5.1). This means that the incentive to shift ridership remains constant throughout specified peak periods. The study could be expanded to develop a multinomial logit (MNL) model comparing how passengers would likely respond to a *stepped* structure for surge fares. Stepped structures are more sophisticated because the incentive is gradually increased (or deceased) based on the desired ridership patterns rail agencies aim to achieve.
- The study demonstrated although passengers respond to fare increases and the current temporal TDM strategy, ridership patterns generally did not change much. Analysis of tables 18 and 19 vaguely suggest that certain classes of passengers may be sensitive to overcrowding. Future work can be done to evaluate how ridership patterns would be influenced if passengers had a means to access instantaneous ridership and crowding levels on the Gautrain, online via smartphone, for example. BART Perks used this approach and it yielded positive results.
- A promotion-based TDM strategy may be evaluated. This could be a strategy in which train service fares are kept constant throughout the day, and there would be a structure in place that *rewards* passengers based on a specified criterion. Once more, BART Perks used this approach and saw positive results from it. It must be emphasised that the pre-requisite for this

strategy to be successful is a thorough qualitative study that seeks to understand the people’s consumer behaviours.

REFERENCES

AEI, 2020. *DC Metro uses 'surge pricing' every day as an efficient way to allocate scarce resources during periods of peak demand* | *American Enterprise Institute - AEI..* [Online]

Available at: https://www.aei.org/carpe-diem/dc-metro-uses-surge-pricing-every-day-as-an-efficient-way-to-allocate-scarce-resources-during-periods-of-peak-demand/.

[Accessed 17 December 2020].

Gautrain Management Agency 2019. *Gautrain Management Agency annual report,* Johannesburg:

Ashford, N. & Benchemam, M., 1987. *Passengers' choice of airport: an application of the multinomial logit model,* Loughborough:

Bao, Y., Xu, M., Dogterom, N. & Ettema, D., 2020. Effectiveness investigation of travel demand management measures in Beijing: Existing measures and a potential measure–tradable driving credit. *Transportation Research Part F: Traffic Psychology and Behaviour,* Issue Bao, Y., Xu, M., Dogterom, N. and Ettema, D., 2020..

Ben-Akiva, M. & Lerman, S., 1985. Discrete Choice Analysis: Theory and Application to Travel demand. *MIT Press, Campbridge.*

Bhattacharjee, D., Haider, S., Tanaboriboon, Y. & Sinha, K., 1997. Commuters' attitudes towards travel demand management in Bangkok.. *Transport Policy,* 4(3), pp. 161-170.

Campbell, M. & Gardner, M., 1988. Statistics in Medicine: Calculating confidence intervals for some non-parametric analyses. *British medical journal (Clinical research ed.),* 296(663), p. 1454.

Cascetta, E. & Coppola, P., 2016. Assessment of schedule-based and frequency-based assignment models for strategic and operational planning of high-speed rail services. *Transportation Research Part A: Policy and Practic,* 3(84), pp. 93-108.

Chan, S. & Miranda-Moreno, L., 2013. A station-level ridership model for the metro network in Montreal. *Canadian Journal of Civil Engineering,* 40(3), pp. 200-234.

Chan, Y., 2003. *Biostatistics 102: quantitative data–parametric & non-parametric tests for blood pressure,* s.l.: s.n.

CTA, 2020. *Ridership Reports - Performance - CTA.* [Online]
Available at: https://www.transitchicago.com/ridership/
[Accessed 02 January 2021].

Dend, J. & Xu, M., 2015. *Characteristics of subway station ridership with surrounding land use: A case study in Beijing.* Wuhan, China, s.n.

Feng, X., Sun, Q. & Liu, J., 2010. *Time Characteristic of Input Passenger in Urban Rail Transit Stations Among High.* Beijing, China, s.n.

Fu, X. & Gu, Y., 2018. Impact of a new metro line: analysis of metro passenger flow and travel time based on smart. *Advanced Transportation.*

Gan, Z., Yang, M., Feng, T. & Timmermans, H., 2020. Understanding urban mobility patterns from a spatiotemporal perspective: daily ridership profiles of metro stations. *Transportation,* 1(47), pp. 247-336.

Garling, T. & Schutema, G., 2007. Travel demand management targeting reduced private car use: effectiveness, public acceptability and political feasibility. *Journal of Social Issues,* 1(63), pp. 139-153.

Graham, D., Couto, A., Adeney, W. & Glaister, S., 2003. Economies of scale and density in urban rail transport: effects on productivity. *Transportation Research Part E: Logistics and Transportation Review,* pp. 443-458.

Greene-Roesel, R. & Smith , E., 2019. *BART Perks Phase II,* San Francisco Bay Area: s.n.

Green, J., Chickola , L., Emanuel, E. & Cruickshank, A., 2005. NATIONAL RAILROAD PASSENGER CORP A CORP OF DISTRICT OF COLUMBIA and Chickola Lawrence. *Automated fare collection system U.S. Patent.*

Halvorsen, A., Koutsopoulos, H., Ma, Z. & Zhao, J., 2016. Reducing subway crowding: analysis of an off-peak discount experiment in Hong Kong. pp. 38-46.

Halvorsen, A., Koutsopoulos, M. & Zhao, J., 2016. Demand management for congestion public: A framework and application.

Hensher, D., 1998. Establishing a fare elasticity regime for urban passenger transport. *Journal of Transport Economics and Policy,* pp. 221-246.

hypertext, 2019. *Uber VS Bolt VS Gautrain - What is the cheapest way to get to O.R Tambo International?.* [Online]

Available at: https://htxt.co.za/2019/07/18/uber-vs-bolt-vs-gautrain-what-is-the-cheapest-way-to-get-to-o-r-tambo-international/.

[Accessed 24 December 2020].

Jiang, M., Li, H. & Miao, J., 2017. Metro passenger flow control with station-to-station. pp. 12-56.

Jiao, L., Shuai, C., Tan, Y. & He, B., 2017. Measuring crowdedness between adjacent stations in an urban. *Journal of Sustainability,,* Volume 9, pp. 1-14.

Kerh, T. & Ting, S., 2005. Neural network estimation of ground peak acceleration at stations along Taiwan high-speed rail system. *Engineering Applications of Artificial Intelligence,,* 18(7), pp. 857-866.

Kothari, C., 2004. *Research methodology: Methods and techniques.* New Delhi: New age publishers.

Krueger, H., 1999. *Parametric modeling in rail capacity planning.* Wisconsin, s.n., pp. 1194-1200.

Lam, W. & Zhou, J., 2000. Optimal fare structure for transit networks with elastic demand. *Transportation Research Record,* Volume 1733, pp. 8-14.

Lin , J. & Shin, T., 2007. Built environment impacts of transit-oriented development on metro ridership: an empirical study of Taipei metro system. *Transportation Planning Journa,* pp. 421-476.

Li, Z., Zhou, Y., Zhou, W. & Zhong, M., 2016. *Impact analysisof new metro line opening on passenger flow: A case study of Shenzhen,* Beijing, China: s.n.

Louviere, J. & Timmermans, H., 1990. *Stated preference and choice models applied to recreation research: a review.,* s.l.: Leisure Sciences.

Ma, C., Wang, Y. & Guo, Y., 2011. Sensitivity analysis on urban rail transit passenger flow forecast. *International Conference on Electric Technology and Civil Engineering,* pp. 1537-1541.
Ma, Z. & Koutsopoulos, H., 2014. Urban rail system planning and capacity evaluation.
Ma, Z. & Koutsopoulos, H., 2019. Optimal design of promotion based demand management strategies in urban rail systems. *Transportation Research Part C: Emerging Technologies,* pp. 155-173.
McCollom, B. & Pratt, R., 2004. Transit pricing and fares. In: *Traveler Response to transportation system changes.* Washington: Transportation research board, pp. (12) 1-58.
MTA, 2019. *Subway and bus ridership for 2019.* [Online]
Available at: https://new.mta.info/agency/new-york-city-transit/subway-bus-ridership-2019.
[Accessed 19 December 2020].
MTR, H. K., 2019. *Annual ridership report: 10 yearly overview,* Hong Kong: s.n.
Mwambeleko, J. & Kulworawanichpong, T., 2019. Battery electric multiple units to replace diesel commuter trains serving short and idle routes. *Journal of Energy Storage,* Volume 11, pp. 7-15.
Paulley, N., Balcombe, R. & Mackett, R., 2006. The demand for public transport: The effects of fares, quality of service, income and car ownership. *Transport policy,* Issue Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M., Shires, J. and White, P., 2006. . , 13(4), pp.295-306., pp. 250-286.
Pelletier, M., Trepanier, M. & Morency, C., 2011. Smart card data usein public transit: a literature review. Volume 557-568.
Preston, J., Pritchard, J. & Waterson, B., 2017. Train overcrowding: investigation of the provision of better information to mitigate the issues. *Transportation research record,* pp. 1-8.

Qin, J., Qu, W., Wu, X. & Zeng, Y., 2019. *Differential pricing strategies of high speed railway based on prospect theory: An empirical study from China.,* China: s.n.

So, Y. & Kuhfeld, W., 1995. So, Y. and Kuhfeld, W.F. *In SUGI 20 conference proceedings,* pp. 1227-1234.

Strategyzer, 2011. *Strategyzer.* [Online]
Available at: https://www.youtube.com/watch?v=QoAOzMTLP5s
[Accessed 20 December 2020].

Sun, Y. & Schonfeld, P., 2016. Schedule-based rail transit path-choice estimation using automatic fare collection data. *Journal of Transportation Engineering,* Issue 142.

Tang, K. & Cheung, L., 2014. Additional demand for railway services during the Occupy central movement. *Legislative Council Panel.*

Taylor, C., Nozick, L. & Meyburg, A., 1997. Selection and evaluation of travel demand management measure. *Transportation Research Record,* pp. 49-60.

Van Audenhove, F., Korniichuk, O. & Pourbaix,, J., 2014. The future of urban mobility. pp. 20 - 34.

Voith , R., 1997. Fares, service levels, and demographics: what determines commuter rail ridership in the long run?. *Journal of Urban Economics,* 122(3), pp. 176-197.

Wang, H., Zhang, K. & Chen, J., 2018. System dynamics model of taxi management in metropolises: Economic and environmental implications for Beijing. *Journal of environmental management,* Issue Wang, H., Zhang, K., Chen, J., Wang, Z., Li, G. and Yang, Y., 2018. .t, 213, pp.555-565., pp. 550-574.

Wang, M. & Bushman, B., 1998. Using the normal quantile plot to explore meta-analytic data sets. *Psychological Methods,* 3(1), p. 46.

Wei, Y., Bai, H., Chen, J. & Yan, X., 2019. Analysis of Space-Time Variation of Passenger Flow. *Sustainability.*

Wen, C. & Lan, L., 2010. Effects of Temporally Differential Fares on Taipei Metro Travelers' Mode and Time of day choices. *International Journal of Transport Economics.*

Werner, C., Brown, B., Tribby, C. & Tharp, D., 2016. Evaluating the attractiveness of a new light rail extension: Testing simple change and displacement change hypotheses. *Transport policy,* Issue Werner, C.M., Brown, B.B., Tribby, C.P., Tharp, D., Flick, K., Miller, H.J., Smith, K.R. and Jensen, W., 2016. . , 45, pp., pp. 15-23.

Whelan, G. & Johnson , D., 2004. Modelling the impact of alternative fare structures on train. *International journal of transport management,,* 2(1), pp. 51-58.

WMATA, 2020. *Cost to Ride.* [Online]
Available at: https://www.wmata.com/fares/basic.cfm
[Accessed 7 January 2021].

WMATA, 2020. *Rail Ridership Data Viewer.* [Online]
Available at: https://www.wmata.com/initiatives/ridership-portal/Rail-Data-Portal.cfm.
[Accessed 10 January 2021].

Yang, C., Yan, F. & Ukkusuri, S., 2018. Unraveling traveler mobility patterns and predicting user behavior in the Shenzhen metro system. *Transportmetrica A: Transport Science,* 14(7), pp. 545-597.

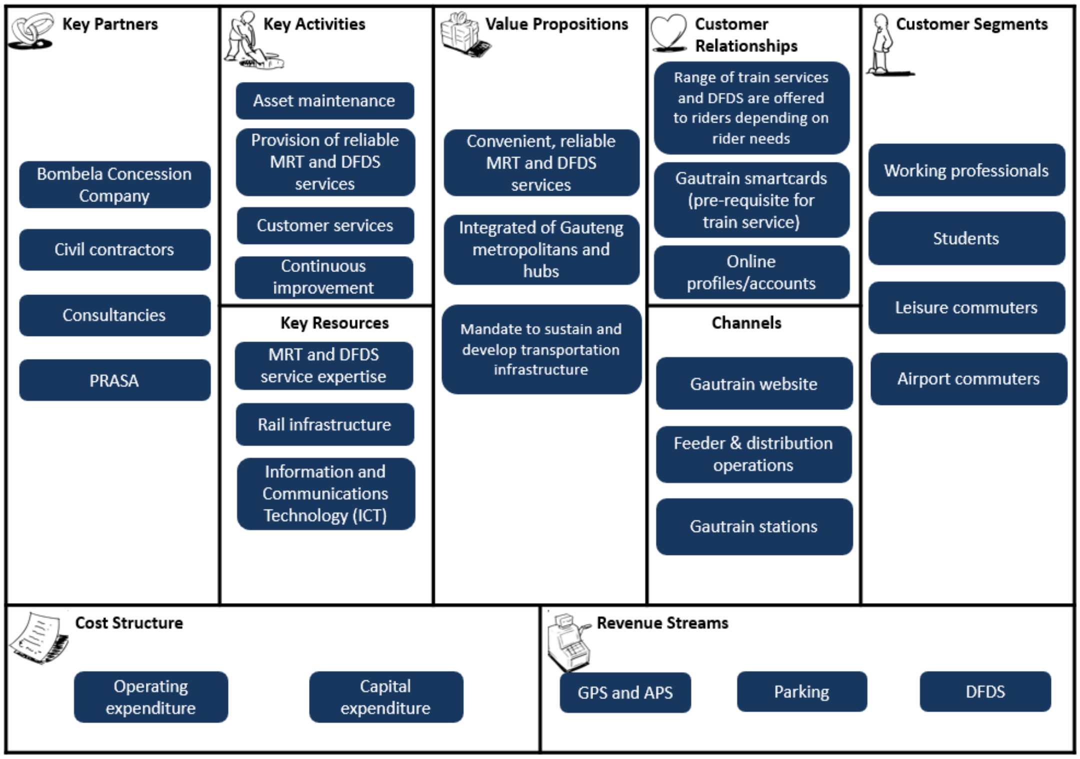
Yang, H. & Tang, Y., 2018. *Managing rail transit peak-hour congestion with a fare-reward scheme,* s.l.: s.n.

Zhang, Z., Fujii, H. & Managi, S., 2014. How does commuting behavior change due to incentives? An empirical study of the Beijing Subway System.. *Transportation Research Part F: Traffic Psychology and Behaviour,,* Volume 24, pp. 17-26.

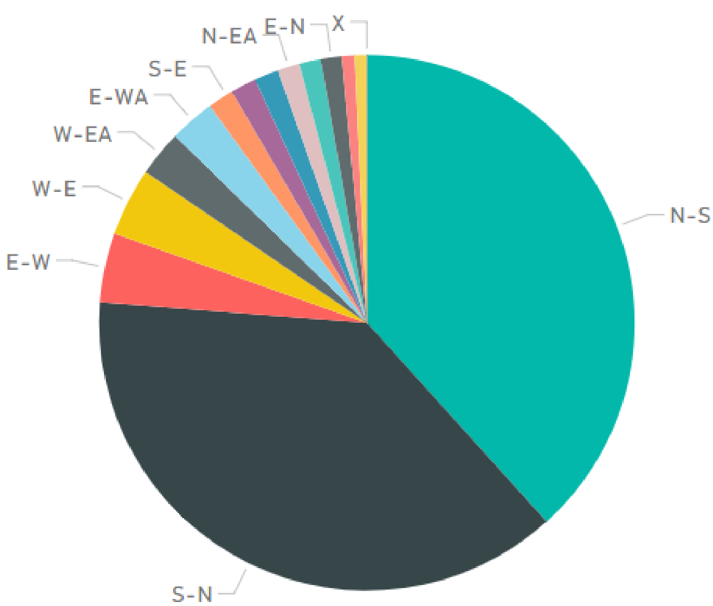
Zhao, J., Rahbee, A. & Wilson, N., 2007. Estimating a rail passenger trip origin-destination matrix using automatic data collection systems. *Computer‐Aided Civil and Infrastructure Engineering,* 22(5), pp. 376-387.

APPENDICES

APPENDIX A – Business model canvas for Gautrain (self-rendered)

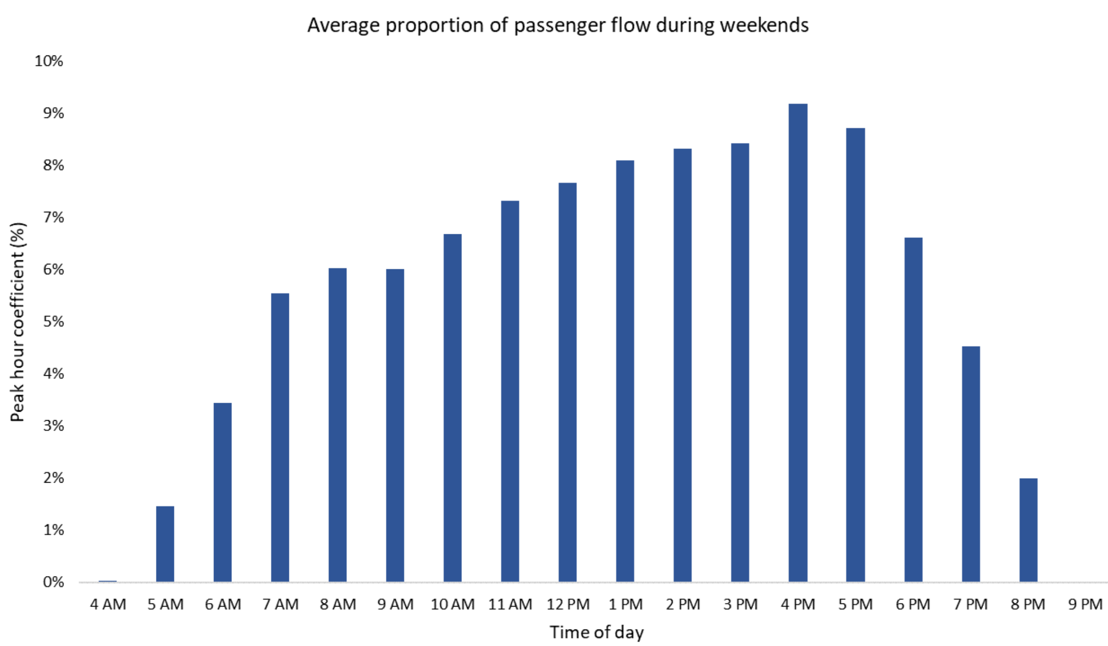


APPENDIX B –Travel directions based on passenger O-D pairs

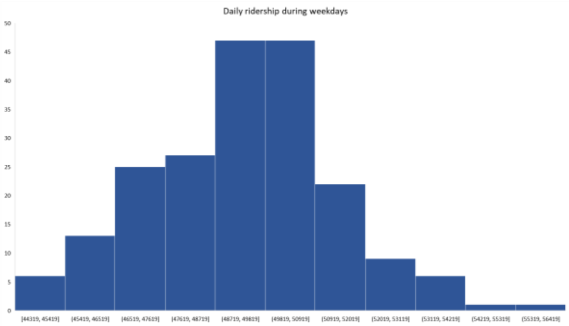


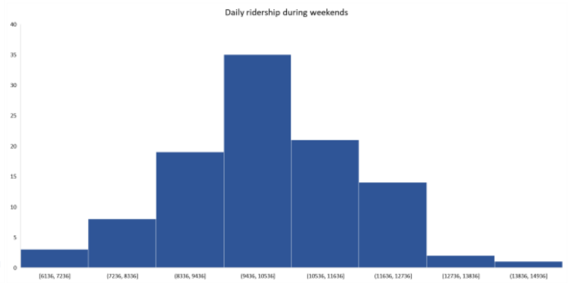
APPENDIX C – Average ridership from Monday to Sunday

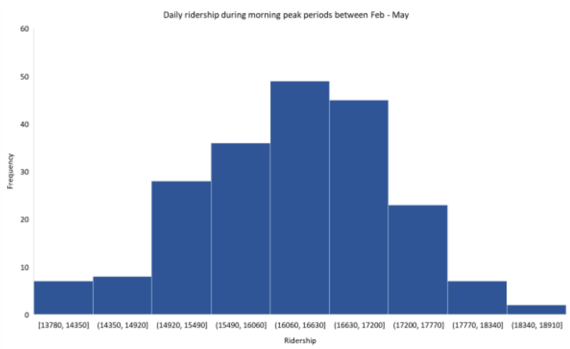
APPENDIX D – Peak coefficient for weekends

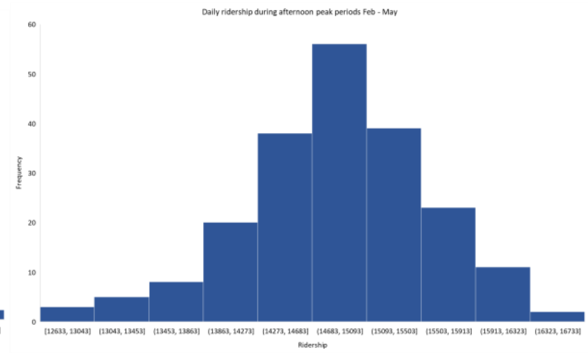


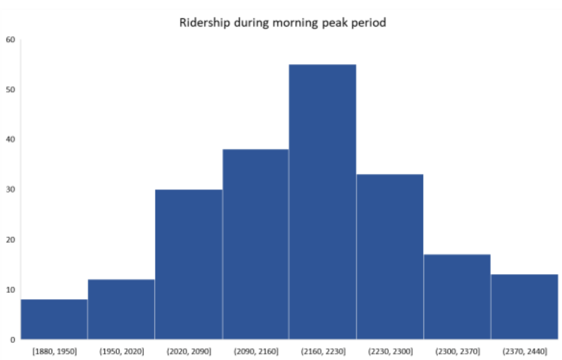
APPENDIX E – Histograms for sample sets

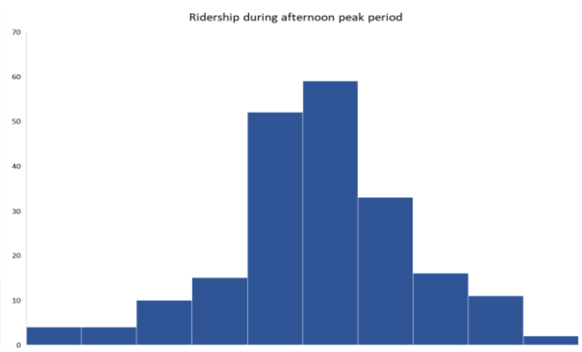


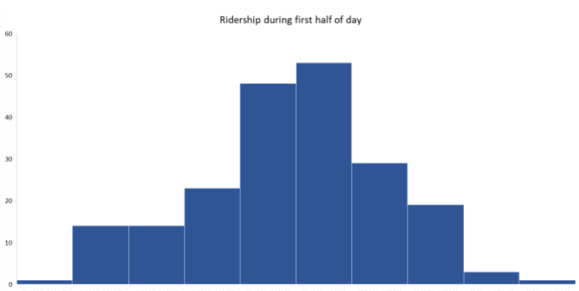


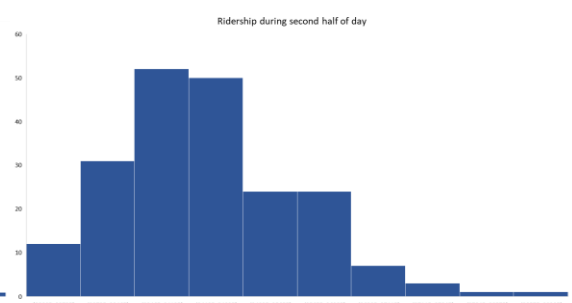




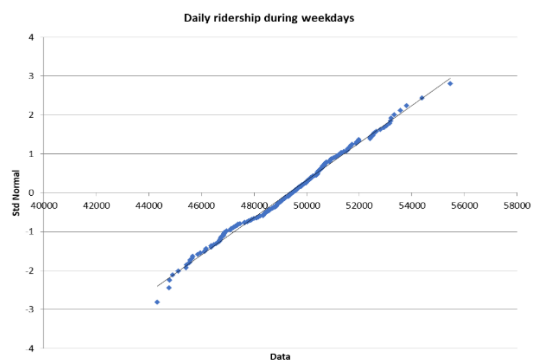


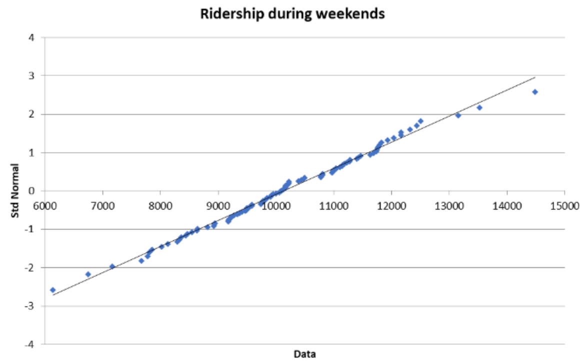


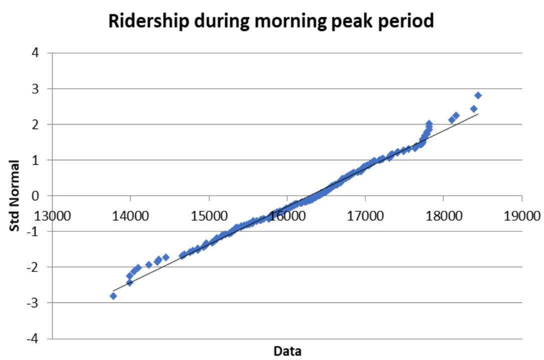


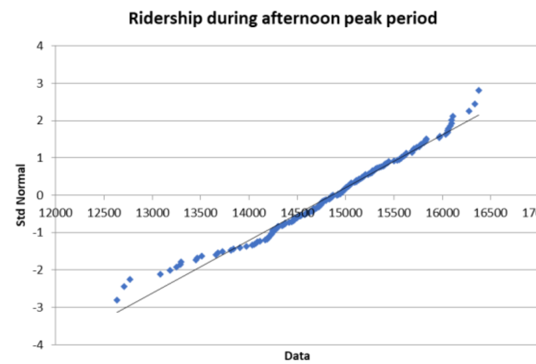


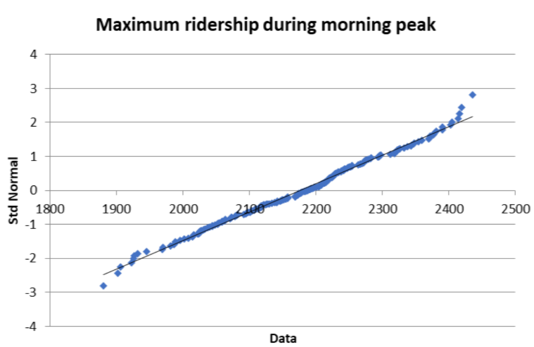
APPENDIX F – Q-Q plots for sample sets

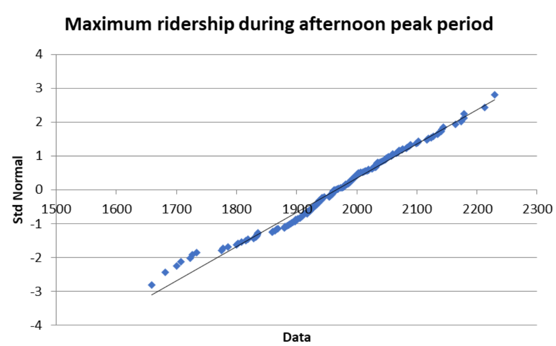


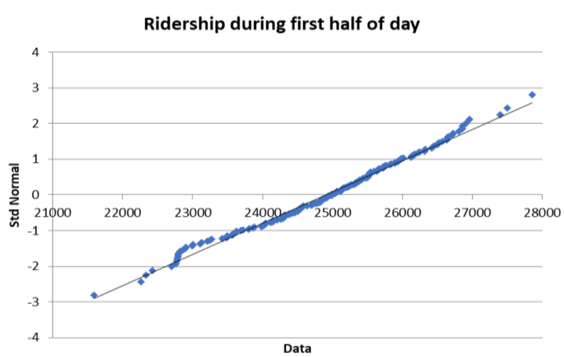


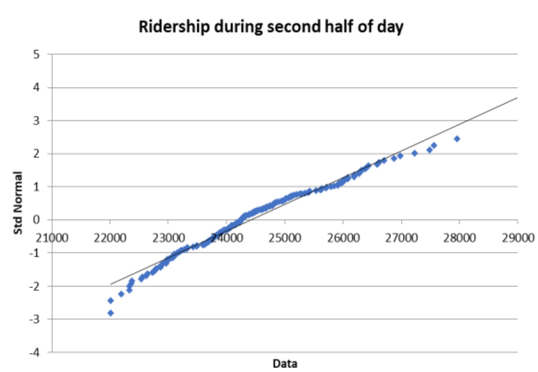












APPENDIX G – F-test for weekday vs weekend variance

Table 21: Results of z-test and f-test for comparison of weekday and weekend ridership

	Daily ridership during weekday	*Daily ridership during weekend*
Mean	49331.36	10145.73
Std. deviation, σ	2072.04	1458.37
Observations	data collected over 205 days	data collected over 103 days
df	204	102
F	2.02	
P(F<=f) one-tail	5.16768E-05	
F Critical one-tail	1.337896347	
Standard deviation	2072.039954	1458.37
Co-efficient of variance	4.20	14.37