

Route Choice Behavior by Time of Day and User Familiarity

Brandon Peij¹, Sanduni Kossinna², Jason Chia³ and Dr Jinwoo (Brian) Lee⁴

¹Undergraduate Research Assistant, School of Civil Engineering and Built Environment, Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

²Undergraduate Research Assistant, School of Civil Engineering and Built Environment, Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

³PhD Candidate, School of Civil Engineering and Built Environment, Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

⁴Senior Lecturer, School of Civil Engineering and Built Environment, Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

Email for correspondence: Brian.Lee@qut.edu.au

Abstract

The following study examines the route choice behaviours of patrons that result from their experience or perception of the network. It considers behaviours in relation to the time of day, focusing on peak and non-peak periods and a patron's transit use frequency. It is intended that this paper form a preliminary investigation for further route choice modelling. This paper will seek to answer the question of whether transit users are more strategic when it comes to route choice and whether they are flexible depending on the time of day when travelling, and their current location. Through the investigation of patron behaviours with regards to boarding and alighting stops as well as their tendencies for inbound and outbound travel, this question will be explored.

There were three significant concepts found. Firstly, preliminary data analysis found that access to certain bus routes were available via a multitude of different bus stops near each other. Hence, the variability of stops accessed and their dispersion per traveller was investigation. The analysis returned that location appeared to be a greater influence on a patron's route choice, more so than their trip direction.

Secondly, a nearest neighbour index concept was introduced to quantify the utilisation of stops of frequent transit users. From this, it was found that patrons were appearing to value travel time over comfort. Further to this finding, confidence appeared to also be a key attribute to a patron's perception and strategy to travel. Lastly, a correlation analysis was utilised to confirm the findings mentioned. The findings of the paper provided reaffirm concepts presented in previous research as well as contesting some- as the paper is intended as a preliminary investigation, it is certainly recommended that the investigation be applied and modelled within a wider scope of areas.

1. Introduction

In the emerging market of public and active transport, it is essential that urban planners are able to contribute towards the attractiveness of these networks (Liu, Bunker, and Ferreira, 2009). Modelling the attractiveness traits that entice a patron into utilising the network may take many forms, one of which is delving into a patron's route choice. Modelling route choice provides planners to appraise a patron's perceptions of the network, forecast behaviours - which then leads on to predicting future traffic volumes and to understand a patron's reactions to information (Eluru and Chakour, 2012). Route choice not only assesses how well the network currently caters towards the demand but also can act as a basis for future developments. In contrast, Prato (2009) pointed out that modelling human behaviour is multifaceted. Human behaviour is based off experience, perception and preference- factors that are difficult to recreate. In saying this, modelling route choice to its best accuracy is again, essential and is a key resource for transit planners (Liu, Bunker, and Ferreira, 2009).

This paper investigates the route choice behaviours of patrons that derive from their experience of perception of the network. It considers behaviours in relation to the time of day, focusing on peak and non-peak periods, and a patron's transit use frequency. From previous research, it is understood that direct trips are preferred and that users also travel strategically. Thus, it is intended that this paper form a preliminary report for further study into route choice modelling. In hindsight, this paper will seek to answer the question is whether transit users are more strategic when it comes to route choice and whether they are flexible depending on the time of day when travelling.

The paper is organized as follows. Section 2 reflects current literature relevant to the study. It follows previous findings and modelling attempts made by previous professionals. Section 3 details the study area and data utilised for the investigating. It provides a brief background and context into the data that was analysed. This is then followed by a brief methodology of what has been attempted. Section 5 outlines the findings of the analysis, before finally concluding.

2. Literature Review

Considerable research has been conducted into the inter-day variability of travel behaviour, with regards to trip purpose, departure time choice, mode choice, and route choice (Schonfelder and Axhausen, 2010). Research suggests that a traveller's trip purpose is a key variable in travel behaviour. Schonfelder and Axhausen (2010) propose that novelty-seeking in activities is a key contributor to a person's travel behaviour- understandably then departure time and destination choice contribute to the variability of such behaviour over longer periods.

Subsequently, early research observed patterns in the variability of trip-making via longitudinal travel surveys (Hanson and Huff, 1981; Hanson and Huff, 1988; Pas and Sundar, 1995). Later research has sought to measure the effects of various possible influences on non-random travel variability. Mannering and Hamed (1990) conducted research into depart time variability of car trips home from work, reporting that congestion had the largest impact. Bhat and Steed (2002) observed variability of departure time in shopping trips as a result of demographics and trip chaining.

Morency, Trépanier and Agard (2007) analysed smart card data, a source commonly utilised within the field, to investigate the degree of day-to-day variability of public transport patronage. Key observation include that demographics had a significant influence – where students and seniors exhibited higher variability – and that individuals frequently used

different stops, changed their frequency of use of particular stops, varied their time of boarding, and had days when no trips were made. Kurauchi, Schmöcker, Shimamoto, and Hassan (2014) analysed smart card data for buses in London to determine the nature of variability of morning commuter route choice. They observed that a considerable proportion of route choice variability was explained by the degree of overlap between routes, and not the day of the week, providing evidence for the theory that travellers have a 'hyperpath' set of candidate routes. The concept of a hyperpath, borrowed from graph theory, following Nguyen and Pallottino (1988) and Spiess and Florian (1989), has been used to categorise the set of routes that a person is willing to take between a given origin and destination.

A number of studies have examined service quality and usage patterns of public transport systems using smart card data. Jang (2010) identified stations in Seoul with high rates of transfers, high average waiting times, and high overall passenger volumes. Tao, Rohde, and Corcoran (2014) analysed the variability of demand amongst Brisbane bus transport corridors throughout the day and by user class (student, pensioner, adult). A similar analysis of Brisbane bus smart card data revealed differences in daily demand profiles between bus rapid transit (BRT) and non-BRT bus trips, as well as differences in the degree of spatial dispersion (Tao, Corcoran, Mateo-Babiano, and Rohde, 2014). The lack of trip purpose information in smart card data has presented a challenge, but various approaches have been proposed to infer trip purpose from the data. For example, Kusakabe and Asakura (2014) estimated trip purposes based on the time between arrival and departure from a station – considering the prior usage of that station by a given passenger in the longitudinal data set.

A wide range of variables have been used to model the public transport route choice behaviour of passengers. Eluru, Chakour and El-Geneidy (2012) observed the number of transfers, followed by in-vehicle time, walking time, then waiting time, as the variables with the most effect on public transport route choice. Qiao, Zhao, Qin (2013) observed that rail passengers have a preference towards routes with which they are familiar with through prior use. Cominetti and Correa (2001) proposed a model of route choice based on the level of congestion at stops and queuing theory. Bouzaïene-Ayari, Gendreau and Nguyen (2001) proposed a model where passengers board the first available bus with spare capacity serving their destination.

Grison Gyselinck, and Burkhardt (2016) explored into the concept of a user profile. A user profile as defined within their paper is the combination of a user's attitude towards the network and their demographic factors. Using this *user profile* as an impact factor on route choice, a macro-level analysis of the factors that may attribute towards route was conducted. This study concluded in three distinct user profiles based off the analysis of a questionnaire that was omitted to public transport users within France. The following list outlines the three profiles found;

- Flexible route choice users – these users travel dependent on efficiency. Attributing factors to this include time and even spontaneity.
- Unimodal and single route users – these users encompass people whom utilise public transport for both utility and efficiency. Often, they are not interested in deviating from their known routes as it caters to factors important to their travel purpose, such as time, reliability or costs.
- Multimodal and single route users – similar to the unimodal users, these patrons are again, motivated by utility and efficiency and prefer a familiar route as it is reliable.

(Grison et al., 2016)

The findings discussed above demonstrate that a comprehensive perception of the network is a contributing factor towards route choice. In fact, the questionnaire suggested that long-time and dependent users of a particular route were not interested in alternating from an

already reliable route (Grison et al., 2016). This poses the question then, of what further attributing factors control this and if there are ways to improve networks to make them more attractive to users.

A paper by Nassir, Hickman, and Ma (2015) discusses how certain boarding behaviours can be attributed to frequency, categorized in to two aspects; “first bus” and “favourite bus”. Utilising this assumption, they assessed the inference of the two on their study group. It was found that this variable certainly effects route choice and demonstrates that most passengers in fact travel with a strategy already in mind.

Given the above, it is apparent that most researches have analysed trips on a stop-by-stop basis. Van Dyck, Deforche, Cardon, & De Bourdeaudhuij (2009) introduce the concept of a person's travel initiating at the point they leave their door. The following paper explores a gap within a patron's route choice behaviour as it explores the variable of an individual's boarding and alighting stops in repetitious travel, where network and urban measures may affect their choice. This gap in the knowledge regarding bus passenger behaviour means there is an area for improved representation of spatio-temporally variable route choice in transport demand models. This would enable more accurate forecasts of patronage, and allow improved service planning. In this paper, the variability in the use of different bus stops is examined, for three classes of users based on trip frequency, in the morning and evening peak demand periods, and in both directions of travel.

3. Background

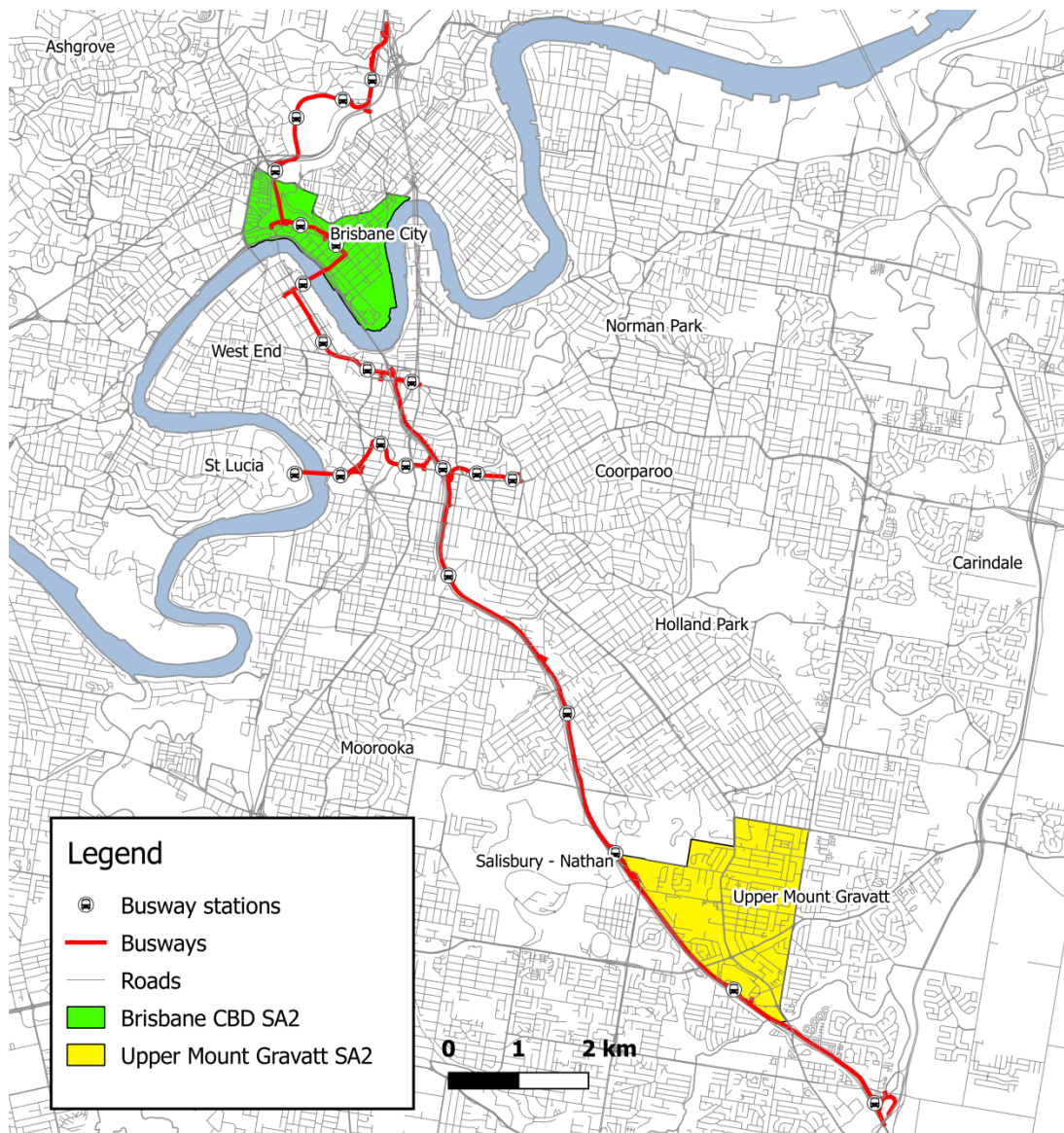
3.1 Study Area

A preliminary investigation was conducted for all the available data to decide the research scope. Data illustrated that between the Statistical Area Level 2 (SA2) of Brisbane City and Upper Mount Gravatt, there were large volumes of trips of all different characteristics. Further to this, the areas had multiple route connections that ran along both the public road network and busways - making for an interesting combination of trip data. Redefining the study area to the two SA2s meant that data was analysed where both the CBD and a major suburban centre were included.

Figure 1 illustrates the location of the two areas in respect to each other and surrounding suburbs of Brisbane. The areas are approximately 12 kilometres apart and have an extensive public road network, as-well-as the South-East Busway connecting them. Furthermore, the chosen areas include residential, commercial, retail and educational land uses.

The corridor along the South-East Busway from the Brisbane Central Business District (CBD) to Upper Mount Gravatt is a major bus travel corridor. On average over the 50 days of data collected, approximately 3,300 people travelled by bus between Upper Mount Gravatt SA2 and the Brisbane CBD SA2 in either direction on the average weekday using direct buses. Journeys are included in the study area if the origin and destination stop are both in either the Upper Mount Gravatt SA2 or the Brisbane CBD SA2. This analysis only investigates direct trips – journeys involving transfers between services have been excluded.

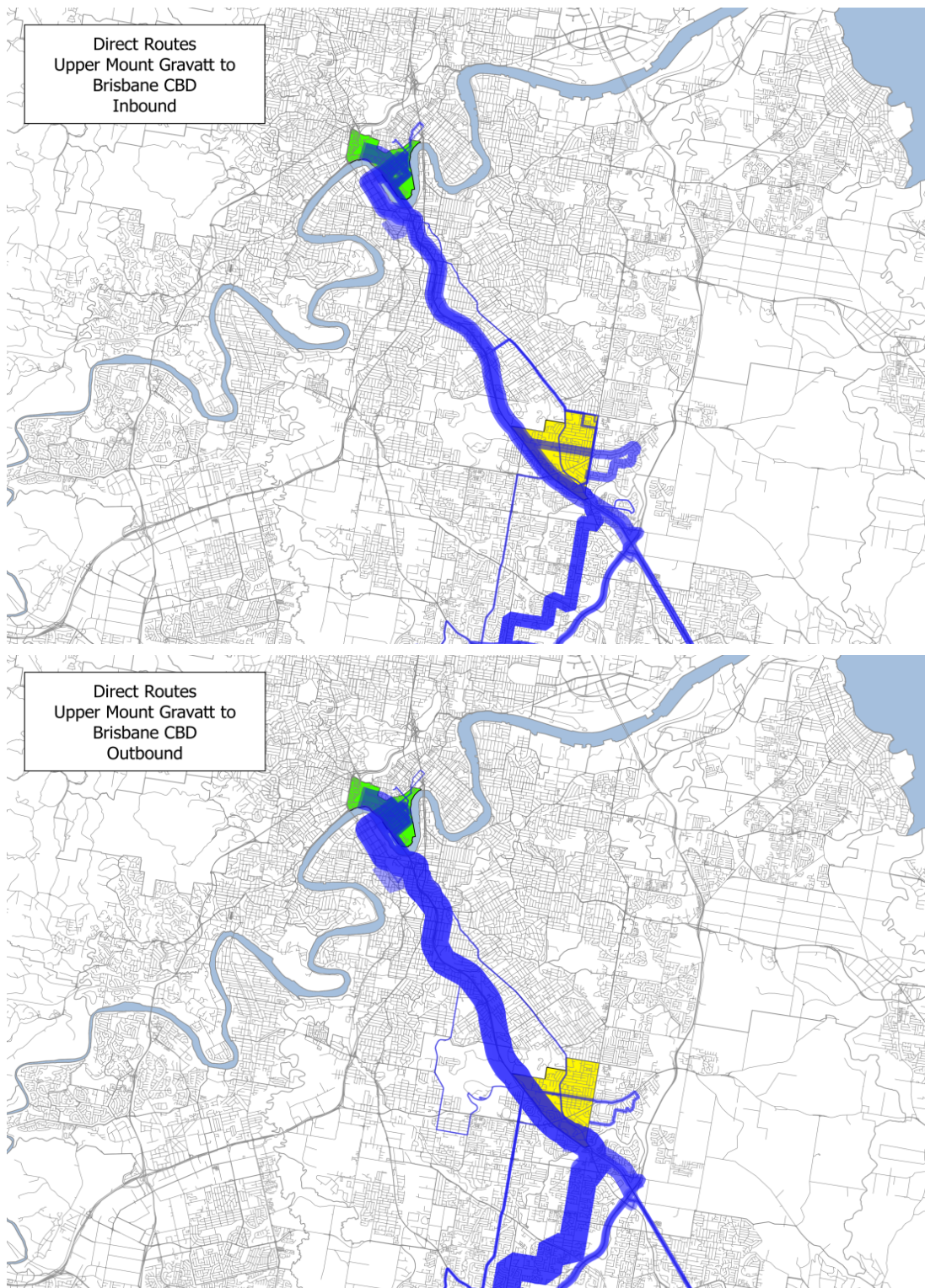
Figure 1: Map outlining the study area



The data set contains 28,691 individual travellers who used direct bus routes between the two areas comprising the study area. Of these travellers, some used up to 14 different routes in the period of seven weeks, and up to 45 trips (sum of direct trips in both directions in the study area) were made by some individuals.

Figure 2 as follows displays the primary route options that passengers travelling between these two areas have used often in the 50-day period. The maps display the direct routes used for inbound and outbound travel between Upper Mount Gravatt and the Brisbane CBD. Routes are scaled in width by the total number of passengers using each over the two months' data collection period. Clearly, the routes using the busway dominate the travel options taken by passengers. There were 61,947 inbound trips and 72,434 outbound trips after erroneous data were removed. Notably, there were 17% more outbound trips than inbound trips in total. This difference appears to be relatively consistent over the whole period, as displayed in the longitudinal breakdown of route share in Figure 4.

Figure 2: Inbound and outbound direct routes scaled by the number of passengers



3.2 Intra-day Variability

Figure 3 as follows displays the variability in boarding by direction over the course of 24 hours. These graphs are based on the total passenger volumes boarding each route by hour, over the 50 days of data.

Figure 3: Breakdown of routes used by time of day for inbound and outbound travel

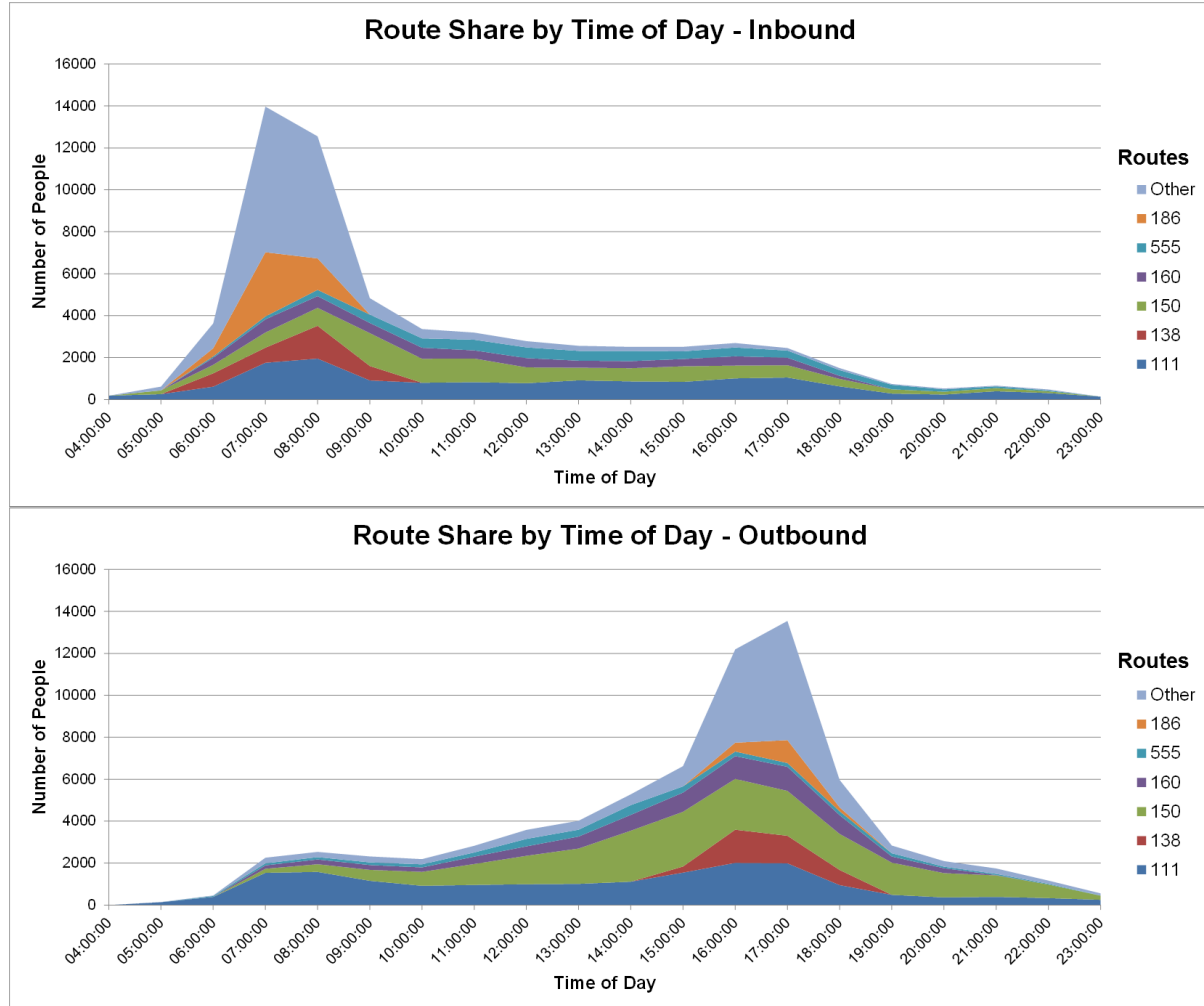
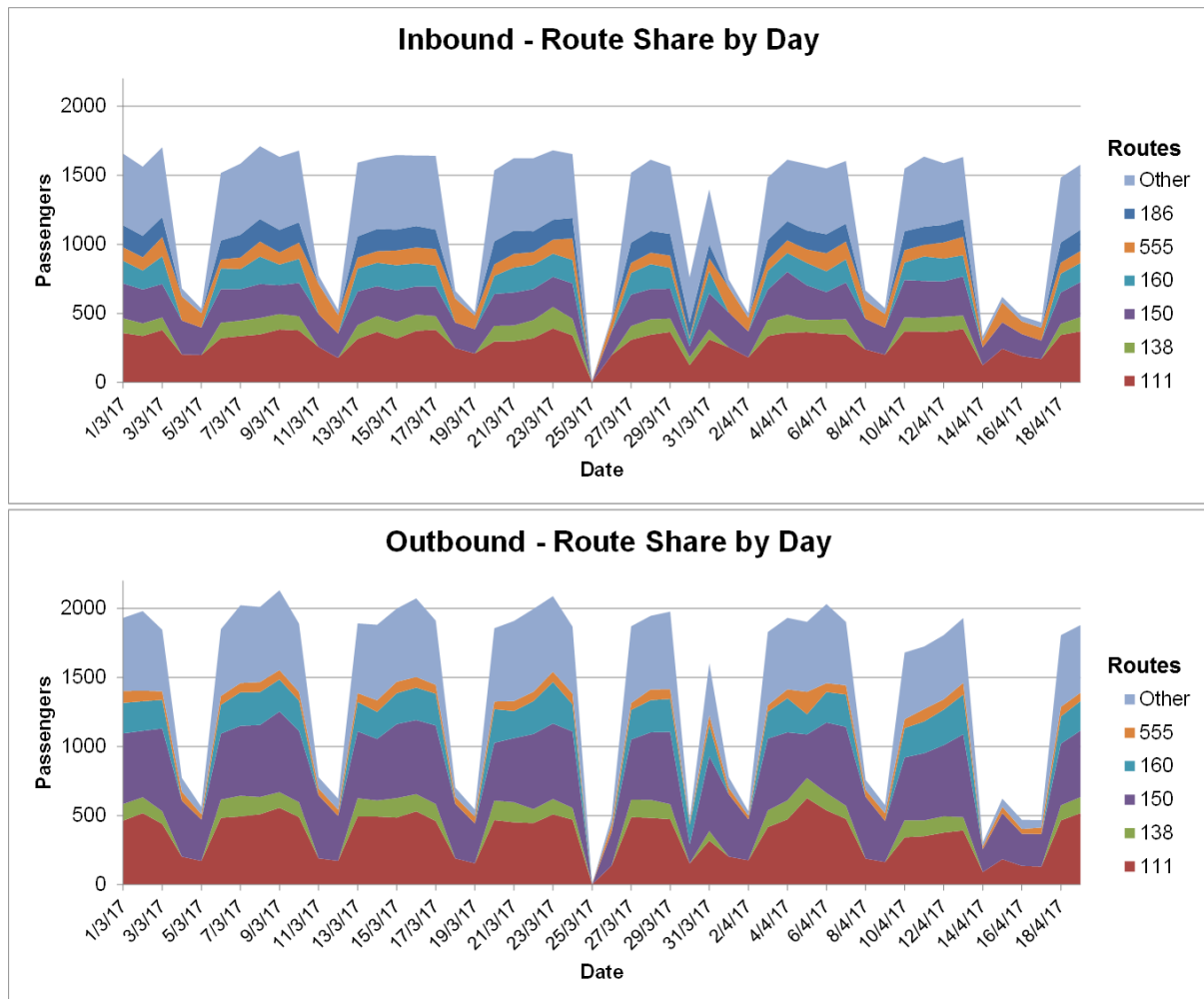


Figure 3 shows that the routes with the largest number of passengers in the 6-10am period in the inbound to the Brisbane CBD direction are the routes following the busway, as shown in Figure 2. This is as to be expected, given that the high frequencies and fast travel times along the busway are attractive to passengers compared to infrequent, slower, less direct routes.

3.3 Longitudinal Variability

Figure 4 as follows displays the number of passengers for each day, by direction, broken down into the major routes used. The inbound and outbound route share and total patronage appear relatively consistent over the 50 day period covered by the data. The clear pattern of weekday versus weekend is evident. Note that patronage was recorded as zero on the 25th of March due to a free travel day for sporting events, and patronage was abnormally low on the Thursday the 30th and Friday the 31st of March due to the severe weather caused by Cyclone Debbie.

Figure 4: Longitudinal breakdown of route share



4. Methodology

First, the *go* card data was cleaned and pre-processed such that only direct trips between the two areas of interest were included. Cleaning involved removing entries that did not have a boarding or alighting stop in the study area and removing entries where the direction of travel provided did not correspond with the boarding and alighting stops recorded.

The number of trips each cardholder made in each direction, by time period, the number of different routes used, and the number of different boarding and alighting stops used was calculated using SQL, and appended to each database entry for each cardholder. Route passenger volumes were calculated and joined to GIS polylines created from the General Transit Feed Specification (GTFS) route geometry data, in order to visualise route volumes using QGIS. The boarding and alighting stop used for each trip was geocoded as a distinct point object, in a layer corresponding to the direction of travel, time period, user frequency class, and boarding or alighting. These layers of disaggregate points were used for nearest neighbour analysis. Aggregated stop layers, where one point object represents each bus stop, were created using the total number of passengers using each stop for the specified direction, time, and boarding/alighting. These were used to create point-pattern maps where the size of the stop points corresponds to the passenger volume.

Figure 5 as follows displays the total number of passengers using each stop to board or alight, in all time periods, in each direction. The size of the stops indicates the number of people using each stop in that direction for boarding (in blue) or alighting (in orange).

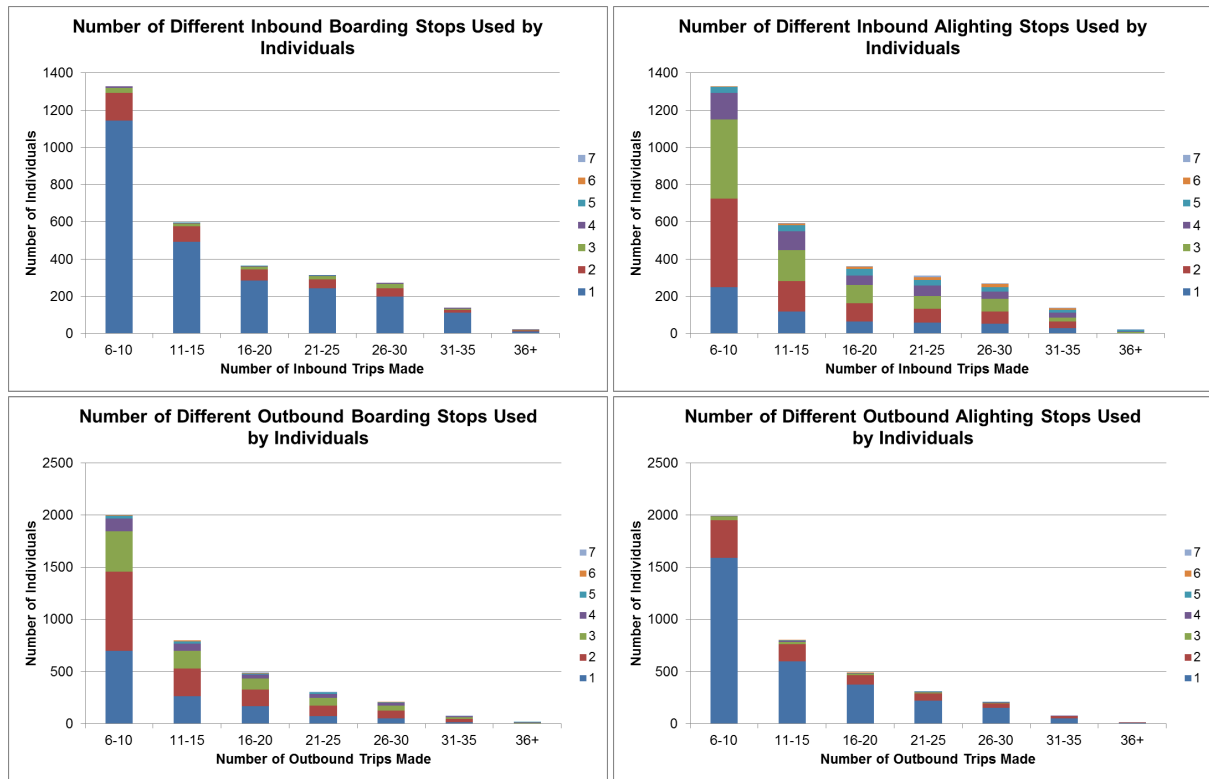
Figure 5: Boarding and alighting bus stops for inbound and outbound trips



5. Results and Discussion

In order to determine if there is systematic variability in the choice of boarding or alighting stop, the number of stops used by each individual for boarding and alighting was examined. Individual passengers were classified into user frequency classes based on the number of trips they had made in either the inbound or the outbound direction over the data collection period. Figure 6 displays the distribution of individual passengers with regards to the number of different boarding or alighting stops used in each direction of travel, broken down by the number of trips each individual had made in that direction overall.

Figure 6: Boarding and alighting stop use variability by direction

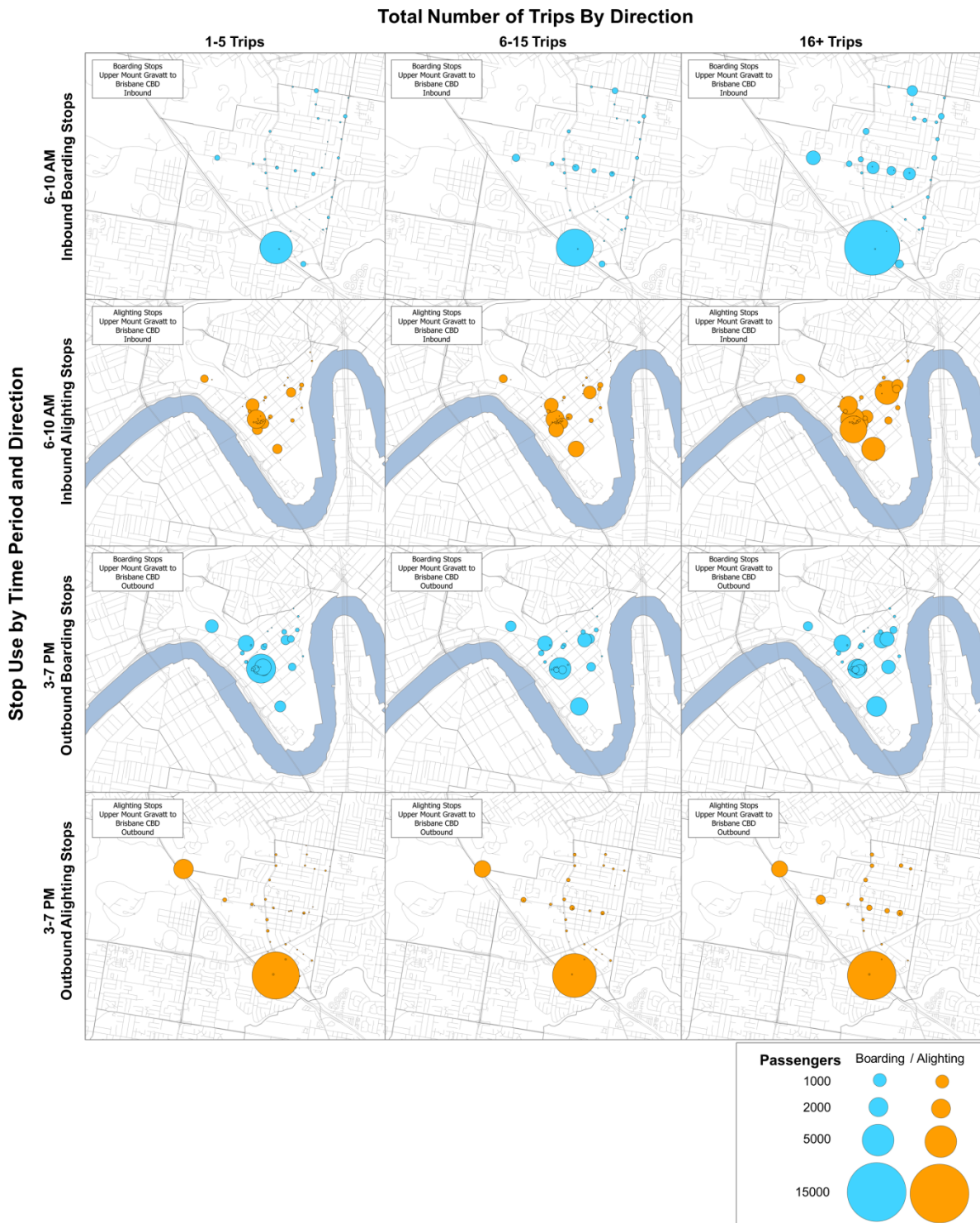


The graphs in Figure 6 show a clear pattern, where the number of different stops used by more frequent bus users is significantly higher. This pattern is even more significant for outbound boarding stops (boarding in CBD) and inbound alighting stops (alighting in CBD). These situations suggest that more frequent bus users (or regular bus users) are more willing to board and alight at different bus stops in the CBD, compared to in Upper Mount Gravatt – denoting that location of the stop may be a great influence on route choice as oppose to the person's direction of travel. From a preliminary study, it was evident that many trip transactions were happening in a few key locations within the Upper Mount Gravatt area (e.g. Garden City Shopping Centre Interchange and Upper Mount Gravatt Bus Station). It is in saying that, that it is understandable the data does not show a vast number of stations being utilised as a result.

Further to this, the spatial dispersion of the stops used by travellers was mapped in a GIS as described in the methodology. These were to assist in determining if there was a difference between the morning and evening peak, inbound and outbound, boarding and alighting spatial dispersion of bus stops used, for different classes of users based on frequency of use, based on Grison et al. (2016). Maps are shown for the peak direction of travel only. The

most notable visual observations are the higher levels of dispersion of stop use amongst travellers who made 16 or more trips in that direction compared to less frequent users. This, to-a-degree, indicates the confidence of frequent travellers using the network.

Figure 7: Stop use by time period, direction, boarding/alighting, and user class



Subsequently, the nearest neighbour index was calculated for each map, using disaggregate stop point layers, where a distinct stop object exists for each passenger-trip boarding stop

and alighting stop. The nearest neighbour index is the distance from each point to the closest neighbouring point, averaged for all points, and divided by the expected mean distance based on random distribution of points (Clark and Evans, 1954).

Table 1 displays the results. As the nearest neighbour index is the observed mean distance divided by the expected mean distance between points, the absolute values of the ratios are not meaningful for comparison between scenarios – the relative difference between different ratios is. Therefore, the results in Table 1 are expressed as ratios of the nearest neighbour index of the boarding stops in the morning peak inbound direction.

Table 1: Nearest neighbour index ratios with respect to inbound 6-10am boarding dispersion

Direction	Time	Number of Trips					
		Boarding			Alighting		
		<6	6-15	>15	<6	6-15	>15
Inbound	6-10am	0.00	1.00	0.72	5.00	4.13	0.84
	3-7pm	2.88	10.27	8.15	3.51	7.76	18.17
Outbound	6-10am	1.65	11.54	6.39	12.67	15.12	13.16
	3-7pm	0.91	0.69	0.32	0.65	2.12	1.86

Table 1 shows that the nearest neighbour ratios for counter-peak travel (afternoon inbound and morning outbound) are significantly higher than those for the peak travel direction. With the nearest neighbour ratio being a representation of the level of dispersion of the bus stops it can be summarised that in the peak direction during the peak period, frequent travellers weigh up heavily the effort it may take to utilise a different stop each morning. In agreeance, with this it was found in a preliminary analysis that passengers were choosing to utilise crowded buses during peak periods. For example, route 150, illustrated as the most popular route in Figure 3 was also the busiest in the peak period whilst still yielding, on-average, a shorter travel time in comparison to other popular routes. Concluding, that transit patrons are willing to sacrifice comfort for a time and effort efficient trip.

A correlation analysis was also performed to determine whether a relationship between the numbers of trips individual travellers made, and the number of different stops they used in a given time period. Table 2 shows the results, which indicate that there are fairly strong correlations present between the numbers of trips made in a period and the number of different stops used in that *same* time period. The diagonal green bands from the upper left to lower right for both boarding and alighting display this pattern. Note that for every cell in the table, the correlation is between the number of trips and the number of stops used *by the same individual* for the time periods and directions in question.

Intuitively, it can be expected that the number of bus stops used by an individual will increase as the number of trips they make increases – simply due to the fact that it is possible for them to use additional stops. If, however, the act of using a different stop was entirely random, the correlation would be uniform between the various time periods and directions. This is not the case, as Table 2 shows. The correlation between outbound boarding trips and outbound boarding stops where both are morning, or both evening, is much stronger than that for the corresponding inbound data. Furthermore, the inbound

alighting stops and the numbers of inbound trips (where both are morning, or both evening) correlate to a much higher degree than the corresponding outbound data. These higher correlation values are all for travel into, or out from, the Brisbane CBD.

Higher correlation between the number of trips and the number of stops used in a given direction for the Brisbane CBD as opposed to Upper Mount Gravatt indicates that travellers are more willing to board or alight at a different stop in the CBD than in Upper Mount Gravatt. This could be related to the increased walkability of the CBD, and higher population and employment densities in the CBD.

Table 2: Correlation analysis summary for the number of trips and the number of stops used

Correlation				Number of Trips			
				Outbound		Inbound	
				6-10 AM	3-7 PM	6-10 AM	3-7 PM
Number of Stops Used	Boarding	Outbound	6-10 AM	0.345	-0.111	-0.075	0.046
			3-7 PM	-0.105	0.478	0.312	0.073
		Inbound	6-10 AM	-0.045	0.100	0.285	-0.050
			3-7 PM	0.025	0.006	0.046	0.154
	Alighting	Outbound	6-10 AM	0.168	-0.052	-0.058	0.041
			3-7 PM	-0.070	0.278	0.208	0.040
		Inbound	6-10 AM	-0.082	0.352	0.560	-0.054
			3-7 PM	0.317	0.053	-0.037	0.566

Table 3 as follows shows the correlation results for the total number of trips in each direction. Similar to in Table 2, there is a much stronger correlation between outbound boarding stops and outbound trips than for inbound boarding stops and inbound trips, and between inbound alighting stops and inbound trips than for outbound alighting stops and outbound trips.

Table 3: Correlation analysis results summary for all travel

Correlation - 24 hours			Number of Trips	
			Outbound	Inbound
Number of Stops Used	Boarding	Outbound	0.523	0.396
		Inbound	0.169	0.304
	Alighting	Outbound	0.287	0.242
		Inbound	0.513	0.613

6. Conclusion

The investigation focused on delving into the route choice behaviours of patrons that derive from their perception of a public bus transit network. The scope of the data utilised for this paper was between two areas within Brisbane; Upper Mount Gravatt and Brisbane CBD. This paper forms as a preliminary study for further route choice modelling.

Previous literature had determined that route-related variables such as travel time, bus frequency and location were all contributing factors towards the attractiveness of a route. To examine these factors further, patterns of a data set were quantified. Firstly, the variability of boarding and alighting stops use depending on the travel direction was analysed. The data depicted that transit users were utilising more stops, regardless of direction, within Brisbane CBD than in Upper Mount Gravatt. Hence, the data suggested that more than travel direction itself, location was a greater influencer on route choice variability. In future, analysis of non-peak periods as well as a variety of study areas with varying land uses would be valuable, in order to determine if this relationship is typical.

The second concept in this paper is the quantification of dispersion of bus stops used. The findings of the nearest neighbour index analysis were in agreement with previous research that theorises that travellers value directness and limited walking distances. However the variability in boarding and alighting stops used in the CBD compared to the suburban centre has yet to be incorporated into models of route choice.

Lastly, the correlation summary presented a final indicator of the findings of the first concept; where, it is thought that location is in fact a greater factor contributing to a person's route choice than the direction or time of travel. It was stated previously that there was a stronger correlation between boarding stops and trips, which also suggests that on the outbound trip passengers are more strategic.

In conclusion, the paper provides an initial foundation for further analysis and modelling work. The findings propose a new factor affecting of passenger route choice behavioural variability, namely the willingness to use a greater number of different bus stops in a given area than another area, possibly related to the walkability. All in all, the paper can contribute to the design considerations of future public transport network design, in the area of walkability analysis of public transport catchments. It is recommended that to investigate such in future, the investigation of stop use variability be looked at in a wider scope of areas all across the city - where the significance of the number of stops utilised and dispersion can be modelled to understand the effects on route choice.

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