Australasian Transport Research Forum 2013 Proceedings
2 – 4 October 2013, Brisbane, Australia
Publication website: http://www.patrec.org/atrf.aspx

Modelling Busway Station Dwell Time Using Smart Cards

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Abstract

Dwell time at the busway station has a significant effect on bus capacity and delay. Dwell time has conventionally been estimated using models developed on the basis of field survey data. However field survey is resource and cost intensive, so dwell time estimation based on limited observations can be somewhat inaccurate.

Most public transport systems are now equipped with Automatic Passenger Count (APC) and/or Automatic Fare Collection (AFC) systems. AFC in particular reduces on-board ticketing time, driver's work load and ultimately reduces bus dwell time. AFC systems can record all passenger transactions providing transit agencies with access to vast quantities of data.

AFC data provides transaction timestamps, however this information differs from dwell time because passengers may tag on or tag off at times other than when doors open and close. This research effort contended that models could be developed to reliably estimate dwell time distributions when measured distributions of transaction times are known. Development of the models required calibration and validation using field survey data of actual dwell times, and an appreciation of another component of transaction time being bus time in queue. This research develops models for a peak period and off peak period at a busway station on the South East Busway (SEB) in Brisbane, Australia.

1. Introduction

Smart card fare collection system is a mode of Automatic Fare Collection (AFC) where it has overtaken other fare collection systems such as magnetic strip and paper tickets due to its reliability to both transit passengers and operators. Smart card transaction data gives the opportunity to find transaction time at particular bus stop for specific buses individually (Sun and Xu, 2012).

South East Queensland's (SEQ) transit agency, TransLink Division, introduced a touch contact smart card called 'go card' in 2009 (Jaiswal et al., 2007). According to TransLink, more than 80 percent of public transport trips are now made using go card (2011).

The use of smart card reduces the vehicle stopping time significantly. According to TransLink, smart card use reduces individual boarding time from upwards of 11s to 3s, which translates to a time saving of up to seven minutes on an average bus trip (Translink, 2011). The other advantage with smart card is richness of transaction data. This provides much larger volumes of personal travel data than it is possible to obtain from other data sources. In addition to that smart transaction data give access to continuous trip data covering longer period of time which is not possible to reach with existing methods (Bagchi and White, 2005). Therefore, TransLink's South East Busway (SEB) has been selected to conduct this research.

Dwell time at stops is understood to be an important component, which can impact on travel time in transit systems and particularly on bus operations (Milkovits, 2008). The dwell time is the time that a transit vehicle spends at a station or stop while passengers board and alight. Although dwell time is highly correlated with passenger boarding and alighting, dwell time differs with stop characteristics such as platform height, door width, fare collection method, internal layout of vehicles, occupancy of vehicles, etc (TRB, 2003a).

The objective of this paper is to develop a model to estimate dwell time using smart card data calibrated using observed dwell time measurements.

2. Literature Review

Earlier research on dwell time is mainly focused on manually collected data and used to find the impact of fare type, boarding and alighting passengers, crowding, and vehicle configuration. Levinson (1983) found that dwell time is equal to 5s plus 2.75s per boarding or alighting passenger in a no-fare bus system until passengers exceed the seating capacity, at which point the service time increases (Levinson, 1983). Guenthner and Sinha (1983) found a 10s to 20s penalty for each stop plus a 3s to 5s penalty for each passenger boarding or alighting (Guenthner and Sinha, 1983). However most of early dwell time models were developed by using limited samples. Another dwell time model was proposed by Puong in 2000, showing linear effects in passenger boarding and alighting but with nonlinear effects in the on-vehicle crowding level (Puong, 2000).

Later, the *Transit Capacity and Quality of Service Manual 2003* (TCQSM 2003) highlighted that dwell time is an important measure in capacity and service planning. TCQSM 2003 gave a standard value for dwell time calculation with passenger service times of 3.5s with smartcards and 4.2s with magnetic stripe tickets (TRB, 2003a). In addition to that, crowded situations and bus type differences are accounted by adding or subtracting 0.5s to or from each service time.

Jaiswal et al. introduced time lost into the dwell time model (Jaiswal et al., 2009). The time lost by the bus is a loading area specific parameter and is included to account for the requirement that the passenger walk along a lengthy Bus Rapid Transit (BRT) station platform to reach the bus entry door. The differences between boarding and alighting times at three loading areas at one station were analyzed in their research. They have come up with following conclusions: a) passenger per boarding time was 5.9s: b) the least time lost resulted from the mid-loading (the second) area, while the greatest time lost resulted from loading at the third area: and C) 85% of the time lost calculated for each of the three loading areas was 7.2s, 4.5s, and 8.7s (Jaiswal et al., 2009, Jaiswal et al., 2010).

More recently, bus dwell time analysis was carried out using on-board video by Fricker, and he developed a linear relationship for the dwell time as number of standees of the bus, number of passengers alight from front door and number of boarding passengers (Fricker, 2011). However their forecast does not include a value for number of passengers alight from front door. Li et al. (2012) introduced dwell time estimation models for BRT stations using traditional survey method (Li et al., 2012). They found that dwell time follows a logarithmic normal distribution with a mean of 2.56 and a variance of 0.53. However, conducting a long survey to see the dwell time distribution can be time consuming and costly.

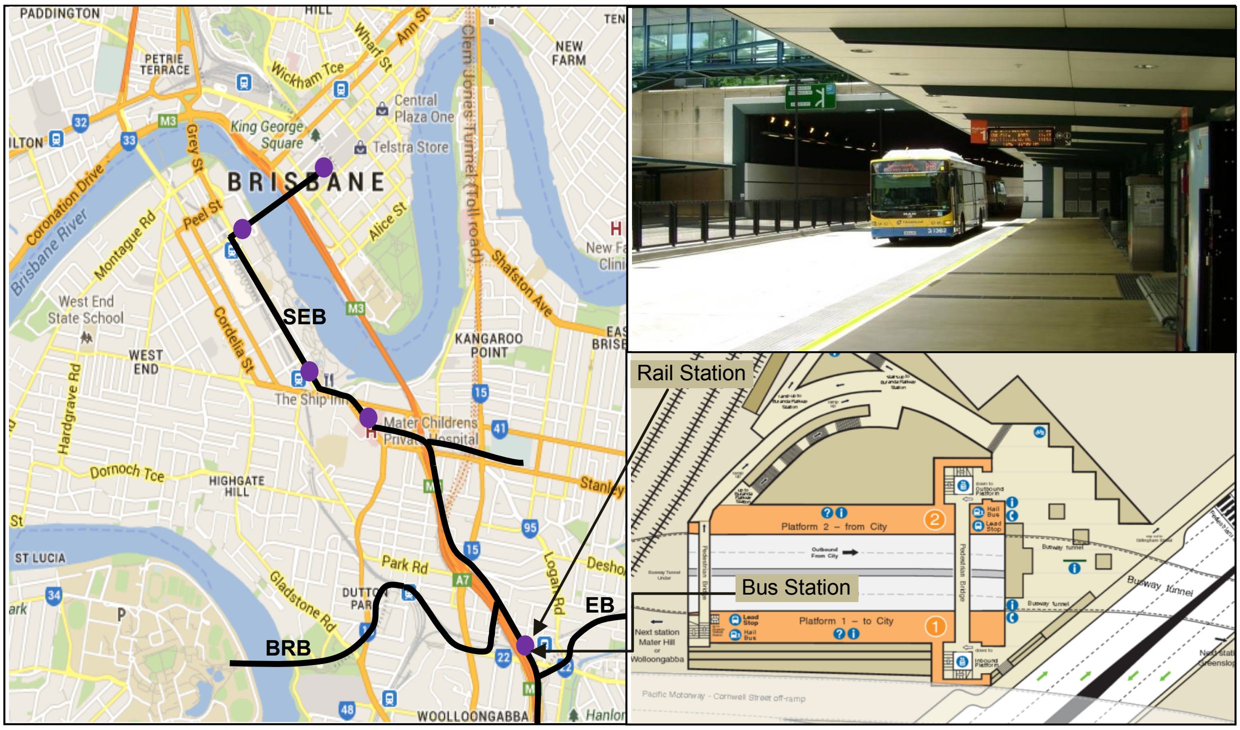
Even though there are some good dwell time models found in the literature, they have limited applicability. Therefore a simple and robust model to estimate dwell time is required. This specific research is designed to develop a dwell time estimation model from smart card data. Structure of the paper starts with busway station selection for the study them followed by methodology, data investigation, dwell time model development, model validation and finally the conclusion.

3. Study Station Selection

Buranda station on the SEB is selected for this study. Buranda experiences high passenger exchange and some bus queuing on the inbound platform during the morning peak period and outbound platform during the evening peak period. Therefore it is perfectly suitable to develop a dwell time model.

Buranda is the fourth of 10 stations along the 16km South East Busway (SEB) and is 4.4km south of the Brisbane CBD Queen Street Bus Station and situated just outside of the inner busway stations (Bitzios et al., 2009). It has one platform in each direction, and on each platform three off-line linear loading areas and a passing lane. With a suburban railway station situated on ground level above, Buranda is an important bus/rail interchange (Figure 1). Furthermore, it is a junction station between the north-south SEB, the 4km Boggo Road Busway (BRB) which connects to the SEB via a signalized T intersection to the north, and the 1.0km Eastern Busway (EB) which connects to the SEB via a signalized T intersection to the south. BRB contains four stations with its western terminus station of University of Queensland being one of Brisbane's second most significant transit destinations after the CBD. EB contains two stations and at its eastern end connects to the high volume Old Cleveland Road on-street bus commuter corridor. All buses through Buranda station are managed by TransLink.

Figure 1: Buranda Busway Station Layout



Note: Black line indicates the sections of SEB, EB and BRB and purple dots indicate Queens Street, Cultural Center, South Bank, Mater hill and Buranda station from top to bottom of the figure (source: www.translink.com.au, www.google.com.au)

Although there are three loading areas on the platform, a fourth itinerant loading area is created during peak periods when bus drivers are able to pull into it and dwell using only the front door to serve passengers.

3.1 Bus Operation at Buranda

Buses passing through Buranda station are operated by Brisbane Transport, Logan City Bus Services, Mount Gravatt Transport, Park & Ridge Transport and Veolia Transport under contracts to TransLink. There are three major service patterns in Buranda (FTA, 2008):

- Bus Upgrade Zone (BUZ) high frequency bus services operating at least every 10 minutes during peak periods and at least every 15 minutes during off-peak periods, seven days a week.
- All-stops services, with variable frequencies and spans of service.
- Weekday peak hour, peak direction CBD focused express services that have limited stopping patterns.

3.2 Fare collection systems at Buranda

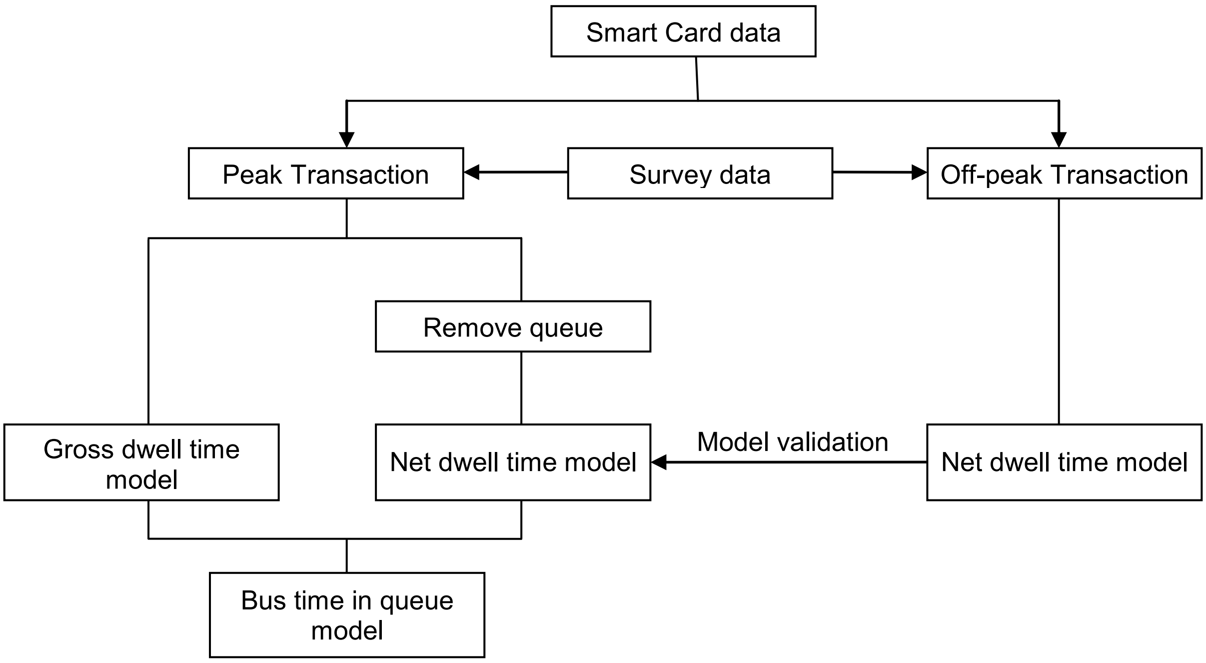
There are two methods of fare collection implemented on the SEB. The most popular amongst passengers is the smart card. Usually, smart card passengers have to tag on using their valid smart card when boarding and tag off when alighting. Each bus is equipped with two smart card readers (two channels) per door. Passengers can alight from either front or rear door but boarding is only permitted through the front door. All fare processing is off-board.

The secondary method of fare collection is by paper transfer ticket. A passenger without a smart card may purchase their paper transfer ticket from the bus driver on boarding, or show the driver a valid paper transfer ticket. They need not show their ticket on alighting. Only a small proportion of passengers still use paper tickets as they are priced at a 30 percent premium over smart card fares. This method is not permitted on prepaid services which are prevalent during peak periods.

4. Methodology

The primary objective of this paper is to develop a dwell time model and bus queuing time model using smart card data. Figure 2 illustrates this process, which includes two phases. The first phase is to develop a gross dwell time model, a net dwell time model and a bus time in queue model, all for a peak time period. The second phase is to develop a net dwell time model for an off-peak time period to validate the peak period net dwell time model.

Figure 2: Research Methodology



5. Data Investigation

Data investigation was carried out in two sections. The first part is to collect field survey data and next section is to extract smart card data for same survey periods.

5.1 Field Surveys

A manual counting method was used to observe bus dwell time characteristics at Buranda. Field surveys were conducted in April 2013 (16/04/13 to 18/04/13). Surveys were conducted for inbound direction from 6:30am to 11:30am. This time slot was selected primarily to account morning peak (6:30am-7:30am) and morning off peak (10:00am-11:00am) periods. A smart phone application was developed to facilitate this survey. Five specific time measurements were made, including: bus arrival time on the available platform loading area, door open time, door close time, departure time and time taken by the bus to clear its own length. In addition, "bus route number", "number of doors (1, 2 or 3 doors)", "vehicle length (12m, 14.5m and 18m)" and "next bus in queue (yes or no)" were recorded. This research subsequently included data only pertaining to two door buses on the basis that over 80 percent of TransLink buses have two doors (2013).

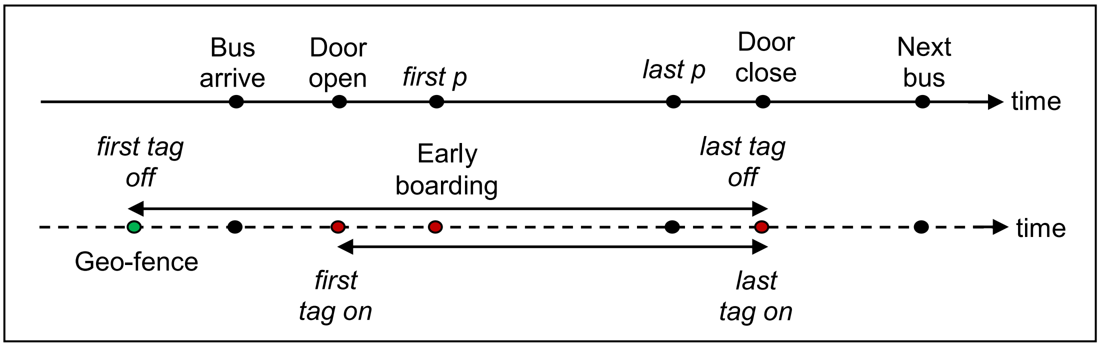
5.2 Smart Card Data Extraction

Raw smart card transaction data from 16/04/13 to 18/04/13 were filtered in order to remove unwanted detail and determine transaction times. A Mat Lab code was developed to calculate the transaction time for a bus at the stop, being equal to the last passenger's (board or alight) transaction timestamp minus the first passenger's (board or alight) transaction timestamp. The transaction times were scrutinised to eliminate any erroneous transaction times.

6. Smart Card Based Dwell Time Models

Figure 3 illustrates the general timeline of a bus observing a busway station. The straight line indicates the timeline of actual passenger exchange while the dashed line shows the timeline of smart card transaction under one particular scenario.

Figure 3: Normal passenger operation and smart card transaction at busway station



Note: *first p* represents the first passenger board or alight while *last p* represents the last passenger board or alight

Once a bus arrives on the platform to serve passengers, the driver opens the door. Sometimes passengers can move very close to the approaching bus door and board early up to 1s after door opening. Tag on activity can occur between door open and door close times. Tag off activity differs. When the bus reaches the geo-fence (which is 50m upstream of the busway station), the on-board smart card reader becomes activated for transactions. As a result, passengers can tag off between the time when the bus reaches the geo-fence and the door close time Figure 3. This study has identified 16 combinations of transaction activity as a consequence of four tag-on and four tag-off scenarios (Table 1).

Table 1: Smart Card Transaction Scenarios

Tag off scenario	Tag on Scenario			
	B1 commenced early and concluded early (within 1s of door opening)	B2 commenced late (after 1s of door opening)	B3 commenced early and concluded late	B4 none occurred
A1 commenced and concluded before bus door opened	B1A1	B2A1	B3A1	B4A1
A2 commenced after bus door opened and concluded before bus door closed	B1A2	B2A2	B3A2	B4A2
A3 commenced before bus door opened and concluded before bus door closed	B1A3	B2A3	B3A3	B4A3
A4 none occurred	B1A4	B2A4	B3A4	B4A4

For instance, B3A1 represents: Tag on has commenced early and concluded late, where as tag off has commenced and concluded before bus door opens.

6.1 Peak Period Dwell Time Model Development

The initial objective is to develop a gross dwell time model for peak period. The gross dwell time model includes cases where buses spend time in queue before reaching an available loading area. Smart card transaction times were obtained and for each bus classified to 16 cases mentioned in Table 1. Survey dwell time information, being the time difference between door close timestamp and door open timestamp (TRB, 2003b), was cross-matched with the smart card transaction times for each bus. Figure 4 shows the smart card transaction times and cross-matched dwell times measured during surveys.

Figure 4: Peak period gross smart card transaction versus survey dwell time relationship

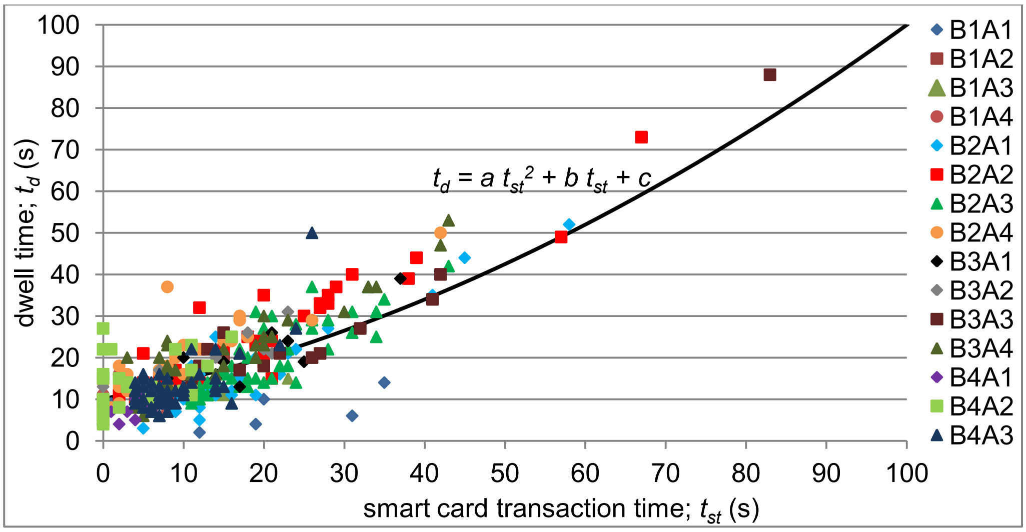


Figure 4 shows that smart card transaction time does not correspond precisely to survey dwell time. One key reason for this is that smart card transaction could over or under estimate than dwell time due to early tag off after the bus enters the geo-fence but before it stops to dwell on the available loading area. This may be exacerbated if the bus needs to wait in queue to enter an available loading area. A second key reason is that a single transaction results in a zero transaction time while a small number of transactions, such as a couple of tag off transactions in rapid succession, may result in very small transaction times. The actual dwell times would still be expected to be larger due to the door opening and closing time plus the physical processing time per passenger through the door(s). Thus, a positive Y axis intercept on Figure 4 is to be expected, as a measure of average minimum dwell time. By inspection of the data of Figure 4 a nonlinear polynomial equation of the form of Equation 1 was determined to be most suitable for this peak period gross dwell time model:

$$\boldsymbol{t_d = a\, t_{st}^2 + b\, t_{st} + c} \qquad \textbf{\textit{Equation 1}}$$

Where;

t_d = dwell time; (s)

t_{st} = smart card transaction time; (s)

a, b, c = curve fitting constants; (s)

Note that constant c in Equation 1 represents the Y axis intercept, in this case an average minimum dwell time.

In order to determine suitable values of the curve fitting constants in Equation 1, it was necessary to reiterate the purpose of the model of Equation 1, which is to provide the best estimate of dwell time for a given smart card transaction time. More generally, we wish to provide the best estimate of the distribution of dwell times given a distribution of smart card transaction times. Our earlier research has shown that dwell time tends to be distributed log-normally (Widanapathiranage et al., 2013); which was also presumed here for model development.

Two objectives were therefore established to determine values of curve fitting constants in Equation 1 that provide the best estimates of (*I*) average measured dwell time and coefficient of variation of measured dwell time, and (*II*) average of the logarithms of measured dwell time and coefficient of variation of the logarithms measured dwell time for distribution shape. Numerical optimisation was applied to achieve both of the following objective functions together:

$$\boldsymbol{Obj\ I\ (a,b,c) = min\left(\left(\bar{t}_{d|meas} - \bar{t}_{d|est}\right)^2 + \left(cv(t_{d|meas}) - cv(t_{d|est})\right)^2\right)} \qquad \textbf{\textit{Equation 2}}$$

$$\boldsymbol{Obj\ II(a,b,c) = min\left(\left(\overline{ln(t_{d|meas})} - \overline{ln(t_{d|est})}\right)^2 + \left(cv\left(ln(t_{d|meas})\right) - cv\left(ln(t_{d|est})\right)\right)^2\right)}$$

Equation 3

Where:

$\bar{t}_{d|meas}$ = average measured dwell time; (s)

$\bar{t}_{d|est}$ = average estimated dwell time; (s)

$cv(t_{d|meas})$ = coefficient of variation of measured dwell time; (s)

$cv(t_{d|est})$ = coefficient of variation of measured dwell time; (s)

The results of the numerical optimisation for the peak period gross dwell time model are provided in Table 2.

Table 2: Peak period gross dwell time estimation using numerical optimisation

$\bar{t}_{d\|est}$	$cv(t_{d\|est})$	a	b	c	$Obj\ I\ (a,b,c)$	$Obj\ II\ (a,b,c)$	R^2 on t_d
16.9s	0.62	0.0016	0.7665	5.7	1.19x10^{-6}	9.66x10^{-6}	0.58

Table 2 shows that for the values of curve fitting constants determined, objective functions are practically zero. Under objective function (*I*) there is negligible difference between average measured dwell time and average estimated dwell time, and negligible difference between coefficient of variation of measured dwell time and coefficient of variation of estimated dwell time. These are both important quantities in transit capacity and quality of service analysis (TRB, 2003b).

Figure 4 includes Equation 1 with the values of the curve fitting constants from Table 2. It can be seen that the second order polynomial fits the data very well.

Figure 5 illustrates the cumulative distributions of both measured dwell time, and estimated dwell time using Equation 1 and the constants from Table 2. By visual inspection, for dwell times larger than 10s, the estimated distribution aligns with the measured distribution very closely as is ensured by objective function (*II*). For small dwell times less than 10s, the estimated dwell time distribution differs from the measured distribution due to the average minimum dwell time of 5.7s. Traditional capacity analysis relies on average dwell time while QoS analysis relies on coefficient of variation of dwell time, so this difference is not critical for these purposes. However, should future study require the dwell time distribution for purposes such as microscopic simulation, the model should be further scrutinised in this small dwell time range.

The Kolmogorov-Smirnov statistic for the two distributions of Figure 5 was determined to be equal to 0.075, which is less than the critical value of 0.093 for a 5 percent confidence level. Thus, the null hypothesis that the samples are drawn from the same distribution was not rejected

Figure 5: Peak period gross cumulative distributions of measured dwell time and estimated dwell time using Equation 1 and Table 2 constants

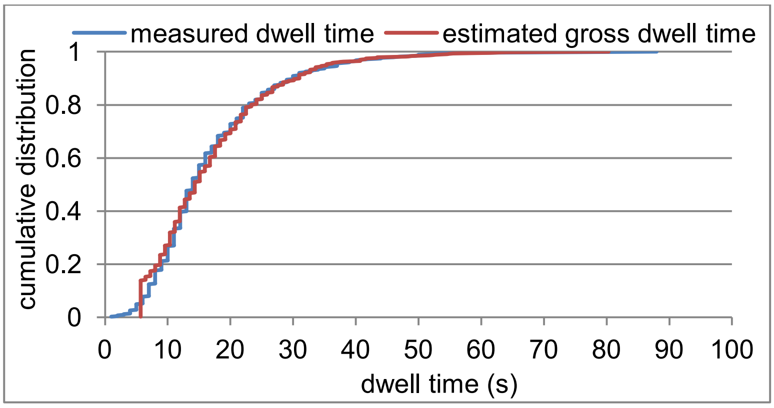
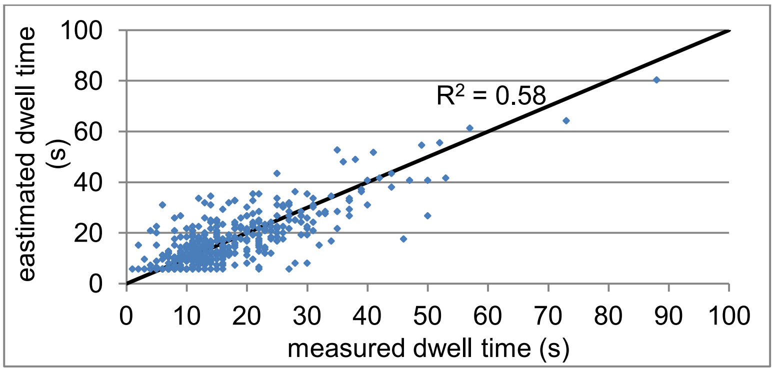


Figure 6 illustrates each peak period measured dwell times versus dwell time estimated using Equation 1 with Table 2 constants for the matching gross transaction time. While spread is evident, the R^2 was determined on a line of equality comparison to be equal to 0.58, indicating that this estimation method can provide for a particular bus a reasonable estimate of its actual dwell time if its gross transaction time is known.

Figure 6: Peak period measured dwell time versus estimated dwell time using Equation 1 and Table 2 constants



6.2 Peak Period Net Dwell Time Model Development

While Equation 1 calibrated using the constants of Table 2 is useful for gross conditions, the data needed to be further investigated to establish a dwell time model net of any effect of bus time in queue.

The on-board smart card transaction readers are activated once a bus reaches the geo-fence. Therefore a passenger can touch their 'go' card any time from the geo-fence arrival.

Any transactions under Tag off scenario **(A1)** and Tag off scenarios **(A3)** may overestimate the transaction time more than dwell time (Figure 3 and Table 1).

Some significantly larger transaction times than actual dwell times were observed during the peak analysis period. It was reasoned that on these occasions the bus must be in queue awaiting an available loading area. A threshold time needed to be established for identification of these occasions. With the distance between busway station and geo-fence being 50m and for an unimpeded, comfortable bus deceleration rate of $1 m/s^2$ the resultant time threshold is an estimated as 10s.

The selection of 10s buffer period was further investigated from the cumulative distribution for A1 and A3 cases. Figure 7 shows the cumulative plot for the A1 cases (B1A1, B2A1, B3A1 and B4A1). Less than 30% of buses under A1 cases; have time difference between the first tag off and the door opening greater than 10 s. This was also evident for the A3 cases.

Figure 7: Cumulative distribution plot for A1 cases

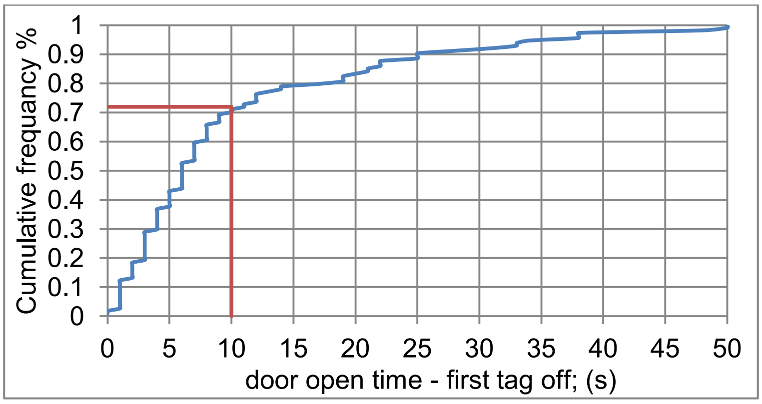
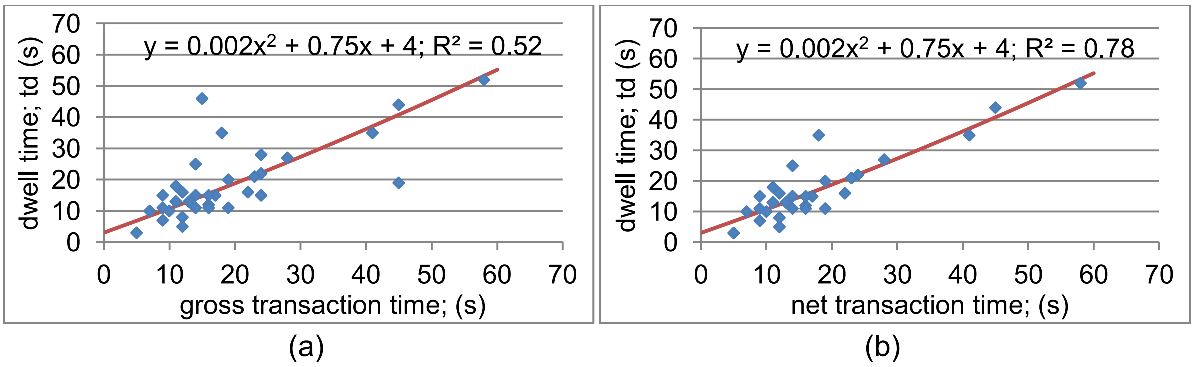


Figure 8 illustrates for case B2A1 as an example the relationship between smart card transaction time and survey dwell time for (a) all data and (b) excluding data where the bus arrives at the geo-fence more than 10s before its door opening time on the available loading area. For this case it is clear that a stronger relationship exists between measured dwell time and transaction time when the data that is considered to reflect bus queuing conditions is excluded.

Figure 8: Case B2A1 data classification



As a consequence of similar investigation across all cases, the data displayed in Figure 4 across all cases was filtered to excluded occasions where the bus arrives at the geo-fence more than 10s before its door opening time on the available loading area, hence excluding bus queuing conditions. Figure 9 illustrates the remaining 84 percent of (gross) data and the optimal second order polynomial equation for a net dwell time model determined using the numerical optimization method described above. The results of the numerical optimisation for the peak period net dwell time model are provided in Table 3.

Figure 9: Peak period net smart card transaction versus survey dwell time relationships

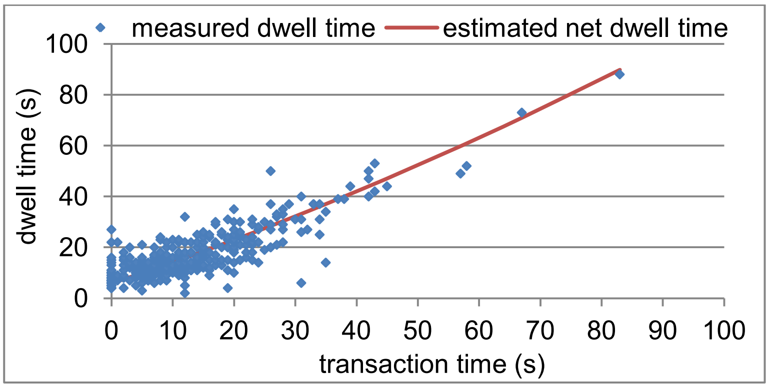


Table 3: Peak period net dwell time estimation using numerical optimisation

$\bar{t}_{d\|est}$	$cv(t_{d\|est})$	a	b	c	$Obj\ I\ (a,b,c)$	$Obj\ II\ (a,b,c)$	R^2 on $\boldsymbol{t_d}$
16.7s	0.62	0.0025	0.8027	5.9	$2.87\text{x}10^{-7}$	$7.85\text{x}10^{-7}$	0.71

Table 3 shows that for the values of curve fitting constants determined by objective function (*I*) and (*II*) is again practically zero showing negligible difference between average measured dwell time and average estimated dwell time, and also negligible difference between coefficient of variation of measured dwell time and coefficient of variation of estimated dwell time. Comparison of these values with those of Table 2 shows average estimated dwell time to be almost identical, and coefficient of variation of estimated dwell time to be identical, which means that using this model with net smart card transaction data can reliably synthesise the measured dwell time distribution.

Figure 9 includes Equation 1 with the values of the curve fitting constants from Table 3. It can be seen that the second order polynomial fits the data very well. The Kolmogorov-Smirnov statistic for the two distributions of Figure 10 was determined to be equal to 0.085, which is less than the critical value of 0.101 for a 5 percent confidence level. Thus, the null hypothesis that the samples are drawn from the same distribution was not rejected.

Figure 10 illustrates the cumulative distributions of both measured dwell time, and estimated dwell time using Equation 1 and the constants from Table 3. By visual inspection, for dwell times larger than 10s, the estimated distribution aligns with the measured distribution very closely as is ensured by objective function (*II*). Again, for small dwell times less than 10s the estimated dwell time distribution differs from the measured distribution due to the average minimum dwell time of 5.9s. The Kolmogorov-Smirnov statistic for the two distributions of Figure 10 was determined to be equal to 0.085, which is less than the critical value of 0.101 for a 5 percent confidence level. Thus, the null hypothesis that the samples are drawn from the same distribution was not rejected.

Figure 10: Peak period net cumulative distributions of measured dwell time and estimated dwell time using Equation 1 and Table 3 constants

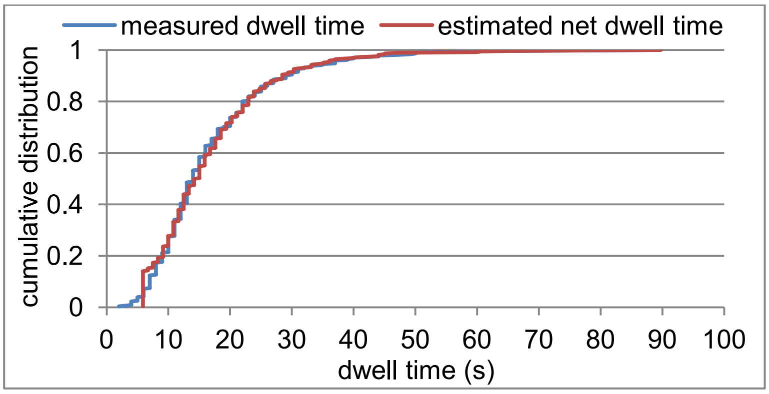
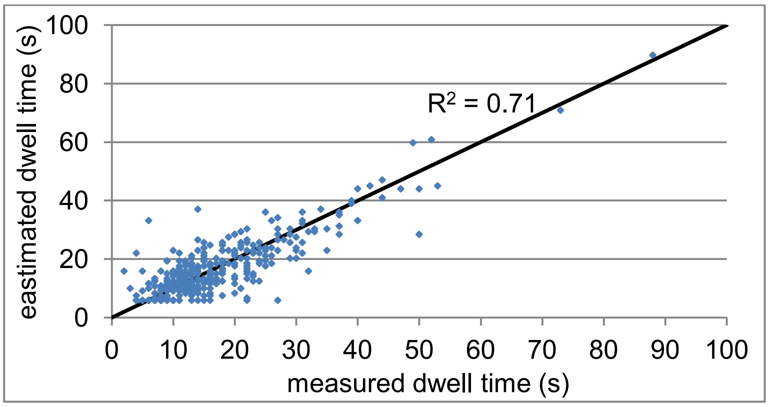


Figure 11 illustrates each peak period measured dwell time versus dwell time estimated using Equation 1 with Table 3 constants for the matching net transaction time. While spread is evident, the R^2 was determined on a line of equality comparison to be equal to 0.71, indicating that this estimation method can provide for a particular bus a good estimate of its actual dwell time if its gross transaction time is known.

Figure 11: Peak period net measured dwell time versus estimated dwell time using Equation 1 and Table 3 constants



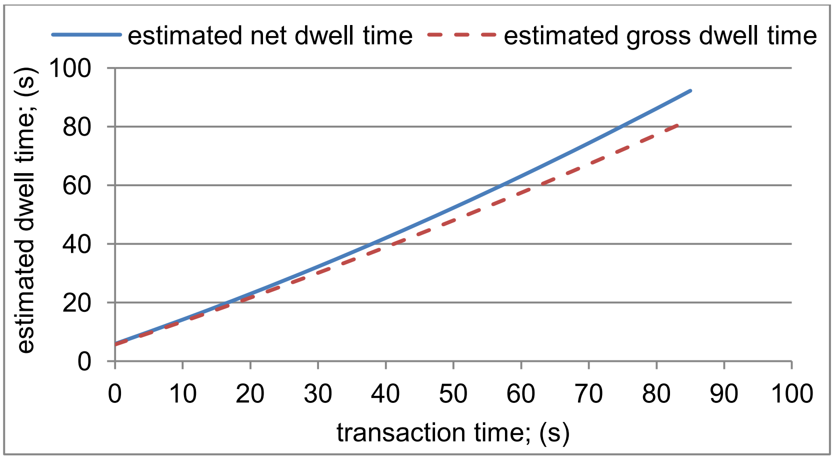
Comparing the polynomial constants of Table 2 and Table 3, for all transaction times the dwell time estimated by the net model is greater than that estimated by the gross model. Alternatively, for a given dwell time the corresponding transaction time from the net model will be less than the corresponding transaction time from the gross model, as illustrated in Figure 12. The difference between the two transaction times represents the effect of excluding transactions corresponding to bus queuing conditions, and thus provides an estimate of bus time in queue as a function of dwell time, given by Equation 4:

$$\boldsymbol{t_q = t_{sn}(t_d) - t_{sg}(t_d)} \qquad \textbf{\textit{Equation 4}}$$

Where:

t_q = bus queuing transaction time; (s)
t_d = bus dwell time; (s)
t_{sg} = gross smart card transaction time; (s)
t_{sn} = net smart card transaction time; (s)

Figure 12: Estimated time in queue given dwell time for measured peak period at Buranda station



If the analyst wishes to estimate dwell times given transaction times under the conditions calibrated here for a peak period at Buranda station, the gross model of Equation 1 with Table 2 constants is appropriate. Equation 4 can then be used to estimate the effect of bus time in queue, which may be useful for other purposes. However, the ideal model should enable the analyst to estimate dwell times given transaction times where there is no bus queuing. The net model of Equation 1 with Table 3 constants is best to use here. The next step of the analysis was thus to establish whether for Buranda station Equation 1 with Table 3 constants is an appropriate model under conditions without bus queuing, such as an off peak period.

6.3 Off-peak Period Dwell Time Model Development

The off-peak morning time period between 10:00 am to 11:00 am (from 16/04/13 to 18/04/13) was chosen to validate the net dwell time model of Equation 1. The number of buses during this period is substantially less than during the peak period as expected. Further, bus queuing was observed to be negligible. Figure 13 illustrates the smart card transaction times with dwell times and the optimal second order polynomial equation for a net dwell time model determined using the numerical optimization method described above and (i) the polynomial constants determined for the peak period net model and (ii) polynomial constants determined specifically using numerical optimization for this period. The results of the numerical optimisation for this off-peak period are provided in Table 4.

Figure 13: Off-peak period smart card transaction versus survey dwell time relationships

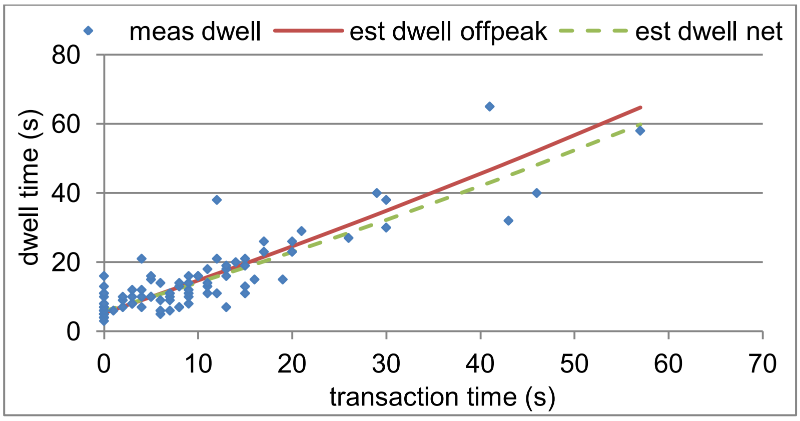


Table 4: Off-peak period dwell time estimation using numerical optimisation

Model	$\bar{t}_{d\|est}$	$cv(t_{d\|est})$	*a*	*b*	*c*	$Obj\ I\ (a,b,c)$	$Obj\ II\ (a,b,c)$	R^2 on t_d
Actual	14.1	0.77						
Off-peak	14.1	0.77	0.0021	0.9223	5.3	3.71×10^{-8}	2.01×10^{-6}	0.77
Net peak	13.7	0.72	0.0025	0.8027	5.9	0.166	8.57×10^{-4}	0.77

From Figure 13 it can be seen that the two estimation models are almost identical for transaction times less than 20s. However, for greater transaction times, the net peak period model produces lower dwell time estimates than does the off-peak model. The off-peak model also reproduces average dwell time and coefficient of variation of dwell time identical to the actual measured values, with negligible value of objective function *(I)* accordingly. The net peak model estimates average dwell time to within 3 percent accuracy, and dwell time coefficient of variation to within 7 percent accuracy. With a small number of transaction times greater than 20s, further distinction of accuracy between these models would be challenging.

Figure 14 illustrates the cumulative distributions of both measured dwell time, and estimated dwell time using Equation 1 and the polynomial constants using (i) numerical optimization for this period and (ii) the peak period net model. By visual inspection, for dwell times larger than 10s, the estimated distribution for this off-peak period aligns with the measured distribution very closely as is ensured by objective function (*II*). Again, for small dwell times less than 10s the estimated dwell time distribution differs from the measured distribution due to the average minimum dwell time of 5.3s. The peak period net model is marginally less accurate.

The Kolmogorov-Smirnov statistic for the measured and (i) estimated off-peak distributions of Figure 14 was determined to be equal to 0.135, which is less than the critical value of 0.196 for a 5 percent confidence level. Thus, the null hypothesis that the samples are drawn from the same distribution was not rejected. The Kolmogorov-Smirnov statistic for the measured and (ii) estimated net peak period distributions of Figure 14 was determined to be equal to 0.125, which is less than the critical value of 0.196 for a 5 percent confidence level. Thus, the null hypothesis that the samples are drawn from the same distribution was also not rejected.

Figure 14: Off-peak period cumulative distributions of measured dwell time and estimated dwell time using Equation 1 and Table 4 constants

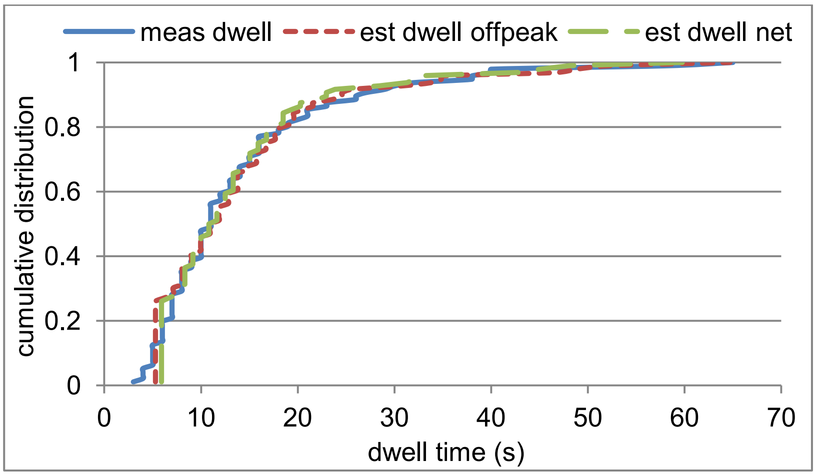
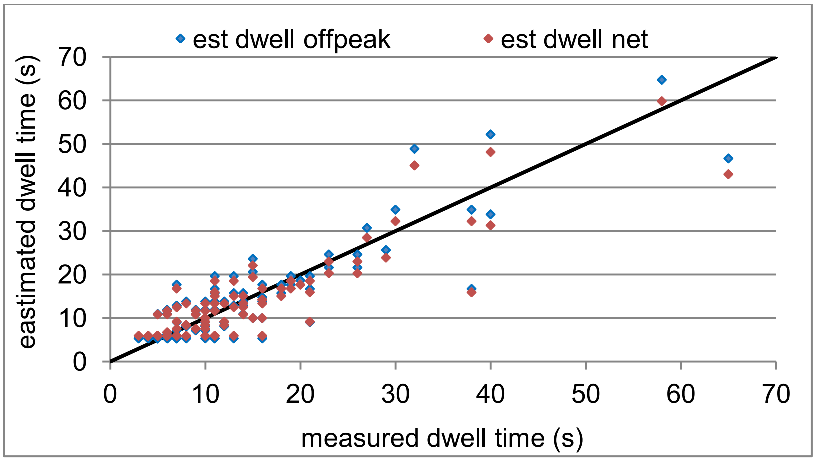


Figure 15 illustrates each off-peak period measured dwell time versus dwell time estimated using Equation 1 with Table 4 constants for the matching transaction time under (i) numerical optimization for this period and (ii) the peak period net model. While spread is evident, the R^2 was determined on a line of equality comparison to be equal to 0.77 and 0.77 by each method, indicating that either estimation method can provide for a particular bus a good estimate of its actual dwell time if its gross transaction time is known. For dwell times less than 20s there is little difference in estimate between each model. For the few data points corresponding to greater dwell times, the peak period net model produces marginally larger estimates.

Figure 15: Off-peak period net measured dwell time versus estimated dwell time using Equation 1 and Table 4constants



For further validation the hypothesis of using net dwell time model was tested using a F-test (Table 5) for off peak measured dwell time and estimated net dwell time. Since, p-value is greater than alpha null hypothesis was not rejected.

Table 5: F test results

	off peak measured	off peak net
Minimum	4.000	5.900
Maximum	65.000	59.776
Mean	14.179	13.741
Std. deviation	10.876	9.786
Degree of freedom	94	94
F (Observed value)	1.235	
F (Critical value)	1.502	
p-value	0.308	
alpha	0.05	

It can therefore be concluded the net dwell time model represented by Equation 1 with constants listed in Table 3 is an appropriate model to estimate dwell time given transaction time for off-peak conditions at Buranda station where there is no bus queuing.

7. Conclusion

This study demonstrated that smart card transaction data can be used to effectively estimate dwell time at a busway station. The gross dwell time model developed in this research for peak period conditions can provide for a particular bus a reasonable estimate of its actual dwell time when the gross transaction time is known. Across all buses during the peak time period, this model can provide a strong estimate of the distribution of actual dwell times greater than 10s from all measured transaction times. For dwell times less than 10s the model is limited by its minimum average dwell time. Particularly pertinent to transit capacity and quality of service analysis, the model can provide precise estimates of average dwell time and coefficient of variation of dwell time.

The net dwell time model proposed in this paper provides a more precise model to estimate the dwell time distribution from available smart card transaction data when situations where buses arriving in queue during the peak period are excluded. Further, use of the gross dwell time model and net dwell time model together can enable bus time in queue to be estimated, which provides useful additional operational information.

Off-peak conditions were also studied in order to validate the net dwell time model. Although the net peak model now does not estimate off-peak average dwell time or coefficient of variation of dwell time identically, its estimates are within 3% and 6.5% of the measured values respectively, and the model is validated by statistical inference.

8. Further Research

The dwell time model developed in this paper is calibrated and validated only for a given platform at Buranda busway station on Brisbane's South East Busway. Future research will include of further refining and validating the dwell time model for other time periods, the opposite platform at Buranda, other busway stations and on-street stops. A further step in this research will be to develop a dwell time model using Automatic Vehicle Location (AVL) data and smart card data.

9. Acknowledgements

Authors would like to acknowledge the support of Translink Division, Department of Transport and Main Roads, especially to Mr. Daniel Ng and Mr. Steve McEvoy in person. Further, the support of Mr. Hao Guo's to develop a smart phone survey application is highly appreciated. Finally, the support of survey team and Queensland University of Technology, Australia is gratefully acknowledged.

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