Developing passenger mode choice models for Brisbane to reflect observed travel behaviour from the South East Queensland Travel Survey

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1 Introduction

Mode choice models generally form a critical part in analysing the travel demand of a study area. In context with revealed preference (RP) data, mode choice models have generally been estimated to determine the current mode shares of the population for different trip purposes (Caldas and Black 1997, Morikawa *et al.* 2002).

This paper presents the methodology used in developing a fully-functional mode choice module capability to be incorporated into the Brisbane Strategic Transport Model (BSTM); capable of estimating mode shares in a multi-modal travel environment. The new mode choice module consists of unique logit models developed for eight trip purpose categories – home based work(white collar) (HBW-W), home based work (blue collar) (HBW-B), home based education (primary & secondary) (HBE-PS), home based education (tertiary) (HBE-T), home based shopping (HBS), home based other (HBO), work based work (WBW) and other non-home based trips (ONHB). All these trip purpose sub-categories were defined as part of the model development framework. This project forms a critical part of the four-step travel demand model being developed by the Main Roads / Queensland Transport Portfolio Transport Modelling Team (PTMT).

The model specification developed for the mode choice module consists of two private vehicle modes of car as driver and car as passenger; three public transport modes of walk to public transport, park and ride and kiss and ride; and two non-motorised modes of walking and cycling all-the-way.

The study area selected for the BSTM is the Brisbane Statistical Division which covers an area of around 4,700 square kilometres, including the contiguous urban region of Brisbane CBD. According to the Australian Bureau of Statistics (2007), the study area has an estimated resident population of 1.85 million, which is expected to grow to 2.53 million by the year 2026 at an annual growth rate of 1.6% (Queensland Government 2006). The travel behaviour of the population is significantly influenced by car, with around 80% of the current trips being private motor-vehicle trips for various trip purposes (Queensland Government 2005). The current public transport network in the study area comprises of six major rail lines, one major busway, a significant bus network, Rivercat ferries and cross-river ferries. The public transport network became coordinated under a single entity, TransLink, during 2003 with the implementation of integrated ticketing[1].

The South East Queensland Infrastructure Plan and Program 2007-2026 was developed to identify the needs of the expected growth, with an estimated cost of $20.5 billion. The plan has listed sixty-five major transport projects for the study area, including busways to serve the northern and eastern suburbs, a rail line to the new major urban development at Springfield and the Gateway Motorway upgrade. In order to examine these infrastructure

[1] This was a contributing factor for considering trains, buses and ferries as a single public transport 'mode'.

initiatives in terms of expected demand for each mode and impact on travel patterns, a multi-modal strategic transport model is essential.

2 Mode choice module development

2.1 Model structure

The development of the mode choice module was carried out in three main steps, broadly categorised as model estimation, model validation and sensitivity analysis. Model estimation mainly included determining the structure of the model and estimating a set of parameters / coefficients, using suitable logit model estimation software. We investigated various forms of simple multinomial logit (MNL) and nested multinomial logit (NL) models. Figures 1 and 2 present the examples of MNL and NL model forms that we tested. They also show the seven travelling modes included in the choice set generated for the study.

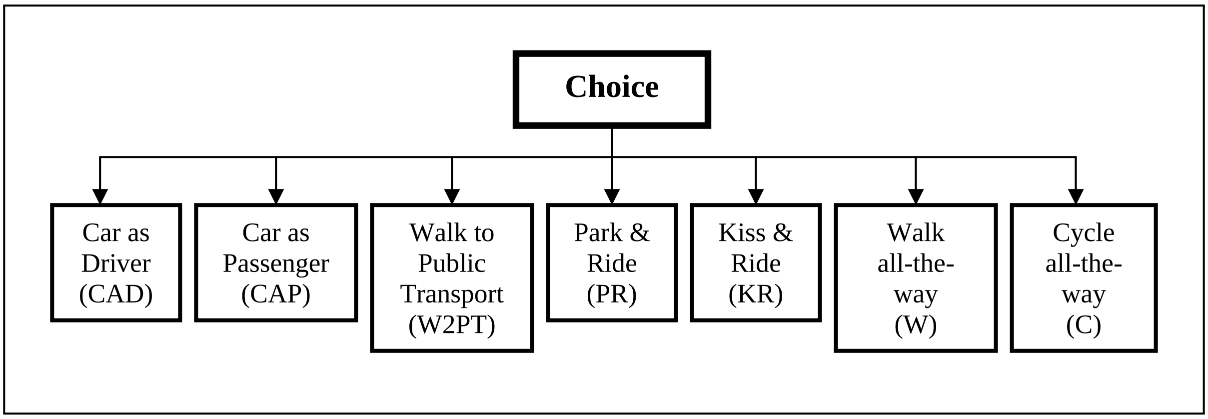


Figure 1 A simple multinomial logit (MNL) model specification

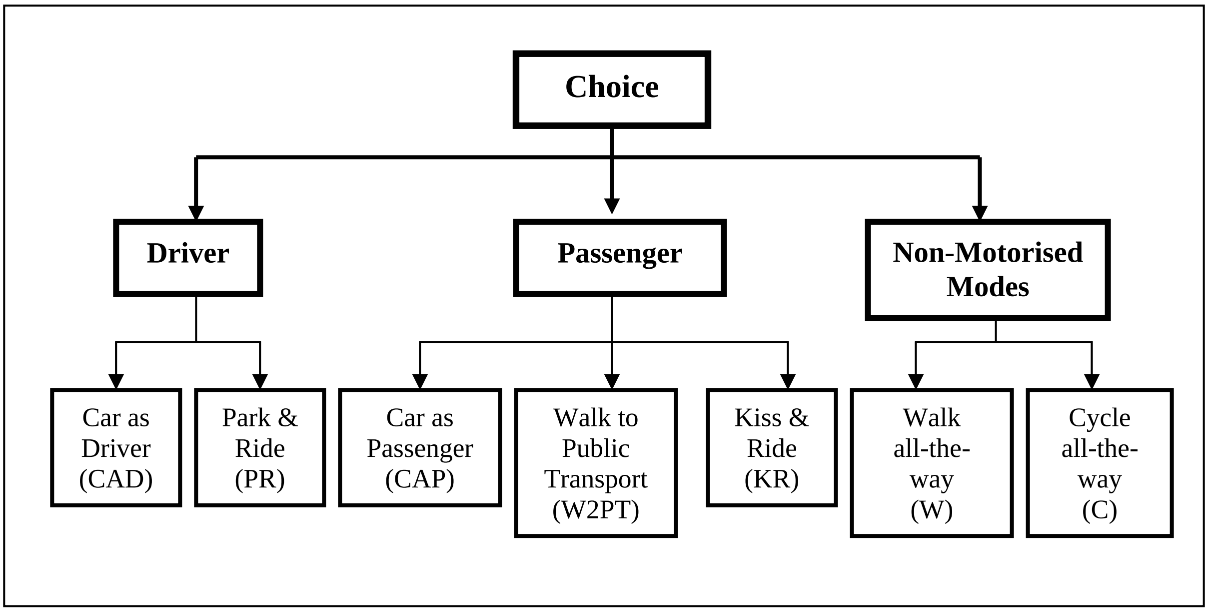


Figure 2 A nested logit (NL) model specification

2.2 Utility functions

The mathematical framework of logit models is based on the theory of utility maximisation and is discussed in detail in Ben-Akiva and Lerman (1985). Briefly presenting the framework, the probability of an individual *i* selecting a travelling mode *m*, out of *M* number of total available modes, is given as,

$$P_{mi} = \frac{\exp(U_{mi})}{\sum_{n \varepsilon M} \exp(U_{ni})} \tag{1}$$

where,

U_{mi} is the utility of mode *m* for individual *i*;
U_{ni} is the utility of a mode *n* in the choice set for individual *i*;
P_{mi} is the probability of selecting mode *m* by an individual *i* from the choice set; and
M is the set of all available travelling modes.

The *utility* is mathematically represented as a linear function of the attributes of the journey weighted by the coefficients which attempt to represent their relative importance as perceived by the traveller. The utility function associated to a mode *m*, as perceived by an individual *i*, is given by the following equation,

$$U_{mi} = \beta_{m0} + \beta_{m1}x_{mi1} + \beta_{m2}x_{mi2} + \ldots\ldots + \beta_{mk}x_{mik} \tag{2}$$

where,

U_{mi} is the utility function for mode *m* for individual *i*;
$x_{mi1}, \ldots, x_{mik}$ are *k* number of attributes of mode *m* for individual *i*;
β_{m0} is the mode specific constant for mode *m*; and
$\beta_{m1}, \ldots, \beta_{mk}$ are *k* number of coefficients (or weights attached to each attribute) of mode *m* which need to be estimated from the survey data

2.3 Attributes

Several attributes were tested with the model specifications developed for each trip purpose, mainly consisting of travel characteristics, socio-demographic characteristics and land use characteristics. A list of the final attributes (along with their notations) which were considered for model estimation runs is presented in Table 1.

The travel characteristics covered measures of various components of time and cost for the trip for each alternative in the choice set. We obtained time and cost data for each mode from the BSTM time and cost skims.

The demographic characteristics were mainly based on the number of adults and number of vehicles, in the household. These demographic measures relate to the production zone of home-based trips. In terms of the input data for the mode choice model calibration, we used household characteristic information illustrated in Queensland Government (2006). These demographic characteristics were used in combination with one another, in order to provide information that can be used as a proxy for the availability of a motor vehicle for a particular type of trip (Bowman and Ben-Akiva 2001).

The land use characteristics comprised of the employment density of each zone of the study area. These land use characteristics provide information that can be used as a proxy for the availability and attractiveness of public transport for a zone.

Table 1 List of attributes considered in calibration of mode choice models

Attributes	**Notation of the Attribute**
General	
Mode specific constant	C
Travel characteristics	
In-vehicle Travel Time (minutes)	TT
Travel cost (cents)	TC
Parking cost (cents)	PC
Combined walk access and egress time to / from the public transport station (minutes)	AT
Car travel time between the public transport stop or station and the production end of the trip (minutes)	CAT
Walk travel time between the public transport stop or station and the attraction end of the trip (minutes)	WAT
Waiting time (minutes)	WT
Household characteristics	
Persons per household	PERS
Adults per household	ADUL
Workers per household	WORK
White collar workers per household	WWRK
Blue collar workers per household	BWRK
Licence holders per household	LIC
Tertiary students per household	TERT
School students per household	SCHL
Vehicles per household	VEHS
Employment Characteristics	
Employment density (jobs per hectare)	EMPD
Retail employment density (retail jobs per hectare)	REMPD

2.4 South-East Queensland Travel Survey (SEQTS)

The South East Queensland Travel Survey (SEQTS) was the primary input dataset for estimating the mode choice models for all trip purposes. The SEQTS was conducted across the Brisbane Statistical Division from October 2003 to March 2004 (excluding the Christmas holiday period). The responses from approximately 4000 households were collected. Each household completed a one day travel diary for each person in the household aged 5 years old and over. The travel diary described in detail the trips made during the day. The information recorded included the start and end location, and time of each part of the trip, and the purpose for visiting those locations. The survey also collected information about the individual and household characteristics, such as the number of people and number of vehicles in the household.

We considered only those trip records for residents, which started and ended both within the study area. We excluded trips that were an attraction-to-production trip which was identical in terms of purpose, mode and trip end locations (albeit in the reverse direction) to a production-to-attraction trip made by the same person. For instance, if person was found to travel directly from home to work and back from work to home using the same mode then the work to home trip record was removed. The resulting data set comprised of 25,392 trip records in total.

We used the SEQTS records for both model calibration and validation purposes. We split the dataset using SPSS (S.P.S.S. Inc. 2006), a standard statistical software package, by randomly selecting two-thirds of the records for the calibration dataset, and the remaining one-third for validating the model.

2.5 Model calibration procedure

We estimated the coefficients associated to each attribute of the travelling modes, for each specification, using *Limdep / Nlogit* (ES 1998) and *ALOGIT* (HCG 1992) software packages. Both packages mainly use the maximum likelihood estimation technique to estimate the coefficients.

With the input data assembled, an iterative approach was used to find the best model specification for the available data. In the first instance, three models were estimated using different levels of constraint on the coefficient estimates as follows,

- i Separate coefficients estimated for each attribute and mode combination. We refer to this later in the analysis as specific coefficients. This specification almost always resulted in a number of coefficient estimates not statistically different from zero, and often with the wrong sign. We believe this was due to the small proportion of travellers in the population using modes such as cycle, park and ride, and kiss and ride, resulting in only a small number of records available in the model calibration data set.
- ii Coefficients for time and cost component by the same mode constrained to be equal – for example, the walk time coefficient for the walk all-the-way alternative and the walk access coefficients for the public transport modes.
- iii All travel time coefficients constrained to be generic.

The model calibration was done through an iterative process; where each new iteration was based on the findings of the previous iteration.

As well as examining the standard statistics, the preferred models were also applied to the calibration data. Aggregate mode shares were calculated by summing the calculated probabilities for each trip record. This was plotted against the aggregate mode shares of the calibration data set in order to observe how well the model could replicate the calibration data mode shares.

For the set of preferred models, they were also validated by applying the model to a separate validation data set. This validation data set was a one-third sample of the SEQTS trip data for each trip purpose. The validation was conducted by applying the mode choice equation to the validation data. Aggregate mode shares were calculated based on the estimated probabilities for each trip record. These were plotted against the mode shares of the validation data set to check how well the model replicated the validation data set mode shares.

Various sensitivity analyses of the estimated level-of-service coefficients were conducted, in order to surmise the influence of a particular parameter on the mode choice of the targeted population for a specific trip purpose (Kockelman and Krishnamurthy 2004). The attributes were mainly subjected to the following analyses,

- varying car in-vehicle travel times and highway costs by 50%
- varying car parking costs by 50%
- varying public transport in-vehicle travel times and trip fares by 50%
- varying public transport waiting times by 50%

The variation in the mode shares with the change in the attribute value was qualitatively assessed for all trip purposes.

3 Model estimation

3.1 Modelling results

After conducting various model estimation runs on all trip purposes, all models, other than the two specified for home-based work trips, were found to be best represented using the simple multinomial logit structure. Nested multinomial logit models were specified for estimating the two home-based work trips, with a tree structure which distinguishes between driver, passenger and non-motorised modes. Various level-of-service modal attributes and household parameters were tested with the utility functions associated with each travelling mode, and assessed on the basis of the t-ratio values and magnitude of standard error obtained from the estimation runs. The final model estimation results for all trip purposes are presented in Table 2.

Table 2 Model estimation results (values of estimated coefficients with t-ratios)

Variable	HBW-W	HBW-B	HBS	HBE-PS	HBE-T	HBO	WBW	ONHB
TT	Generic		CAD					
	-0.0374 (-7.2)	-0.0345 (-3.0)	-0.0403 (-3.9)	-0.1234 (-9.0)	-0.0439 (-2.8)	-0.0138 (-2.3)		
TC+PC	CAD/W2PT/PR/KR		CAD				CAD	
	-0.0042 (-8.3)	-0.0016 (-1.5)	-0.0019 (-5.8)				-0.0009 (-3.0)	-0.0027 (-4.4) -0.0013 (-10.5)
TT_{CAP}			-0.0611 (-6.3)	-0.1270 (-9.5)	-0.0508 (-2.5)	-0.0181 (-2.9)		-0.0440 (-6.4)
TT_{W2PT}			-0.0382 (-5.2)	-0.0538 (-3.9)	-0.0401 (-2.4)			-0.0179 (-2.3)
WT	W2PT/PR/KR		W2PT					
	-0.0845 (-4.8)	-0.0919 (-2.6)	-0.0382 (-5.2)					

AT_{W2PT}	-0.0305 (-4.0)	-0.0203 (-1.4)	-0.0382 (-5.2)					-0.0184 (-2.2)
$WAT_{PR/KR}$	-0.0305 (-4.0)	-0.0203 (-1.4)						
$CAT_{PR/KR}$	-0.0305 (-4.0)	-0.0203 (-1.4)						
TT_{W}			-0.1020 (-11.1)	-0.0813 (-9.8)	-0.0508 (-2.4)	-0.0696 (-9.0)	-0.0954 (-2.6)	-0.1305 (-14.7)
TT_{C}			-0.1721 (-2.9)	-0.0752 (-3.5)		-0.1227 (-4.1)		
C_{CAD}			-2.7877 (-11.2)	-0.9902 (-5.7)		-1.7360 (-7.8)		-1.0862 (-9.5)
C_{CAP}	-2.7553 (-19.1)	-2.3713 (-11.0)	-2.7514 (-10.9)	-1.1060 (-4.6)	-1.7900 (-3.6)	-1.6520 (-7.4)	-2.6913 (-16.0)	-1.7280 (-15.1)
C_{W2PT}	-0.4048 (-1.5)	-1.3725 (-2.6)	-2.1085 (-5.7)	-3.1110 (-12.6)	-1.9020 (-3.3)	-3.5850 (-14.5)	-4.7330 (-7.9)	-3.7920 (-17.9)
C_{PR}	-3.2527 (-10.6)	-4.3356 (-6.0)	-7.0043 (-15.0)		-4.0900 (-6.5)	-5.1490 (-13.0)		-5.9579 (-21.8)
C_{KR}	-2.0207 (-7.5)	-3.1270 (-5.4)	-7.0733 (-14.5)	-4.6820 (-12.8)	-4.0440 (-6.2)	-5.3940 (-12.5)		-5.9595 (-20.8)
C_{W}	-1.1594 (-5.4)	-1.5627 (-3.5)					-1.0296 (-2.1)	
C_{C}	-4.1134 (-14.3)	-4.0050 (-7.7)	-4.9781 (-8.5)	-2.9220 (-9.0)	-3.3390 (-5.4)	-2.4690 (-7.4)		-7.0195 (-19.7)
$TERT_{W2PT}$ / $SCHL_{CAP}$				0.1282 (2.6)	0.4353 (2.0)			
$VEHS_{CAD}$						0.7745 (8.2)		
$VEHS_{CAP}$						0.5882 (6.1)		
$VEHS/ADUL_{CAP}$			0.5385 (3.3)	0.4498 (2.0)				
$VEHS/ADUL_{W2PT}$			-2.8579 (-6.7)					
$VEHS/ADUL_{W}$			-1.8755 (-6.4)					
$VEHS/PERS_{CAD}$			2.1389 (12.10)					
ADUL-VEHS	CAD/PR				CAD			
	-2.4963 (-7.5)	-1.8048 (-2.8)			-0.9310 (-4.4)			
EMPD / REMPD	W2PT/PR.KR		W2PT				W2PT/W	W2PT
	8.31e-04 (6.1)	1.09e-03 (2.5)	0.0112 (4.2)				1.15e-03 (2.2)	7.76e-04 (2.9)
IV_{DRIVER}	0.4497 (8.8)	0.5192 (3.1)						
$IV_{PASSENGER}$	1.0000 (0.0)	1.0000 (0.0)						
$IV_{NON-MOTORISED}$	1.0000 (0.0)	1.0000 (0.0)						
ρ^2 value	0.5840	0.7000	0.5998	0.2235	0.2690	0.3955	0.7420	0.5643
Number of RP Observations	1880	772	3267	1846	183	2718	680	5033

where IV is the inclusive value for the nest.

3.2 Discussion on the Results

From the final model estimation runs for each trip purpose, as shown in Table 3.1, most of the estimated coefficients, along with mode-specific constants, were found to be statistically significant and stable at the 95% confidence interval. It was a satisfactory finding considering the fact that these attributes generally associate considerable variability and considerable correlation. The signs of all the level-of-service attributes, along with some household parameters, came out to be negative; a finding consistent with previous mode choice studies (Hensher and Rose 2007), indicating that deterioration in the level of service offered by any mode will reduce its respective market share. Contrarily, the signs of some household attributes, such as $VEHS/ADUL_{CAP}$ and $SCHL_{CAP}$, were determined to be positive illustrating that the specific mode shares are likely to increase with the increasing values of these parameters. The goodness-of-fit values determined for each trip purpose were satisfactorily high (Miller *et al.* 2003), other than those established for HBE-PS and HBE-T trips.

A brief discussion on the model estimation results for each trip purpose is presented below, with particular focus on overall goodness-of-fit for each trip and some interesting findings from the final model estimation run.

3.2.1 Home-based Work (White Collar) Trips (HBW-W)

A total of 1880 RP observations were used for calibrating the logit model for home-based work (white collar) trips. Extensive analysis of a number of model specifications found a remarkable degree of robustness in the parameter estimates of the attributes, along with all the household characteristics. The overall goodness-of-fit achieved for the specific trip purpose was satisfactorily high with a ρ^2 value of 0.5840.

All the parameter estimates were found to be statistically significant and stable at the 95% confidence interval, and associated right signs. The lowest absolute t-statistic value was determined to be -4.0 for AT_{W2PT} and $WAT_{PR/KR}$, showing a strong influence of all these variables on the mode choice. All the mode-specific constants, other than that for W2PT mode, were also observed to associate significantly high t-ratios. The value of the scale parameter of 0.4497 for driver modes was statistically significant and different from 1.0, assigned to passenger and non-motorised modes, complying with the global utility maximisation condition of ranging between 0 and 1 (Train and McFadden 1978).

In addition to modal trip attributes, three household parameters were found to significantly influence the mode choice for home-based work (white collar) trips, particularly for 'car as driver' mode. Although the variable of employment density, associated to public transport modes, was estimated to have a small, but significant, value, it was found to have a noticeable impact on the public transport mode shares for destinations in or around Brisbane CBD area.

The relative value of waiting time compared to travel time was found to be 2.26 (WT / TT = (-0.0845)/(-0.0374)), which is consistent with the commuter-based models developed earlier (Jovicic and Hansen 2003), while that for access time came out to be 0.82, lower than previous studies. The reason for determining low value for (access time/in-vehicle time) may be due to having to adopt a generic coefficient for travel time.

3.2.2 Home-based Work (Blue Collar) Trips (HBW-B)

A total number of 772 observations were used for calibrating the logit model for home-based work (blue collar) trips. Similar to the model developed for white-collar workers, the nested multinomial logit model structure was found to best represent the blue collar work trips too. However, the final model estimation results showed considerable differences between the models developed for the two trip purposes.

The coefficient of travel cost (sum of highway cost and parking cost) for car for home-based work (white collar) trips was determined to be 2.6 times of that estimated for blue collar work trips, indicating that white collar workers value their travel cost very highly, as compared to their blue collar counterparts. However, this ratio may not be totally reflective of the trip-makers' behaviour, as statistical analysis conducted on the RP data indicated that most of the white collar work trips were destined for Brisbane CBD or other charged-parking areas, while those of blue collar workers were mainly distributed outside the city frame area.

The household parameter of the difference of adults and vehicles, associated to the two driver modes, was found to influence the white collar work trips more than that of blue collar work trips, which indicates that the sample of blue collar workers may contain a substantial number of car captive users, who have to drive their cars as part of their work requirement and may be unable to switch to public transport or non-motorised modes with the increase in the adults in the household.

The mode shares for both white and blue collar work trips, as shown in Figure 3, were also estimated to be significantly different, with a low usage of public transport and non-motorised modes found for blue collar workers.

3.2.3 Home-based Shopping Trips (HBS)

A considerably large sample of 3267 RP observations was employed for calibrating home-based shopping trips. A satisfactorily high goodness-of-fit value ($\rho^2 = 0.5998$) was attained from the final model estimation run, as shown in Table 3.1, along with expected signs of the coefficients.

An interesting finding from the model estimation was the high values attained for the mode-specific constants for park and ride, kiss and ride and cycling. It indicates that there may be qualitative attributes, such as comfort and convenience, which may substantially influence the mode choice for non-car modes for shopping trips, and subsequently decrease their mode shares due to the fact that car trips associate high comfort and convenience (Johansson *et al.* 2004). The mode shares estimated for home-based shopping trips, as shown in Figure 3, further corroborates the dominance of car modes over other travelling alternatives.

3.2.4 Home-based Education (PS) Trips (HBE-PS)

Although a considerable sample of 1846 RP observations was used for estimating the mode choice model for home-based education (PS) trips, the goodness-of-fit ($\rho^2 = 0.2235$) determined was not as high when compared to those associated with other trip purposes. However, all the estimated coefficients, along with the mode-specific constants, were found to be highly stable and statistically significant at the 95% confidence interval.

The interesting finding from the model estimation was that the household parameters, such as VEHS/ADUL and SCHL, were found to dominantly influence the mode choice, contrarily to the conventional level-of-service modal attributes. The finding was further verified as the sensitivity analysis conducted on these parameters indicated significantly low elasticities for all level-of-service attributes. Additionally, no respondent was found to use 'park and ride' mode for conducting a primary or secondary education trip from home.

3.2.5 Home-based Education (Tertiary) Trips (HBE-T)

The model calibration set generated for home-based education (tertiary) trips comprised of a small sample set of 183 RP observations. Among all the significant attributes, the household parameter of the number of tertiary students per household (TERT) was found to substantially influence the mode choice; driving the modal split in the favour of 'walk to public transport' mode.

The overall low value of goodness-of-fit (ρ^2 = 0.2690) can probably be attributed to the small sample size. Nonetheless, all the estimated coefficients, along with the mode-specific constants, were determined to be statistically significant, but associated high standard error values. Therefore, the estimated coefficients and the resulting mode shares may not be highly representative of the characteristics of the trip-makers; but may still be vital from transportation planning perspective.

3.2.6 Home-based Other Trips (HBO)

A total number of 2718 RP observations was used in estimating the mode choice model for home-based other trips. An interesting finding from the model estimation was that the utility functions associated to all the public transport modes contained mode-specific constants only. It indicates that all the public transport level-of-service attributes, such as time and fare, do not significantly influence the mode choice for home-based other trips.

Similar to home-based shopping trips, the mode-specific constants estimated for park and ride, and kiss and ride had highly negative values, pointing towards the unobserved qualitative attributes, such as comfort and convenience, which may negatively influence their respective mode shares. This finding is further verified in Figure 3, illustrating a substantially high car usage for home-based other trips.

3.2.7 Work-based Work Trips (WBW)

Work-based work trips were found to have a distinct mode share patronage, as no respondent was found to use park and ride, kiss and ride and cycling for these trips. It is a rational observation as these modes can be viewed as highly inconvenient, considering the trip-ends.

No household attribute was tested in the model estimation, as the trip-ends are non-home-based. However, the employment parameter of EMPD was determined to be statistically significant, indicating that mode shares may vary by the trip destinations.

3.2.8 Other Non-Home-based Trips (ONHB)

Other non-home-based trips (ONHB) comprised of the highest sample size of 5033 RP observations for model calibration, as compared to other trip purposes. The overall goodness-of-fit (ρ^2 = 0.5643) obtained was also satisfactorily high, with all the estimated coefficients determined to be statistically significant and stable.

Unlike work-based work trips, the input data generated for other non-home-based trips comprised of all the travelling modes, with a high degree of variation among the attributes. However, the mode-specific constants of park and ride, kiss and ride and cycling were estimated to associate highly negative values, indicating insignificant percentage modal split for these modes due to the presence of qualitative attributes (comfort, convenience, reliability, etc.) in mode choice decision-making process for other non-home-based trips.

3.3 Estimated Mode Shares

After calibrating the logit models on the mode choice data for each trip purpose, all the models were subjected to model validation by applying the estimated coefficients on the validation input data set. All the models, other than the home-based education (tertiary) trips model[2], were found to be representative of the characteristics of the targeted population, and

[2] The main reason for the difference between the observed and estimated mode shares for home-based education (tertiary) trips seems to be the small sample size, which might have introduced sample bias.

thus can be fully employed in the mode choice module for the Brisbane Strategic Transport Model (BSTM).
After determining the values for disaggregate utility functions associated to each travelling mode (using Equation 2), the mode shares for each trip purpose were estimated (using Equation 1) and shown in Figure 3.

As expected, the 'car as driver' mode was found to dominate the mode choice for all trip purposes, with the percentage modal split reaching as high as around 80% for WBW and HBW-B trips. Conversely, for HBE-PS and HBE-T trips, the 'car as driver' mode was found to be less dominant as the mode shares were estimated to be less than 50%. The main reasons for such travel behaviour can be the car availability for primary and secondary school students, and the parking fees normally employed at the tertiary educational institutions.

The mode shares for 'car as passenger' were estimated to be significantly high for each trip purpose, particularly for HBS and HBE-PS trips. The high 'car as passenger' usage for both these trip purposes can be justified by the high vehicle occupancy, found in the previous updates of BSTM (Sinclair Knight Merz 2006) indicating that the car trips designated for these trip purposes are highly likely to contain more than one person in the vehicle. It further indicates that there may exist a substantial bias among the respondents towards the car attributes, which can significantly influence their perception towards public transport and the non-motorised modes.

For the mode of 'walk to public transport', a considerable usage was determined for the trip purposes of HBE-T and HBW-W, where the percentage modal splits were estimated to be around 24% and 10% respectively. It is a satisfactory result pointing towards the positive perception of tertiary students and white collar workers towards public transport. The main reason for attaining high public transport usage for white collar workers can be attributed to the fact that a big number of them are generally employed in Brisbane CBD, or nearby areas, which associates substantial parking fees.

The mode of 'walk all-the-way' was also determined to influence the mode shares, particularly for the trip purposes of HBE-PS, HBS and ONHB. The main reason for having high mode shares specifically for HBE-PS and HBS may be the fact that a considerable number of school students are enrolled at schools located near their residing suburbs (Australian Bureau of Statistics 2007) and similarly, a big percentage of the population mostly shop in the shopping centres near to their homes.

In addition the above-mentioned four modes, low market shares were estimated for the modes of park and ride, kiss and ride and cycling all-the-way for all trip purposes. The only trip purposes for which the mode shares of park and ride were noticeable were HBW-W and HBE-T trips.

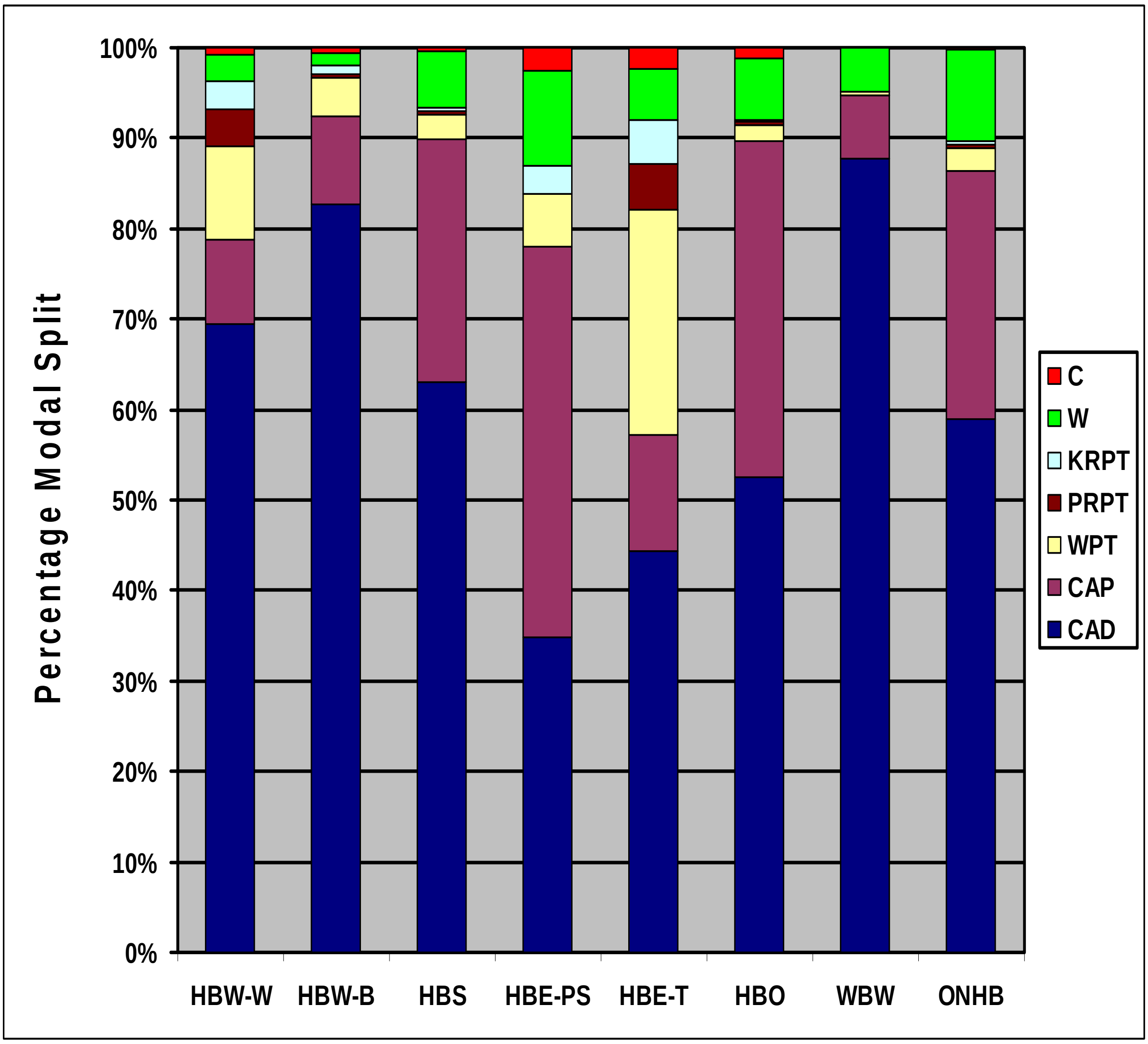


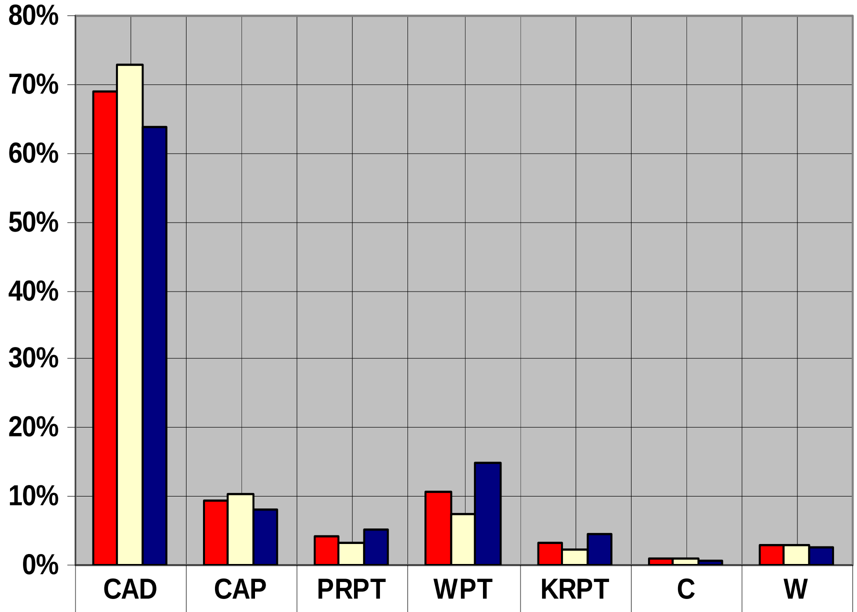
Figure 3 Estimated mode shares for each trip purpose

3.4 Sensitivity Analysis of Level-of-Service Attributes

Sensitivity analysis was conducted for various level-of-service attributes, in order to surmise their relative elasticity for each travelling mode for a certain type of trips. In order to deduce the sensitivity of a particular attribute, all other variables were kept constant in order to observe the varying percentage modal split for all travelling modes with a 50% change in the value of the attribute.

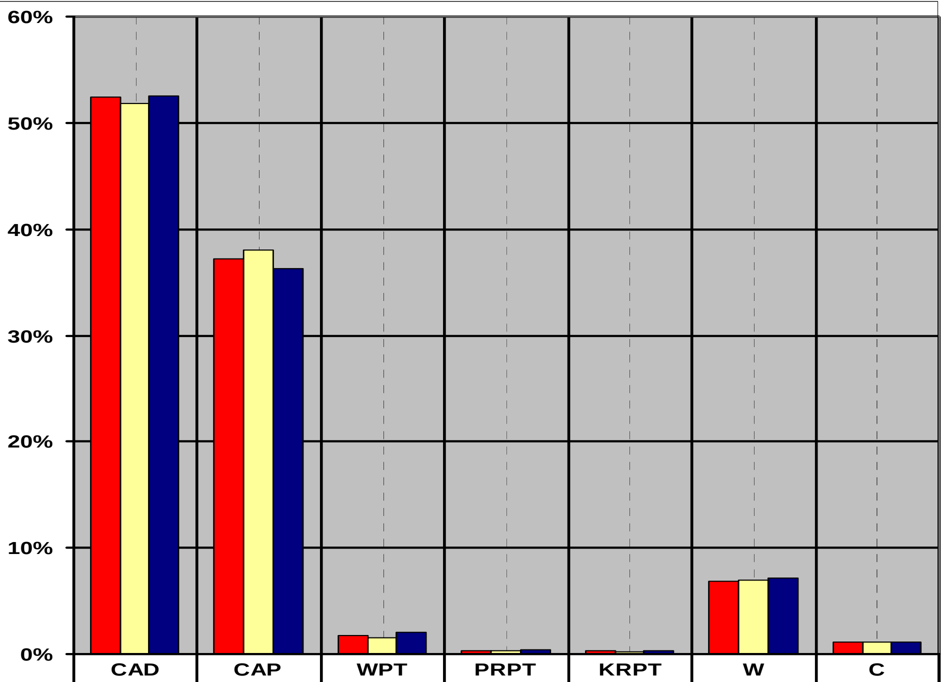
A few examples of the sensitivity analyses conducted on various level-of-service attributes for different trip purposes are presented in Figures 4, 5 and 6.

From Figure 5, it can be noted that the mode share for car as driver decreases with the reduction in car travel time when it is intuitively expected to increase, while the modal split for car as passenger behaves expectedly. This counter-intuitive result is due to the relative car travel time coefficient values for these modes, where the car as passenger travel time coefficient is 1.3 times as that of car as driver. The larger coefficient for car as passenger occurs to partly incorporate the unobserved effects of the traveller being a car passenger.



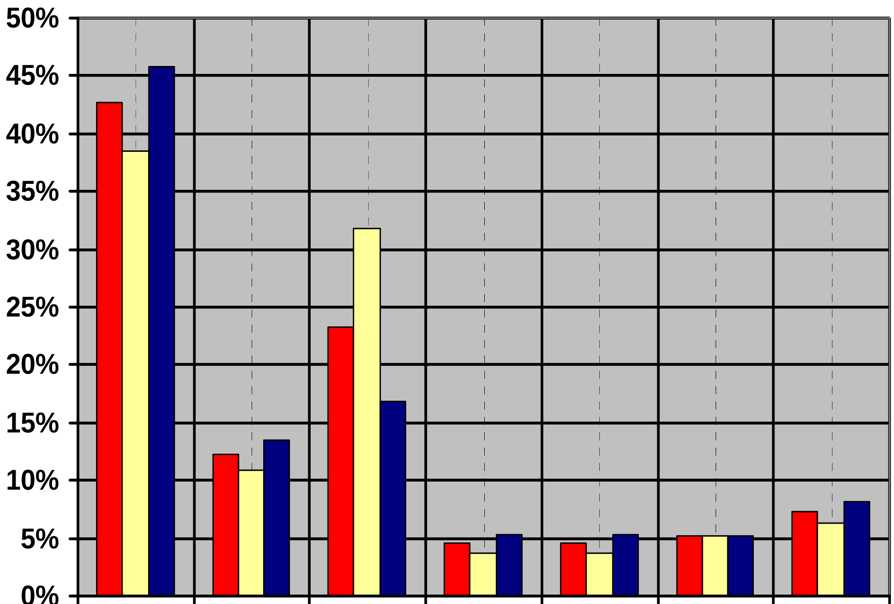
	CAD	CAP	PRPT	WPT	KRPT	C	W
Model Output	68.88%	9.43%	4.29%	10.53%	3.17%	0.86%	2.85%
Model Output (50% increase in PT fare)	72.82%	10.51%	3.12%	7.48%	2.14%	0.95%	2.98%
Model Output(50% decrease in PT fare)	63.81%	8.15%	5.33%	14.84%	4.41%	0.76%	2.70%

Figure 4 Sensitivity of public transport fare for home-based work (white collar) trips



	CAD	CAP	WPT	PRPT	KRPT	W	C
Model Output (Original)	52.48%	37.25%	1.72%	0.33%	0.26%	6.85%	1.11%
Model Output (50% decrease in TTCAR)	51.87%	38.04%	1.49%	0.28%	0.22%	6.98%	1.11%
Model Output (50% increase in TTCAR)	52.55%	36.33%	2.04%	0.40%	0.31%	7.19%	1.17%

Figure 5 Sensitivity of in-vehicle travel time of car for home-based other trips



	CAD	CAP	WPT	PRPT	KRPT	W	C
Model Output (Original)	42.70%	12.29%	23.29%	4.60%	4.63%	5.22%	7.28%
Model Output (50% decrease in TTPT)	38.47%	10.89%	31.75%	3.70%	3.71%	5.20%	6.28%
Model Output (50% increase in TTPT)	45.76%	13.43%	16.87%	5.26%	5.31%	5.24%	8.13%

Figure 6 Sensitivity of in-vehicle travel time of public transport for home-based education (tertiary) trips

In Figure 6, an interesting finding is that 50% reduction in travel times of public transport unexpectedly results in the decrease of mode shares for park and ride, and kiss and ride. The main reason for such behaviour is due to the unique utility function specifications associated to these two modes, comprising of mode specific constants only (due to small sample size of the model calibration dataset for home based tertiary education trips). Therefore, the varying public transport travel times only affect the utility for walk to public transport mode; hence changing the shares of all other travelling modes in opposite direction and in proportion to that change and their original mode share. It can be noted that the walk mode share is less affected because of the smaller number of trip records where the walk mode is part of the choice set.

4 Summary

This paper has presented the methodology used in developing a fully-functional mode choice module capability to be incorporated in Brisbane Strategic Transport Model (BSTM); capable of estimating mode shares in a multi-modal travel environment. The new mode choice module consists of unique logit models developed for eight trip purpose categories namely home based work (white collar), home based work (blue collar), home based education (primary & secondary), home based education (tertiary), home based shopping, home based other, work based work and non-home based other trips. All these trip purpose sub-categories were defined as part of the model development framework. The final model calibration results were also presented, as shown in Table 2, with a discussion on the main findings from the model estimation runs for each trip purpose.

The model estimation results for home-based work trips, modelled separately for white and blue collar workers, indicated a significant difference in the estimated coefficients' values pointing towards the distinctly dissimilar travel behaviour of the two set of respondents for travelling to work. The mode shares estimated for the two set of work trips also showed a significant difference; with 'car as driver' mode shares determined to be 69% and 82%, while that for public transport modes as 17.5% and 5.5% for HBW-W and HBW-B trips respectively. The different set of estimated coefficients and mode shares justify the utilization of two separate mode choice models for the two set of home based work trips.

Similarly the models calibrated for HBE-PS and HBE-T showed a substantial disparity in the values of estimated coefficients and the resulting mode shares. The choice sets generated for the two set of education trips were also dissimilar, with the one determined for HBE-PS not containing park and ride as a valid travelling alternative for the trip-makers. The estimated mode shares showed a considerable difference; with a percentage modal split of 43% and 12% for 'car as passenger' mode, and 9% and 35% for public transport modes, for HBE-PS and HBE-T respectively. Furthermore, in the case of models developed for the two non home-based-trips, the estimated coefficients and percentage modal split determined was significantly different, as shown in Table 2 and Figure 3 respectively.

The demographic characteristics of the household were found to have a significant influence on the mode choice for most of the trip purposes. An interesting finding from the model estimation runs was that these variables, when employed in the utility functions of car modes, mostly showed an enormous influence in driving the mode shares in favour of car. It indicates that the car-ownership and household variables play a considerable role in the mode choice decision-making process for each trip purpose.

Moreover, there were a few interesting findings from the final model estimation that came to our notice. The household variable of TERT was found to influence the mode choice of HBE-T trips, in the favour of public transport, indicating that the percentage modal split of public transport is likely to increase substantially with the increase in the number of tertiary education students. The coefficient of travel cost for car for home-based work (white collar) trips was determined to be 2.6 times of that estimated for blue collar work trips, indicating that white collar workers value their travel cost very highly, as compared to their blue collar counterparts. The model estimation for home-based shopping trips illustrated highly negative values for the mode-specific constants for park and ride, kiss and ride and cycling. It indicates that it is likely that some unobserved qualitative attributes, such as comfort and convenience, may be driving the mode choice for the specific trip purpose.

The overall goodness-of-fit values determined for each trip purpose were satisfactorily high, with exception for home-based education (PS) and home-based education (tertiary) trips. The reason for attaining a low ρ^2 value for HBE-T trips can be attributed to the small sample size employed for model calibration. Most of the estimated coefficients, along with mode-specific constants, were also found to be statistically significant and stable at the 95% confidence interval.

The sensitivity analyses conducted on the level-of-service attributes illustrated their relative elasticity surmised for each travelling mode for a certain trip purpose. For the trip purposes of HBW-B, HBS, HBO, WBW and ONHB trips, the level-of-service variables were found to be adequately inelastic. Since all these types of trips associate high estimated mode shares for car, it was concluded that the respondents of these trips are insensitive to the variation in the modal parameters. For trips purposes such as HBW-W, HBE-PS and HBE-T, the mode shares were observed to substantially change with the variation in the level-of-service attributes. Hence, it is concluded that apart from these three trip types, even a 50% reduction in the values of mode choice influencing parameters, such as in-vehicle travel time or out-ofpocket trip fare for public transport, are not likely to considerably divert the mode shares in favour of non-car modes.

5 Future Direction

From the findings of this study, following topics were identified that require further investigations,

- A stated preference survey was carried out by Queensland Transport during 2006 for use in the development of mode choice models. Due to the time constraints, we were unable to develop a joint revealed preference – stated preference (RP-SP) data set and model structure. However, this analysis will be the next logical step. This data may provide us with additional information about park & ride and kiss & ride modes that will allow us to specify less generic coefficients;
- Data from the 2006 SEQTS for the Brisbane Statistical Division will become available by the end of 2007. We intend to run further validation checks on the mode choice models using the new dataset;
- We will give consideration to reviewing the trip purpose classification with regard to the classification trips involving a serve passenger component. The options are still being considered, however, the change will affect all stages of the BSTM, and not just the mode choice model;
- Modelling car and public transport captivity can be investigated further. We need to develop a methodology that can be used in the model, which will be robust and valid for both base year and future year scenarios. This requires a literature review on mode captive data analysis and an in-depth analysis of the SEQTS data;
- All school buses (both private and public) can be described in BSTM as a special public transport mode, available to primary and secondary school students only with concession fares; and
- Given the new SEQTS data will be available in future; off peak travel time for public transport needs to be implemented.

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