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Joint estimation of mode and time of day choice accounting for arrival time flexibility, travel time reliability and crowding on public transport

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ABSTRACT

This study develops joint choice models of mode and departure time for implementation in MetroScan, a new version of TRESIS (Hensher and Ton, 2002). Separate models are estimated for work and non-work purposes, testing all practical alternatives of model structure with a rich set of explanatory variables. The contributions of the current work to the existing TRESIS are twofold. First, travel demand for non-work purposes such as shopping, social and recreation are explicitly modelled in MetroScan as opposed to TRESIS that scales the demand for work purposes to obtain non-work travel demand. Second, choices of travel mode and departure time become more sensitive to situational factors such as the flexibility of arrival time, the reliability of travel time and crowding. Willingness to pay for various improvements to the level of service is derived. We describe and demonstrate how the proposed models are applied in the general modelling framework of MetroScan.

1. Introduction

It has long been recognised that the ability to simulate individual's choices of when to travel and what mode to use is critical to travel demand management and policy evaluation. These two decisions, together with route choice, are taken at an individual or household level, but when aggregated they determine the temporal distribution of traffic flows on both road and public transport networks. The importance of modelling these decisions to the success of travel demand management in congested/crowded areas has produced a number of models describing mode and time of day choices (Bhat, 1998a; de Jong et al., 2003; Hess et al., 2007b). While these models contribute substantially to our understanding of how travellers choose a time of day to travel and how this decision interacts with mode choice, they are far too complex and data-intensive to be operational in large scale travel modelling systems (Hess et al., 2007a). As a result, most regional travel demand models in use today do not have the temporal element of travel. For example, the latest version of the Sydney Strategic Travel Model (STM3) uses time-of-day factors, derived from the Sydney Household Travel Survey (HTS), to distribute the originally estimated 24-h travel into different times of day (Bureau of Transport Statistics, 2011). Using time-of-day factors to obtain temporal travel demand is also adopted in other 4-step regional travel demand models such as the South California Regional Model (Southern California Assiciation of Governments, 2008) and Greater Toronto Area Transport Model (Miller, 2007). As these factors are the same for the base year and the prediction years, these models are insensitive to temporal changes to network conditions while in reality travellers can choose to respond by switching their departure times to a less congested/crowded periods and staying with the same mode or by switching to a different mode to travel.

In contrast to 4-step models, advanced activity-based models (ABM) explicitly consider time of day choices. These models typically divide a 24-h day into discrete time periods to take advantages of discrete choice models in the estimation and application process (Vovsha and Bradley, 2004; Davidson et al., 2007). Although differences exist between operational ABMs, they all model time choices of outbound and return legs simultaneously such that "knock-on" effects are captured throughout the day. An example of the knock-on effect is that if a commuter goes to work early in the morning to avoid the morning peak congestion/crowding, he is more likely to return home early in the afternoon too. Although ABMs represents a significant improvement over 4-step models in many aspects, including how time of day choices are handled at the individual level, the adoption of ABMs has been limited due to the costs relating to data requirements, model development and long run times for forecasting.

Given the importance of incorporating temporal choices into regional travel demand models and the popularity of 4-step models, it is necessary to develop a simplified time of day choice models that are compatible with the 4-step modelling framework. This is the main

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motivation of the current work. In particular, this study aims to develop mode and time of day choice models for application within a simulation framework of MetroScan, an improved version of the Transportation and Environment Strategy Impact Simulator Transportation or TRESIS (Hensher and Ton, 2002). The contributions of the current work to the existing TRESIS are twofold. First, joint choice of mode and time of day for non-work purposes such as shopping, social and recreation are explicitly modelled in MetroScan as opposed to TRESIS that scales the demand for work purposes to obtain non-work travel demand. Second, a rich set of variables, including arrival time flexibility, travel time reliability, and crowding (that are collectively referred to as temporal dimensions) are used to explain individual's joint choice of travel mode and time of day. The inclusion of temporal dimensions is important for modelling departure time choice because, for example, workers with flexible working hours may choose to avoid crowding by travelling outside the peaks, while those with fixed working hours do not have such choices. Thus, MetroScan is more sensitive to temporal changes to network conditions which are important for the analysis and evaluation of transport policy focused on spreading the peaks.

Briefly, MetroScan is a simulation framework that is based on the random utility maximisation theory (McFadden, 1974). MetroScan is a fully integrated transport and land use model that endogenously simulates many decisions, ranging from land use and urban developments (such as firm location choice, urban density, housing price, residential and work location choices) to transport demand (tour generation, destination choice, mode and departure time choice, arrival time flexibility) and transport supply (network assignment). MetroScan deals with not only passenger movement, but also services and freight movement, all within one integrated modelling framework. This is an on-going work with new modules and refinements added as more data become available. For the latest development of MetroScan, the reader is referred to Ho et al. (2017) and Hensher et al. (2020).

The remainder of this paper is organised as follows. The next section provides a review of pertinent literature on mode and time of day choice models with a particular focus on operational models. This is followed by a description of data and modelling approach used in this paper. Estimation results are then presented, followed by a description of how these models are calibrated and applied as part of the MetroScan system. The paper concludes with a summary of the main findings and recommendations for future work.

2. Review of relevant literature

A number of models have been proposed to study time of day choice. These models can be broadly classified into two groups, depending on whether time of the day is treated as a continuous or a discrete variable. While small scale models work fine with continuous time information, large scale modelling systems require an aggregation of continuous time into a manageable number of time periods to reduce run times as well ensure practical and reliable calibration. Given that practical implementation of models is the main focus of the current paper, this section limits itself to the literature on discrete time models (see Habib et al., 2009 for a review of continuous time models).

The approach to modelling trip timing, be it the departure time or arrival time, as a discrete entity was first proposed by Cosslett (1977) and Small (1982). Typically, time period choice models are formulated in a multinomial logit model (MNL) form to describe a decision that travellers make: paying a higher cost to travel at the preferred time or switching to another time period to pay less (e.g., shorter journey or lower cost). Initially, trip timing models focused on the morning commute by car (Abkowitz, 1981; Hendrickson and Plank 1984, Arnott et al., 1990); however, studies have been extended to cover non-commute trips and the interaction between departure time choice and mode choice (Bhat, 1998b; de Jong et al., 2003; Hess et al., 2007a). The latter extension is very important as each mode is associated with different levels of service throughout the day, and thus the two decisions of what mode to use and what time to travel are likely to be interdependent. For example, travellers may prefer the car to public transport during off-peak hours when traffic congestion is low and public transport service is not good (e.g., low frequency). By contrast, public transport may be more attractive during peak hours as it offers higher service levels and can compete with the car mode that is likely to suffer from greater traffic congestion. Motivated by this observation, a number of modelling approaches has been proposed to account for the interdependency of mode choice and time of day choice.

In the development of a mode and time of day joint choice model, two issues needs to be addressed. The first relates to the correlation structure of the error terms (i.e., unobserved utility components). There are many reasons for this issue to arise, but the main source relates to the aggregation of the continuous time space into a finite number of time periods for the application of discrete choice models. As a result, adjacent time period alternatives may share unobserved utility, leading to correlated error terms. This correlation issue can *methodologically* be addressed by the use of advanced discrete choice models. For example, de Jong et al. (2003) and Hess et al. (2007b) used an error component model (ECM) and Börjesson (2008) used an error component mixed MNL to jointly model mode and departure time choices. *Practically* speaking, however, these models are far too computational intensive to be operational in large scale modelling systems. Thus, for practical works, mixed logit models, of which ECM is a member, need to be replaced by simpler models with a closed form (e.g., MNL and NL) to maintain computational costs at an acceptable level (Hess et al., 2007a).

The second issue that needs to be addressed, for practical reasons, relates to the specification of explanatory variables. A vast majority of time of day choice models are based on Vickrey's (1969) equilibrium scheduling theory. This theory uses the concept of schedule delay to quantify the loss in utility associated with shifting the trip time away from the preferred departure/arrival time. As Hess et al. (2007a) pointed out, the schedule delay formulation works well in exploratory modelling of sample data, but this can be highly problematic when it comes to model application as the precise information on the preferred departure/arrival time is not available in a forecasting context. To deal with data unavailability, operational trip timing models use a set of constants associated with different time periods to capture traveller's preferences for a particular departure/arrival time. Although this approach may lead to problems with model identification and interpretation (see Hess et al., 2005 for in-depth discussion, Ben-Akiva and Abou-Zeid, 2013) it does not associate with any operational issues for large scale modelling systems.

On the basis of the two issues discussed above, Hess et al. (2007a) conduct an extensive analysis, using three separate Stated Preference (SP) datasets and three ways of defining time periods, to identify whether one nesting structure (e.g., mode conditions time of day choice) is better than the other (e.g., time choice conditions mode choice) and whether the preferred nesting structure varies across specifications of time periods (i.e., temporal resolutions). The data were collected in the UK and the Netherland (the latter is used in de Jong et al., 2003). Separate models were estimated for commuter, business and leisure purposes with models for commuters being segmented further by flexible work hours. Table 1 summarises the results of this important work. As can be seen from Table 1, the preferred nesting structure varies across datasets, and within the same dataset, varies across travel purposes and to a lesser extent, temporal resolutions. In general, their results show that travellers are more likely to switch time of day and stay with the same mode than the other way around (i.e., the preferred structure is nesting mode choice above the time period choice). This finding is supported by the works of Börjesson (2008) and Lizana et al. (2014) who found a statistically significant correlation between time period alternatives under the same mode. In addition, Hess et al. (2007a) found that the degree of substitution between time period alternatives is reduced when broader time periods are used. This

Table 1
Preferred nesting structure of mode and time period choice models by dataset and length of time periods (Hess et al., 2007a).

Dataset	Length of TP	Commuter	Business	Leisure	Flexible commuter	Inflexible commuter
APRIL	5 coarse periods	TP > Mode	Mode > TP	Mode > TP	n/a	n/a
	1 h	TP > Mode	Equivalent	Mode > TP	n/a	n/a
	15 min	TP > Mode	n/a	n/a	n/a	n/a
PRISM	5 coarse periods	MNL	Mode > TP	Mode > TP	MNL	MNL
	1 h	Mode > TP	MNL	Mode > TP	n/a	n/a
	15 min	MNL	n/a	n/a	n/a	n/a
Dutch	5 coarse periods	Mode > TP	MNL	Mode > TP	Mode > TP	Mode > TP
	1 h	Mode > TP	MNL	Mode > TP	Mode > TP	Mode > TP
	15 min	Mode > TP	n/a	n/a	Mode > TP	Mode > TP

Note: TP = Time period; TP > Mode = preferred structure is nesting time period above mode choice; Mode > TP = preferred structure is nesting mode choice above time period; Equivalent = two nesting structures are equivalent and statistically better than MNL. MNL = preferred structure is MNL (i.e., NL model is not statically better than MNL); n/a = models were not estimated due to small sample sizes.

empirical result lends support to the argument that the longer the length of time period, the less correlation between time period alternatives, and hence the more likely that MNL is the preferred structure.

A common element to all of the studies cited in the previous paragraph is that mode and time of day choice models are based on SP surveys that include multiple departure time options (usually three: depart earlier, later, or same as currently observed) for the current mode but only one departure time option for the alternative mode (usually the reported time if alternative mode is used). This raises a critical question as to whether the preferred nesting structure found in empirical analysis of these datasets (i.e., mode conditions departure time choice) is a product of the SP design, since respondents have more options to switch time and stay with the same mode than to switch mode and maintain the same departure time. The current paper aims to contribute to the debate.

Another area that needs more attention is that most trip timing models have relied on SP data and cover car drivers only, although some exceptions can be found. This limitation stems from the fact that Revealed Preference (RP) data on trip timing are difficult to collect, and that most trip timing models are developed to study how car drivers would respond to increasing road congestion and road pricing. However, crowding on public transport represents an increasing concern and this calls for an extension of trip timing models to cover public transport users. In addition, concerns have been raised towards the use of SP data for analysing and forecasting departure time choice (Börjesson, 2008). That is, one cannot be sure if respondents, when faced with the real world situation, would respond in the same way as they did in the SP experiment. This problem is known as hypothetical bias, and can be overcome by joint SP/RP analysis. This is the approach the current paper follows. The next section describes the data sources and modelling approach.

3. Data collection and descriptive analysis

This section describes the main data sources that are used for the development of mode and time of day joint choice models for MetroScan. Descriptive analysis of the data is then presented as a precursor to model development.

3.1. Data collection

A computer-assisted personal interview (CAPI) survey was purposely designed to collect data for the development of mode and time of day joint choice models. A pilot survey was conducted on 14th November 2013 on a sample of 20 interviewees to test the comprehendability of the questionnaire and to collect feedback from both interviewers and interviewees. A number of edits were made after the pilot survey to improve the layout of the questionnaire and to reduce respondent burden in terms of the number of SP tasks each interviewee is required to complete in order to proceed to the next part of the survey. The main survey was conducted from 20 November 2013 to 4th May 2014. Fig. 1 shows the locations of the eight interview sites, which were selected to provide a good mix of travel modes and to cover the study area of MetroScan – the Sydney Greater Metropolitan Area (SGMA).

The survey was conducted using a face-to-face interview method. Respondents were recruited on site by a recruiter who made sure that the respondent is eligible for the interview (i.e., live in the study area, undertook at least one motorised trip in the last seven days and had an alternative motorised mode available to use) and that consent was obtained before a formal interview was conducted by one of the interviewers who accessed the survey instrument via a desktop computer. Recruitment and interviews were conducted for one week at each site, starting on Monday and ending on Sunday. Each respondent was given a $5 gift card to the supermarket of their choice (i.e., Woolworth or Coles) for an average interview time of 28 min. Interviewers sat with the respondents to provide any advice that was required in working through the survey, while not offering answers to any of the questions. A preset sample of 150 interviews was contracted for each of the eight sites. The survey data were analysed on a daily basis when the survey was in progress to ensure a good balance of travel purposes for each site. A sample of 1221 interviews (with a response rate of 65%), spreading almost equally across the six travel purposes (i.e., to work, from work, education, shopping, personal business, and social), were obtained.

In terms of the information collected, the questionnaire consisted of six parts. In the first part, interviewees were asked to select a motorised trip (in terms of travel purpose and departure time) that they recently undertook and were able to provide details on trip origin, destination and timing. The second part included questions relating to trip origin and destination (in terms of postcode and suburb), departure and arrival times, main travel mode (car as driver, car as passenger, bus, train, ferry and light rail), alternative mode for the trip if the chosen mode were not available, and the departure time if the alternative mode were used. Conditioned on the chosen and non-chosen modes provided, follow-up questions were used to obtain, *where relevant*, door-to-door travel times in the last three occasions, one-way toll fee, distance driven, car occupancy, the availability of reserved parking and parking cost per day if the car mode was used, access and egress modes (including walk, park and ride, kiss and ride, public transport), access and egress times, waiting time at station/stop, public transport fares (for access, main, and egress legs), number of transfers, the availability of seats on public transport, and the time that the interviewee arrived at their final destination, be it the activity location or home. Note that these questions were asked for both chosen and non-chosen alternatives (i.e., mode and departure time) such that RP data were revealed by the respondent rather than being inferred by the analyst. The third part of the questionnaire aimed to elicit how much flexibility the respondent

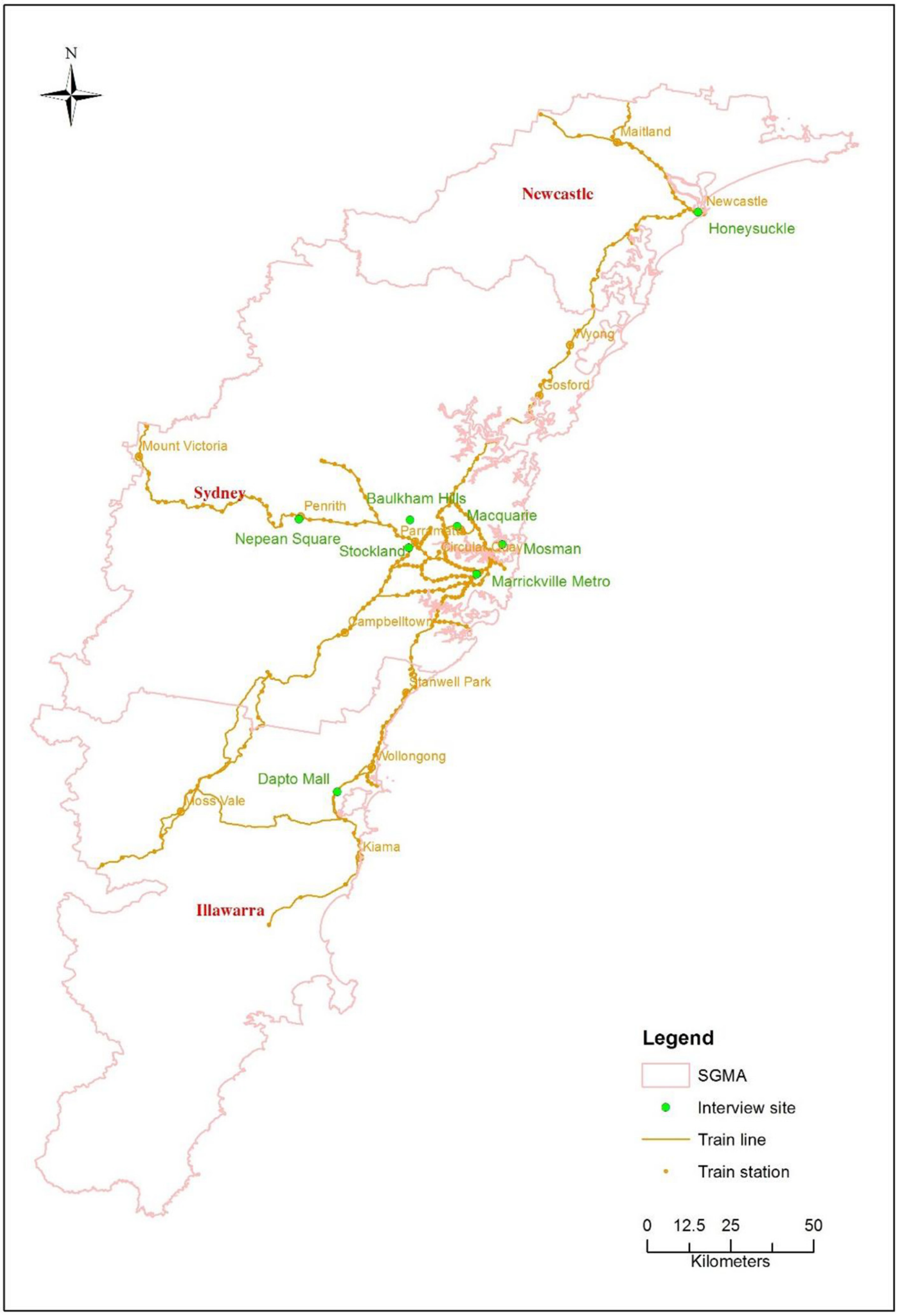
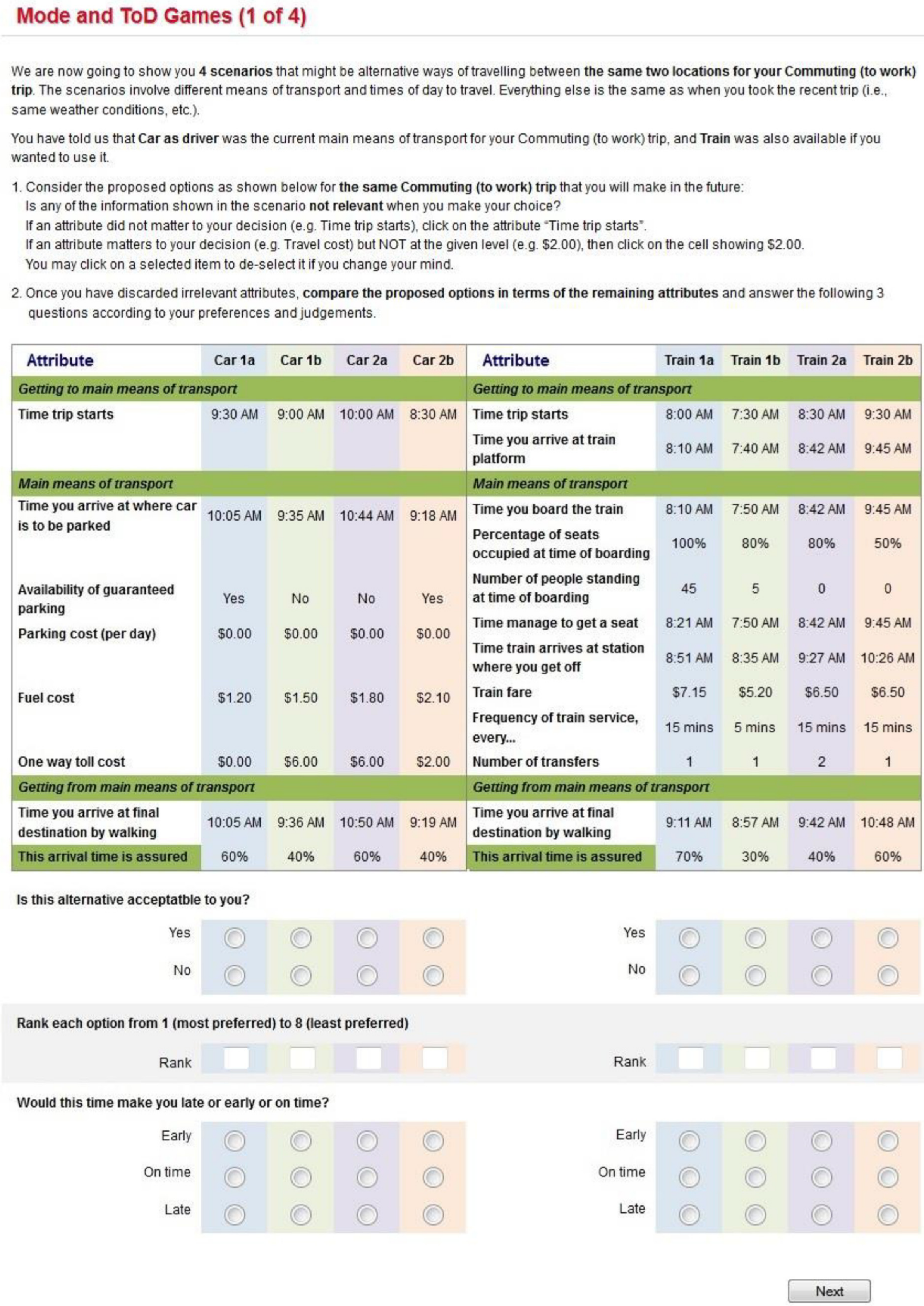


Fig. 1. Study area and interview sites.

has in terms of arrival time at the final destination, with six selectable options: no flexibility at all, within 15 min, 30 min, 45 min, 60 min of the planned/agreed time, and 'does not really matter'. The 15-min intervals were used to provide a possibility of developing departure time choice models with a fine time resolution of 15 min or 30 min (Bowman and Bradley, 2006; Shiftan & Ben-Akiva, 2011). From a behavioural standpoint, people may adjust their departure time preferences that might not be captured in models with coarser time periods. Also, temporal variables such as crowding during the peak hour may vary substantially in a short period, and thus, a shift of 15-min may see a completely different level of crowding, especially on public transport. Individual responses to this question were used to develop discrete choice models, predicting how much flexibility each individual has in terms of their arrival time using travel purpose, socio-demographic and working industry as explanatory variables. The logsums of this model are then fed into the mode and time of day choice (see model structure in Fig. 4). The fourth part included questions relating to the features of car and public transport modes. In this part, respondents were asked to indicate for the car mode: the maximum travel time, toll cost per trip, fuel cost per trip, parking cost per day, and for the public transport mode: the maximum access/egress times, wait time, time standing on public transport, and public transport fares that they would consider using these modes if they make the same trip again.

The information about the recent trip acquired from respondents over the first fourth part was used to design a customised SP survey in the fifth part of the questionnaire. Each SP task offered 8 alternatives: four alternative departure times under the chosen mode (i.e., observed to use for the recent trip) and four alternative departure times under the non-chosen mode (revealed by the respondent). Each alternative was described by a set of relevant attributes with the exact levels shown to



Mode and ToD Games (1 of 4)

We are now going to show you **4 scenarios** that might be alternative ways of travelling between **the same two locations for your Commuting (to work) trip**. The scenarios involve different means of transport and times of day to travel. Everything else is the same as when you took the recent trip (i.e., same weather conditions, etc.).

You have told us that **Car as driver** was the current main means of transport for your Commuting (to work) trip, and **Train** was also available if you wanted to use it.

1. Consider the proposed options as shown below for **the same Commuting (to work) trip** that you will make in the future:
   Is any of the information shown in the scenario **not relevant** when you make your choice?
   If an attribute did not matter to your decision (e.g. Time trip starts), click on the attribute "Time trip starts".
   If an attribute matters to your decision (e.g. Travel cost) but NOT at the given level (e.g. $2.00), then click on the cell showing $2.00.
   You may click on a selected item to de-select it if you change your mind.
2. Once you have discarded irrelevant attributes, **compare the proposed options in terms of the remaining attributes** and answer the following 3 questions according to your preferences and judgements.

Attribute	Car 1a	Car 1b	Car 2a	Car 2b
Getting to main means of transport				
Time trip starts	9:30 AM	9:00 AM	10:00 AM	8:30 AM
Main means of transport				
Time you arrive at where car is to be parked	10:05 AM	9:35 AM	10:44 AM	9:18 AM
Availability of guaranteed parking	Yes	No	No	Yes
Parking cost (per day)	$0.00	$0.00	$0.00	$0.00
Fuel cost	$1.20	$1.50	$1.80	$2.10
One way toll cost	$0.00	$6.00	$6.00	$2.00
Getting from main means of transport				
Time you arrive at final destination by walking	10:05 AM	9:36 AM	10:50 AM	9:19 AM
This arrival time is assured	60%	40%	60%	40%

Attribute	Train 1a	Train 1b	Train 2a	Train 2b
Getting to main means of transport				
Time trip starts	8:00 AM	7:30 AM	8:30 AM	9:30 AM
Time you arrive at train platform	8:10 AM	7:40 AM	8:42 AM	9:45 AM
Main means of transport				
Time you board the train	8:10 AM	7:50 AM	8:42 AM	9:45 AM
Percentage of seats occupied at time of boarding	100%	80%	80%	50%
Number of people standing at time of boarding	45	5	0	0
Time manage to get a seat	8:21 AM	7:50 AM	8:42 AM	9:45 AM
Time train arrives at station where you get off	8:51 AM	8:35 AM	9:27 AM	10:26 AM
Train fare	$7.15	$5.20	$6.50	$6.50
Frequency of train service, every...	15 mins	5 mins	15 mins	15 mins
Number of transfers	1	1	2	1
Getting from main means of transport				
Time you arrive at final destination by walking	9:11 AM	8:57 AM	9:42 AM	10:48 AM
This arrival time is assured	70%	30%	40%	60%

Is this alternative acceptatble to you?

Yes
No

Rank each option from 1 (most preferred) to 8 (least preferred)

Rank

Would this time make you late or early or on time?

Early
On time
Late

Next

Fig. 2. Illustrative choice screen of mode and time of day survey in Sydney GMA, 2014.

Table 2a
Stated Preference attributes and rules-based pivoting levels.

Attribute (unit)	Mode applied	Pivot levels
Getting to main means of transport		
Departure time (mins)	All modes	± 60, ± 30, 0
Access time (mins)	All PT modes	± 20%, ± 10%, 0%
Parking cost ($)	PT modes accessed by PnR	± 4, ± 2, 0 ≥ 0
PT fare ($)	All PT modes	± 20%, ± 10%, 0%
Time arrive at platform/wharf/stop (mins)*	All PT modes	± 5, ± 2, 0
Main means of transport		
In-vehicle travel time (mins)	All modes	± 20%, ± 10%, 0%
Availability of guaranteed parking	Car	Yes, No
Parking cost per day ($)	Car	± 20%, ± 10%, 0%
Fuel cost one way ($)	Car	± 30%, ± 15%, 0%
Toll cost one way ($)	Car	see look up Table 2b
Time wait for main mode (mins)*	All PT modes	± 15, ± 10, ± 5, 0
% seats occupied at time of boarding (%)	All PT modes	see look up Table 2c
# people standing at time of boarding (people)	All PT modes	see look up Table 2c
Time standing on PT (mins)	All PT modes	± 25%, 0%
PT fare ($)	All PT modes	± 20%, ± 10%, 0%
Frequency of service or headway (mins)	All PT modes	5, 10, 15
Number of transfers	Train, Ferry, Light Rail	0,1,2
% Time bus in a bus lane (%)	Bus	± 30%, ± 20%, ± 10%, 0%
Getting from main means of transport		
Time walk to egress mode (mins)	All modes egressed by PT	0%
Time wait for egress mode (mins)	All modes egressed by PT	0%
In-vehicle time for egress leg (mins)	All modes egressed by PT	± 20%, ± 10%, 0%
PT fare for egress leg ($)	All modes egressed by PT	± 20%, ± 10%, 0%
Time walk to final destination (mins)*	All modes	± 5, ± 2, 0

Note: * conditions applied to ensure the consistency of times shown to respondents (e.g., time board main mode must be later than time arrive at the platform/wharf/stop).

Table 2b
Look up table for one-way toll fee levels.

	One-way toll fee incurred on recent trip				
	$0.00 - $4.00	$4.01 - $8.00	$8.01 - $12.00	$12.01 - $16.00	> $16.00
One-way toll fee levels shown in SP tasks	0	0	4	8	8
	2	4	8	12	16
	4	8	12	16	32
	6	12	16	20	40

each respondent varying, depending on the combination of departure time, main mode, access and egress modes reported for a recently undertaken trip. For most attributes, the levels shown in the SP tasks are obtained by pivoting around the current perceived levels (for both chosen and non-chosen modes); however, there are some attributes such as the availability of guaranteed parking (for car mode), frequency of PT services, and number of transfers that are fixed while other attributes such as crowding and one-way toll costs are linked to the recent trip experience via a look-up table. The look-up table for toll fee was based on the Sydney toll road network and toll charges in 2013 (see Appendix A). Table 2 shows the set of relevant attributes for each mode (grouped into access, main or egress legs) and the pivot levels used in for the generation of SP tasks. Fig. 2 shows an illustrative choice task for a respondent who reported that he left home for work at 9:00 by car on an alternative departure time at 8:30 if train were used for the same trip (Table 2a).

Crowding required a careful consideration as it is one of the factors that influence mode and time of day choice, a focus of the current study. This study adopted the approach proposed by Hensher et al. (2011) in which crowding on public transport is presented by two measures: percentage of seats occupied and the number of people standing at the time of boarding the train, bus, and light rail. The presentation of the crowding attribute involves both a written description and visual presentation of the seating configuration for each mode, showing the people seated and standing. An example visualisation of crowding level is shown in Fig. 3 for the combination of these two measures defining the crowding levels by departure time are shown in Table 2c. Different from the previous study by Hensher et al. (2011), however, this study links crowding levels to the departure time such that the chance that public transport is crowded will be higher during peak hours than during the off-peak. The selection of the crowding levels for peak and off-peaks hours was determined based on the distribution of crowding levels by departure time (see Appendix B) derived from a 2012 train load survey (Bureau of Transport Statistics, 2012). This aims to replicate the crowding levels that public transport users in Sydney experience in their daily travel, and hence making the SP tasks more realistic.

Respondents were asked to review four SP tasks and indicate, in each choice task, whether there are any attributes or attribute levels that are not relevant to their decisions on what mode to use and what time to travel when they undertake the same trip in the future. Under

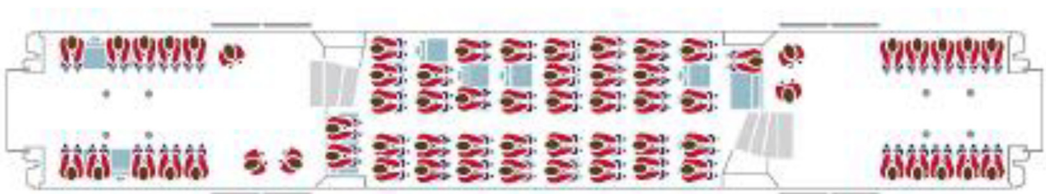


Fig. 3. Example of crowding on train: level 8 (90% seats occupied, 5 people standing) applied to both peak and off-peak.

Table 2c
Crowding level by departure time and mode.

Level	Cumulative Probability	% Seats occupied	Standing on Bus	Standing on Train	Standing on LR
1, off-peak	0.40	25%	0	0	0
2, off-peak	0.65	50%	0	0	0
3, off-peak	0.70	60%	0	0	0
4, off-peak	0.75	70%	0	0	0
5, off-peak	0.80	80%	0	0	0
6, off-peak	0.85	80%	5	5	5
7, off-peak	0.90	90%	0	0	0
8, off-peak	1.00	90%	5	5	5
5, peak	0.40	80%	0	0	0
6, peak	0.50	80%	5	5	5
7, peak	0.60	90%	0	0	0
8, peak	0.65	90%	5	5	5
9, peak	0.70	100%	0	15	0
10, peak	0.75	100%	3	30	3
11, peak	0.80	100%	7	45	7
12, peak	0.85	100%	11	60	11
13, peak	0.90	100%	15	75	15
14, peak	0.95	100%	19	90	19
15, peak	0.97	100%	23	105	23
16, peak	1.00	100%	27	120	27

Note: Peaks are defined based on departure time between 7 and 9 AM or 4 and 6 PM; off-peak = any departure time outside the peaks.

the respondent's indication, interviewers helped respondents to select irrelevant attributes/attribute levels and then asked them to compare the proposed options in terms of the remaining attributes and indicate whether each of the eight alternatives is acceptable to them. Responses to this first SP question effectively classified the eight alternatives on offer into two groups: acceptable alternatives and non-acceptable alternatives. The interviewers then asked the respondent to rank the eight alternatives from 1 (most preferred) to 8 (least preferred), starting with the acceptable group and then the non-acceptable one. Finally, respondents were required to indicate whether they are late, early or on time under each of the eight alternatives. The respondents were then shown a new game and the same process repeated.

Although four SP tasks were offered, respondents were required to complete a minimum of two SP tasks before they can go to the final part of the survey (on average each respondent completed 3.50 tasks). This final part includes standard questions relating to individual and household characteristics such as age, gender, employment status, occupation, personal income, household income, household structure, household size, number of household adults, children, full-time and part-time workers, and number of vehicles owned by the household.

3.2. Descriptive analysis

This section provides a socio-economic profile of the sample and an overview of the mode and departure time profile obtained from the RP data.

Table 3 provides a socio-economic profile of the sample, segmented by travel purpose. As discussed in Section 3.1, the sampling method focuses more on obtaining enough observations for model development, with much less attention being paid to the representativeness of the sample. Thus, a comparison of the sample profile with that of the population is considered not necessary. However, it is important that the sample from which model parameters are to be estimated cover a wide spectrum of the population in terms of personal and household characteristics. This is indeed the case for both commuter and non-commuter samples where a good mix of gender, age, employment status, occupation, household structure, and car ownership can be observed from Table 3.

Table 4 provides a simple crosstab of mode choice against departure time for commuting trips. The subsample of commuting trips includes 392 respondents, but only two reported that they use ferry or light rail

Table 3
Socio-economic profiles of the commuting and non-commuting samples.

	Commuting sample	Non-commuting sample
Average age (in years)	43	45
Gender		
Male	34%	33%
Female	66%	67%
Employment status		
Fulltime worker	63%	14%
Part-time worker	20%	16%
Casual worker	15%	12%
Unpaid voluntary worker	2%	1%
Unemployment	0%	56%
Occupation		
Labourer	3%	1%
Trade and Plant	4%	3%
Professional	40%	17%
Management and Admin	23%	10%
Clerk	3%	2%
Self employed	4%	7%
Sales	12%	10%
Other	12%	51%
Average personal income ('000$)	90	76
Licence holder	93%	89%
Number of household vehicle		
0	7%	8%
1	32%	40%
2	39%	33%
3+	21%	19%
Household structure		
Lone person	12%	17%
Couple with children ≤ 14 and > 14 years	5%	5%
Couple only	22%	23%
Single parent with children over 14 years	6%	5%
Couple with children over 14 years	20%	16%
Single parent with children < 15 years	2%	2%
Couple with children < 15 years	14%	7%
Single parent with children ≤ 14 and > 14 years	1%	1%
Other household types	19%	25%
Average household income ('000$)	211	216
Arrival time flexibility		
No flexibility	40%	39%
Within 15–30 min	24%	21%
Within 60 mins	5%	2%
Does not matter	32%	38%
Sample size	*392*	*829*

for commuting. These observations are excluded from further analysis. It is worth noting that obtaining a decent sample size for ferry and light rail is difficult in Sydney as these modes have very limited spatial coverage in the local context. This applies to even the large-scale Sydney Household Travel Survey which interviews about 3500 households every year but still having difficulty in obtaining a decent sample size for these modes (Bureau of Transport Statistics, 2014; Statistics, B. o. T, 2014a). With a recent rollout of smartcard data across the Sydney Greater Metropolitan Area (Ho, 2020 Forthcoming) every public transport journey is captured and this provides a great source of RP data to incorporate transport modes with a small market share (i.e., light rail, bus rapid transit, and ferry) into strategic models.

An examination of column-wise percentage in Table 4 indicates that 21% of car commuting trips start during the morning peak (7–9 AM). The shares of commuting trips by public transport are considerably higher during the same period (34% for bus commuters and 31% for train commuters). The same patterns are observed for the afternoon peak, although the differences are to a lesser extent. Similarly, an examination of row-wise percentages in Table 4 shows that about 70% of commuting trips undertaken before 7:00 involve the use of a car while

Table 4
Cross-tabulation of main mode and departure time for commuting trips (to and from work).

Departure time choice	Main mode				Total
	Car	Bus	Train	Ferry/LR	
Frequency					
Before 7 AM	44	8	12	0	64
7–9 AM	52	17	29	0	98
9 AM–3 PM	41	6	10	1	58
3–4 PM	18	3	4	0	25
4–6 PM	58	9	30	0	97
After 6 PM	33	7	9	1	50
Total	246	50	94	2	392
Percent within column (mode)					
Before 7 AM	18%	16%	13%	excluded	n/a
7–9 AM	21%	34%	31%	excluded	n/a
9 AM–3 PM	17%	12%	11%	excluded	n/a
3–4 PM	7%	6%	4%	excluded	n/a
4–6 PM	24%	18%	32%	excluded	n/a
After 6 PM	13%	14%	10%	excluded	n/a
Total	100%	100%	100%	excluded	n/a
Percent within row (departure time)					
Before 7 AM	69%	13%	19%	excluded	100%
7–9 AM	53%	17%	30%	excluded	100%
9 AM–3 PM	72%	11%	18%	excluded	100%
3–4 PM	72%	12%	16%	excluded	100%
4–6 PM	60%	9%	31%	excluded	100%
After 6 PM	67%	14%	18%	excluded	100%

this value decreases to 53% if a commuting trip starts during the morning peak. Clearly, there appears to be a correlation between mode choice and departure time choice with public transport being more popular to peak commuters and peak-avoiding commuters are much more likely to be car commuters.

Table 5 offers similar indications, with stronger tendencies than those seen in Table 3. For non-commuting trips (including education, shopping, personal business and leisure), it is found that a majority of car trips (63%) are undertaken during the inter-peak (between 9:00 and 15:00) while train-based non-commuting trips spread more evenly between the morning peak (38%) and the inter-peak (40%). These two time periods (morning peak and inter-peak) accounts for a majority of commuting trips as the sample includes trips from home to activity locations (i.e., no trips from activity to activity or from activity to home in the non-commuting sample). The maximum percentage point difference in the case of non-commuting trips is 23% (63% - 40% = 23%), which is much higher than that observed for commuting trips (32% - 18% = 14% during PM peak). Similarly, 51% of the non-commuting trips undertaken during the morning peak are car-based, while this percentage increases to 69% for non-commuting trips starting between 9:00 and 15:00. Once again, there is a strong correlation between mode choice and departure time choice for non-commuting trips.

Table 5
Cross-tabulation of main mode and departure time for non-commuting trips.

Departure time choice	Main mode				Total
	Car	Bus	Train	Ferry/LR	
Frequency					
Before 7 AM	14	12	13	0	39
7–9 AM	110	49	56	0	215
9 AM–3 PM	322	87	59	3	471
3–4 PM	16	2	4	0	22
4–6 PM	30	10	10	0	50
After 6 PM	19	7	6	0	32
Total	511	167	148	3	829
Percent within mode					
Before 7 AM	3%	7%	9%	excluded	n/a
7–9 AM	22%	29%	38%	excluded	n/a
9 AM–3 PM	63%	52%	40%	excluded	n/a
3–4 PM	3%	1%	3%	excluded	n/a
4–6 PM	6%	6%	7%	excluded	n/a
After 6 PM	4%	4%	4%	excluded	n/a
Total	100%	100%	100%	excluded	n/a
Percent within departure time					
Before 7 AM	36%	31%	33%	excluded	100%
7–9 AM	51%	23%	26%	excluded	100%
9 AM–3 PM	69%	19%	13%	excluded	100%
3–4 PM	73%	9%	18%	excluded	100%
4–6 PM	60%	20%	20%	excluded	100%
After 6 PM	59%	22%	19%	excluded	100%

What we cannot draw from these crosstabs, however, is whether mode choice conditions departure time choice or time choice conditions mode choice or the two decisions are made simultaneously, since other factors such as differences in personal and household characteristics between public transport and car users need to be accounted for. This can only be done using multivariate analysis described in the next section.

4. Model specifications and estimation results

4.1. Model specification

For practical reasons discussed in Section 2, models specified for mode and time of day choice presented in this paper are limited to MNL and NL forms. The review of the literature in Section 2 also suggests that alternative nesting structures (mode choice conditions departure time choice vs. departure time choice conditions mode choice) should be explored, such that the preferred nesting structure can be decided on empirical evidence. Thus, for each travel purpose, three alternative model structures are specified to examine three possible relationships between mode choice and departure time choice. These are that the mode choice and departure time choice are made simultaneously (MNL model); second that the mode choice is determined first and conditions the departure time choice (nesting mode choice above time period); and finally that the departure time choice comes first and influences mode choice (nesting time period above mode).

In addition to the sequence of the model structure, it is necessary that scale differences between RP and SP data be accounted for when models are based on combined RP/SP data to enrich model behavioural responses and to overcome weaknesses associated with each data type. To this end, the 'artificial tree structure' mechanism is employed (Ben-Akiva and Morikawa, 1990; Hensher and Bradley, 1993; Ortuzar and Iacobelli, 1998). In addition, a decision on temporal resolution (i.e., how many time periods are to be used for modelling) needs to be made. Given the sample sizes obtained from commuters and non-commuters discussed in Section 3, we decide to group the 24-h day into six time periods for model development. These are the morning period (DT1 = before 7:00), am peak (DT2 = 7:00–9:00), inter-peak (DT3 = 9:01–14:59), pre-pm peak or school time (DT4 = 15:00–15:59), pm peak (DT5 = 16:00–18:00) and the evening (DT6 = after 18:00).

Another issue that model specification needs to take care of relates to the impact that the flexibility in arrival time or the lack thereof has on departure time choice and mode choice. Previous studies deal with this issue by segmenting the sample and using separate models for commuters with and without flexible working hours (see for example de Jong et al., 2003; Hess et al., 2007a). This segmentation approach works well in model development but it can be problematic when the models are being applied for forecasting because of two reasons. First, the information on flexible work hours is unlikely to be available for future years, and also that it is not typically included in the synthetic (or prototypical) households used in applications. Second, the influence of arrival time flexibility on mode and departure time choice extend to non-work travel, which is highly unlikely to be accompanied by any information on flexible arrival time. Thus, for this practical work, we develop a model to predict the probability that one has the flexibility in

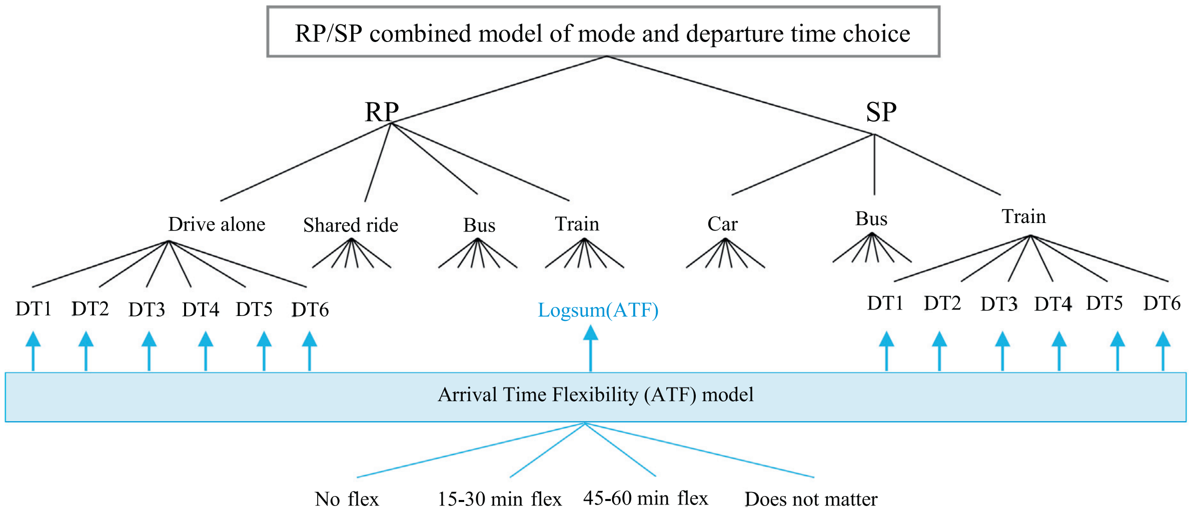


Fig. 4. Structure of mode and departure time choice model: mode conditions departure time.

arrival time, and then feed this information into the mode and departure time choice model using the expected maximum utility (or logsum) concept. This approach is analogous to the latent desired departure/arrival time described in Ben-Akiva and Abou-Zeid (2013).

Fig. 4 shows an overall structure of the mode and departure time choice model developed for MetroScan. Note that in Fig. 4, we assume (and test below) that the mode choice decision comes first and conditions departure time choice. This overall structure, however, can easily be modified to reflect the other two possibilities (i.e., swapping mode and departure time to define an alternative NL model in which departure time conditions mode choice, and pooling two decisions into one level to define a MNL model in which both mode and departure time are made simultaneously).

4.2. Estimation results

An extensive number of MNL models were first explored to identify the set of potential variables explaining the joint choice of mode and departure time for each trip purpose using Nlogit 5 (Econometric Software, www.limdep.com). Models for 'to work' and 'from work' purposes deliver similar behavioural outputs such as values of travel time savings and willingness to pay to travel on a less crowded train/bus. On the other hand, separate models for each purpose of the non-commuting segment (i.e., personal business, education/childcare, shopping, social and leisure) did not deliver statistically significant parameters for key variables such as travel costs for car and access/egress time for PT. This is likely to be due to small sample sizes of each of the non-commuting sub-samples (i.e., personal business, education/childcare, shopping, social and leisure), which when combined into one category (i.e., non-work) delivers significant parameter estimates for all the important variables. Based on these results, we decided to pool the non-commuting samples for more detailed analysis of the preferred model structure. To work and from work purposes remain separated; however, for brevity, we only report results of the mode and time of day choice model for the 'to work' trips.

In searching for the preferred nesting structure, we found that the model nesting mode choice conditioned on departure time choice is rejected in all travel purpose segments, with the estimated logsum parameters lying outside the acceptable [0,1] range. On the other hand, the commuting to work models nesting mode choice above departure time choice which gave acceptable logsum parameters but this failed to reject the MNL model, while the same model for non-commuting trips took on unacceptable logsum parameters (i.e., larger than 1). In addition, a number of variables which are highly significant under the MNL specifications become insignificant under this NL structure. Thus, for each dataset (RP and SP) the preferred structure is the MNL.

Table 6 presents the estimation results of the preferred models of mode and departure time choice for commuting and non-commuting purposes. Both models fit the data very well with the McFadden pseudo-R^2 (McFadden et al., 1973; Hensher et al., 2015) of 0.710 for commuting trips (867 observations, 194 persons) and 0.689 for non-commuting trips (3665 observations, 829 persons).

The scale parameters of the SP datasets are larger than one at the 1% level, suggesting that the SP dataset has more noise (i.e. greater unobserved variance) than the corresponding RP dataset, in line with findings in most studies that combine RP data with SP data (Börjesson, 2008). With two exceptions, parameter estimates all have the expected sign with most of them highly significant. The first parameter with an unexpected sign measures the effect of crowding (#people standing) on commuter's choice of train mode; however, this parameter is not statistically significant. The second variable that has an unexpected sign and insignificant parameter is the observed PT fares for commuting; however, the same variable in the SP data has a strongly significant parameter with the expected sign. This suggests that there is not enough variation in RP public transport fare for its corresponding parameter to be significant.

Overall, the model results suggest that the levels of service such as travel times, travel costs, frequency of service and travel time reliability are the main drivers of mode choice while having flexibility in arrival time is the main driver of departure time choice. However, there are factors that influence both decisions. These are personal income and number of household vehicles, which influence commuter's choice of mode and departure time. Interestingly, high income car commuters appear to avoid the morning peak and they do so by commuting earlier; however, if they come from households with more children, the likelihood of switching departure time from peak to off-peak reduces. A possible explanation is that workers with children tend to drop-off their child at school *en route* to work, and as school starts between 8:00 and 9:00, peak commuting seems to be unavoidable.

Travel time reliability significantly influences mode choice for both commuting and non-commuting purposes. The parameters associated with this variable are significantly negative, suggesting that individuals prefer alternatives with more reliable travel time, measured by the standard deviation of travel time for repeated trips between the same origin-destination pair. Note that a direct comparison of parameter estimates is not meaningful, and thus a willingness to pay for more reliable travel time was derived and shown in Table 7. Overall, commuters are willing to pay more than non-commuters for reliable travel

Table 6
Estimation results of mode and departure time choice models for commuting and non-commuting trips, Sydney GMA 2014.

Variable (RP/SP utility)	Alternative applied	Commuting (to work)			Non-commuting		
		Parameter	Sig.	t-value	Parameter	Sig.	t-value
Car in-vehicle time (RP = SP)	Car	−0.052	***	−4.14	−0.031	***	−9.74
Egress time in mins (RP)	Car	−0.189	**	−2.31	−0.004		−0.18
Fuel cost in $ (RP = SP)	Car	−0.148	***	−3.56	−0.231	***	−5.25
Toll cost in $ (RP = SP)	Car	−0.148	***	−3.56	−0.533	***	−9.31
Travel time reliability (RP)	all	−0.144	**	−2.21	−0.088	***	−10.43
Parking cost in $ (RP)	Car	−0.028		−0.65	−0.067	***	−5.04
Availability of guaranteed parking (RP)	Car	1.443	*	1.77	−		−
Egress time in minute (RP)	Car	−0.117	***	−3.02	−0.072	***	−4.70
Parking cost in $ (SP)	Car	−0.087	***	−2.90	−0.148	***	−7.83
Availability of guaranteed parking (SP)	Car	0.413	**	2.16	0.850	***	6.28
Access time in minute (RP)	Bus, Train	−0.084	***	−3.51	−0.041	***	−5.23
PT in-vehicle time (RP = SP)	Bus, Train	−0.038	***	−4.17	−0.031	***	−9.74
Egress time in mins (RP)	Bus, Train	−0.093	***	−3.54	−0.021	***	−3.88
PT fare in $ (RP)	Bus, Train	0.079		0.79	−0.168	***	−4.28
Accessed by car (RP = SP)	Train	−		−	−1.541	***	−5.53
Accessed by bus (RP = SP)	Bus, Train	4.976	***	3.21	−0.440		−1.53
Egress by PT (RP = SP)	Bus, Train	1.308	**	2.09	−		−
Access time in minute (SP)	Bus, Train	−0.059	***	−3.04	−0.049	***	−5.39
Egress time in minute (SP)	Bus, Train	−0.072	***	−3.47	−0.034	***	−5.40
PT fare in $ (SP)	Bus, Train	−0.180	***	−2.67	−0.375	***	−7.13
Number of people standing (SP)	Bus	−0.031		−0.96	−0.033	*	−1.82
Number of people standing (SP)	Train	0.005		1.05	−0.006		−1.28
Headway in minute (SP)	Bus	−0.058	*	−1.69	0.028	*	1.82
Headway in minute (SP)	Train	−0.039		−1.29	−0.002		−0.09
Number of transfers (SP)	Train	−0.296	*	−1.71	0.004		0.04
Logsum parameter of ATF (RP = SP)	DT1	0.845	***	6.21	1		fixed
Logsum parameter of ATF (RP = SP)	DT2	0.872	***	6.52	0.273	**	2.04
Logsum parameter of ATF (RP = SP)	DT3	0.697	***	4.55	0.344	**	2.21
Logsum parameter of ATF (RP = SP)	DT4	1		fixed	0.152		0.79
Logsum parameter of ATF (RP = SP)	DT5	0.341	***	2.81	0.164	**	2.09
Logsum parameter of ATF (RP = SP)	DT6	0.076		0.73	0.094		1.19
Management and admin worker (SP)	DT1	−0.392		−0.88	1.248	*	1.95
Management and admin worker (SP)	DT6	−		−	2.177	**	2.21
Self-employed worker (SP)	DT1	−2.446	**	−2.43	−		−
Part-time worker (SP)	DT3	2.257	**	2.55	−		−
Couple with kids > and ≤ 14 (SP)	DT1	−1.305	*	−1.95	−		−
Couple with kids ≤14 (SP)	DT1	1.107	**	2.09	−		−
Personal income in 1000$ (RP)	Car_DT1	0.026	*	1.91	−		−
Personal income in 1000$ (RP)	Car_DT2	−0.004		−0.58	−		−
Personal income in 1000$ (RP)	Car_DT3	0.018		1.06	−		−
Number of household children (RP)	Car_DT2	0.432	**	2.02	−		−
Number of household vehicles (SP = RP)	Car	−		−	0.259	***	3.38
Male (RP = SP)	Car	−		−	−0.310	***	−4.07
Age 45–54 (SP = SP)	Car	−		−	0.771	***	4.03
Age 55–64 (SP = RP)	Car	−		−	0.261	*	1.72
RP data scale		1		fixed	1		fixed
SP data scale		1.360	***	4.28	1.799	***	9.99
Log-likelihood (pseudo-R^2;#observations)		*−1186 (0.710;867)*			*−5387(0.689; 3665)*		

Note: *** Significant at 1% level; **5% level, *10% level; − variables not included in models; ATF = Arrival time flexibility model.

time as we may expect. For the same travel purpose, however, travellers are willing to pay more for reliable public transport services, compared to the private car.

Having a flexible arrival time is, as expected, a significant driver of departure time choice for both commuting and non-commuting trips. This is reflected in the parameters associated with the logsum of the Arrival Time Flexibility (ATF) model nested below the mode and departure time choice (see Fig. 4). ATF models, for commuting and non-commuting, have the four alternatives of arrival time: must be at the destination on the planned/agreed time (i.e., no flexibility at all), must arrive within 15–30 min of the planned/agreed time; must arrive within 45–60 min of the planned/agreed time; and arrive at any time (i.e., arrival time does not matter). These models are based mainly on socio-demographic characteristics such that future arrival time flexibility can be predicted for any synthetic household without relying on data availability when it comes to model application. Table 6 shows that the logsum parameters of ATF are bounded between zero and one, indicating that the model structure is consistent with the assumption of global utility maximisation. Also, the commuting model has more and strongly significant logsum parameters than the non-commuting models. This suggests that having flexible working hours plays an important role in commuter's choices of departure time.

Crowding on public transport, measured as the number of people standing on the vehicle at the time of boarding, was also found to influence mode and departure time choice but this influence was significant only for non-commuting trips by bus. The corresponding parameter is negative (−0.033) and significant at the 10% level, suggesting that non-commuting travellers prefer less crowded buses. Number of people standing on trains does not have a significant parameter, suggesting that crowding on train does not significantly influence individual choice of mode and departure time. One possible explanation is that trains are often crowded during the peak hours when a lot of commuters have to use train travel to work (i.e. captive train users). Further investigation is required to separate the influence of captive users (i.e. preferences) from crowding on mode and departure time choices.

Table 7
Willingness to pay for improved levels of service ($2014).

Level of service	Unit	Commuting	Non-commuting
In-vehicle time, car	$/hour	23.13	5.93
Standard deviation of time, car	$/hour	51.65	13.82
Egress time, car	$/hour	63.75	16.86
In-vehicle time, PT	$/hour	12.83	4.94
Access time, PT	$/hour	19.87	7.80
Egress time, PT	$/hour	23.89	5.49
Standard deviation time, PT	$/hour	65.39	25.29
Transfer, train	$/transfer	1.65	−0.01
Crowding on bus	$/ one less person standing	0.17	0.09
Crowding on train	$/ one less person standing	−0.03	0.02
Frequency of bus services	$/ 1-min reduction in headway	0.32	−0.07
Frequency of train services	$/ 1-min reduction in headway	0.22	0.00

A specific issue arising in the pooling of RP-SP datasets relates to the selection of parameter estimates to form utility functions. Specifically, which parameters (RP or SP) are to be used for model application, especially when dataset-specific parameters are used in estimation? A common practice is to discard the RP parameters estimates and the SP constant terms and use the remaining parameters to form composite utility functions (Hensher et al., 2015). This practice is supported by the model results, which suggest that SP parameters are more significant and robust than RP parameters. Also, the SP parameters account for a greater variation in the attribute levels than the RP data and are hence of greater value in applications where we are making significant changes in the levels of the attributes. The model constants (23 in total), although estimated, are not shown in Table 6 as they are not informative (the sample used for model development is not representative of the population). These constants will be updated when the models are calibrated to replicate the population shares in the base year.

Using the composite utility functions, we derive the willingness to pay for various improvements to the levels of service. Table 7 gives these estimates in 2014 dollars. Overall, these values appear to be realistic and reflect what people are willing to pay for. For example, car commuters (per person) are willing to pay $23 for an hour travel time savings and they are willing to pay twice as much ($51.65) to reduce one hour in the standard deviation of their commuting time (i.e., value of travel time reliability or VTTR). The values are much lower for non-commuting trips. When bus is crowded, bus commuters are willing to pay $1.70 more to have 10 less people standing on the bus.

5. Placement of models in MetroScan

The proposed model for the joint choice of mode and departure time represents a part of the MetroScan modelling system developed for Sydney GMA. The model has been calibrated and applied in this modelling framework to provide travel demand forecasts for a number of transport infrastructure investments in Sydney. Fig. 5 shows an overall structure of the MetroScan passenger travel and location choice model system. MetroScan is an integrated package of choice models structured in a certain way to reflect the interdependencies of travel decisions.

The modelling system is implemented sequentially at the household, the individual and the network levels in a micro-simulation fashion with numerous feedbacks and links between modules. As shown in Fig. 5, the joint choice models of mode and departure time are applied conditional on work and non-work location choice (see Ho and Hensher, 2016 for details). On the one hand, the mode and time of day choice model receives logsums from the ATF model. That is, the AFT model is implemented first, using data from the synthetic households (Ellison and Hensher, 2016) and its logsum is computed and fed into the mode and departure time choice models. The logsums come out of these models are then fed to the work and non-work location choice models to simulate the destination of work and non-work trips (Ho and Hensher, 2016). Once these models have been executed, their logsums can be computed and fed to the residential location choice model (Ho et al., 2017), together with the logums of other models including vehicle fleet size choice, work practice (Hensher, 2008), and tenure and dwelling type choice (Ho and Hensher, 2014). Passenger models interact with light commercial vehicle and freight models through network assignments which reflect the competition for road space amongst these three segments.

6. Model application

This section describes an example application of MetroScan to assess the impact of crowding level on the commuting trips whose destination or origin are in the inner area of Sydney, including Botany Bay, Leichhardt, Marrickville, Sydney Inner, Sydney East, Sydney South, Sydney West and Randwick SLAs. To obtain patronage forecast under various settings of crowding level of trains, we report in this paper the MetroScan forecast of changes to the incoming and departing commuting trips in 2036.

To evaluate the impact of crowding level on train commutes, we consider two scenarios of increasing the crowding levels for all trips to Sydney Inner for six time periods by 5% and 10% respectively, and compare the number of morning commute trips by train in 2036 (Fig. 6) with that under the business as usual or do nothing scenario. The top two maps in Fig. 6 demonstrate difference in the predicted incoming morning commute trips by train between the *do nothing* and the two scenarios. Similarly, the bottom two maps show the difference in the predicted morning commute trips that depart from these 8 SLAs between the *do nothing* and the same two scenarios. It can be seen that an increase in train crowding level results in a slight drop in train commute trips to Sydney Inner in the morning, while the decrease of trips by train departing from Sydney Inner is not so evident. It can be concluded that the increasing crowding level can lead to change of transport mode of people and thus decrease train trips.

7. Conclusions and discussion

This paper has examined practical approaches to modelling mode and departure time choice in a large-scale regional travel demand modelling framework. Three possible model structures for the joint choice of mode and departure time were explored in the search for the preferred structure, using the dataset recently collected in Sydney by face-to-face interviews. By combining RP with SP data collected from this survey, a rich set of variables was derived and used to explain the interdependencies of mode choice and departure time choice. We found that Sydney residents seem to make the two decisions simultaneously with alternative relationships (e.g., the mode choice come first and conditions the departure time choice or vice versa) being rejected by the empirical data.

This finding is in sharp contrast to what has been found in the UK and the Netherland in which empirical data suggest a nesting structure with mode choice being placed above departure time choice (Hess et al., 2007a; Hess et al., 2007b). While it is hard to find a conclusive explanation for this difference, we suspect that differences in data quality may play a role. The differences come from two sources. First, we used SP tasks with an equal number of departure time options for the chosen mode (the mode actually used in recent trips) and non-chosen mode (alternative mode reported by the respondents) while all previous studies used SP tasks with only one time option for the non-chosen mode. In reality, there is no reason why travellers should not have alternative departure times for the mode that is observed to not be used for a recently undertaken trip. Second, a rich set of attributes

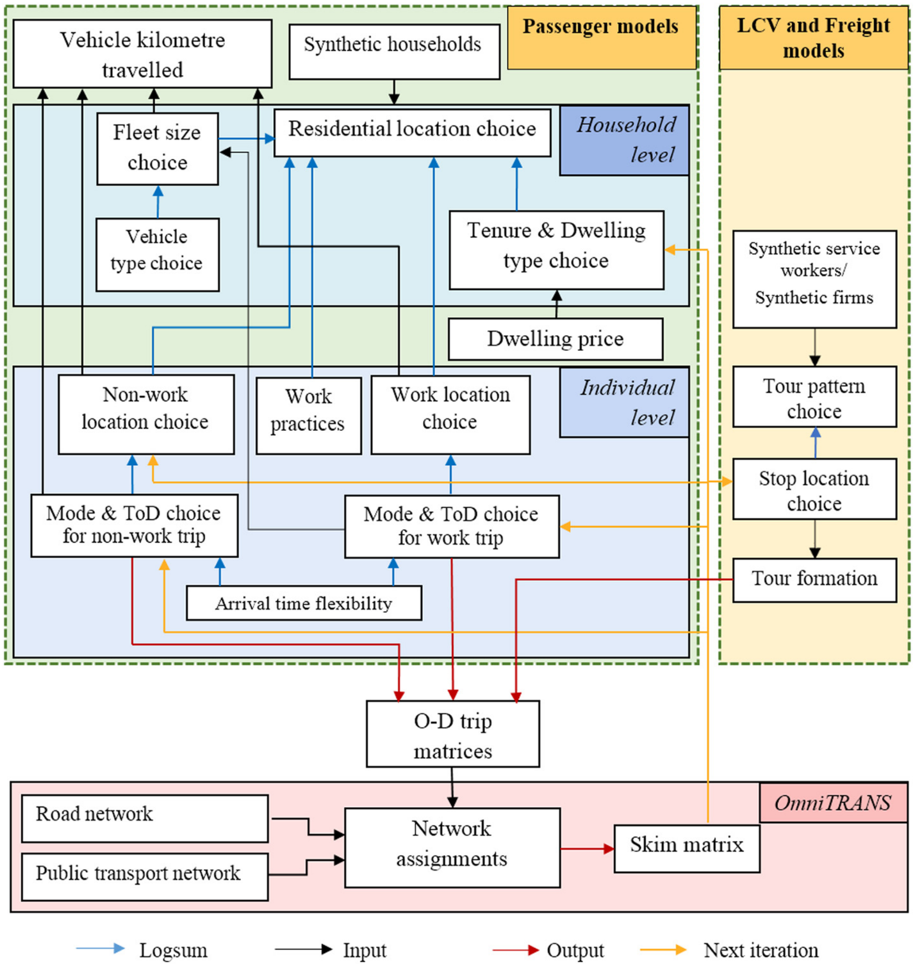


Fig. 5. Placement of mode and departure time choice model in the general modelling framework of MetroScan.

(including crowding, access/egress time for PT modes, parking availability and parking costs for car mode) were used to describe the alternatives offered in our SP tasks, while previous studies typical formulated trade-off between, on the one hand, temporal travel times and travel costs, and on the other hand travellers' preferences for a certain departure time. As a result, potential trade-offs such as facing a crowded bus to have a less expensive journey or using a car and paying a high cost of being stuck in traffic congestion, are left out and potentially end up in the unobserved (random error) terms. As model structures are *econometrically* driven by the variances and correlations of unobserved influences (i.e., error terms), it may be more likely to find that such the SP task will provide data that require the use of a NL model. By contrast, when all potential influences are included in the observed component of the utility expression (and we have far more to consider than most other studies), the error terms may indeed be independent and the MNL models may be found to be sufficient.

This paper has demonstrated a practical way to deal with the unavailability of data on schedule delay and time flexibility for forecasting applications. These are critical inputs into most of the departure time choice models, but they are unlikely to be available at the same level of temporal precision as that available in the sample from which model parameters are derived. In this work, we used a set of constants associated with the different mode and time period combinations to capture temporal preferences of travellers for a particular travel mode. In addition, an arrival time flexibility model was developed to forecast how much flexibility travellers have in terms of time they need to be at a certain place. The predicted information is then fed into the mode and time choice models for application. We have developed separate models for commuting and non-commuting purposes and found that this approach works well in operational modelling.

Perhaps the most interesting and useful evidence for policy formulation and economic appraisal of transport investment relates to the average WTP for improving travel time reliability, both for road-based and track-based modes. Reducing the variation in car travel time would see average commuters willing to pay about \$23.13 per hour, while an hour saving in car travel time is valued at \$12.83 by commuters. This means that for car commuting, the reliability multiplier is 1.80 (= 23.13/12.83). For public transport commuters, the WTP to reduce the variation in travel time is higher, at \$65.39 per hour. Note that public transport journeys in Sydney, particularly train, are typically longer than car journeys (Ho and Mulley, 2013), and public transport travel time are more reliable, with 95% of buses and trains in Sydney being on time (Bureau of Transport Statistics, 2014). These facts may explain why commuters are willing to pay more to improve travel time reliability on PT than by car, while the reverse is true when it comes to saving travel time for different modes (car users are willing to pay more than PT users, i.e., \$23.13/car-hour vs. \$12.83/PT-hour).

Declaration of Competing Interest

None.

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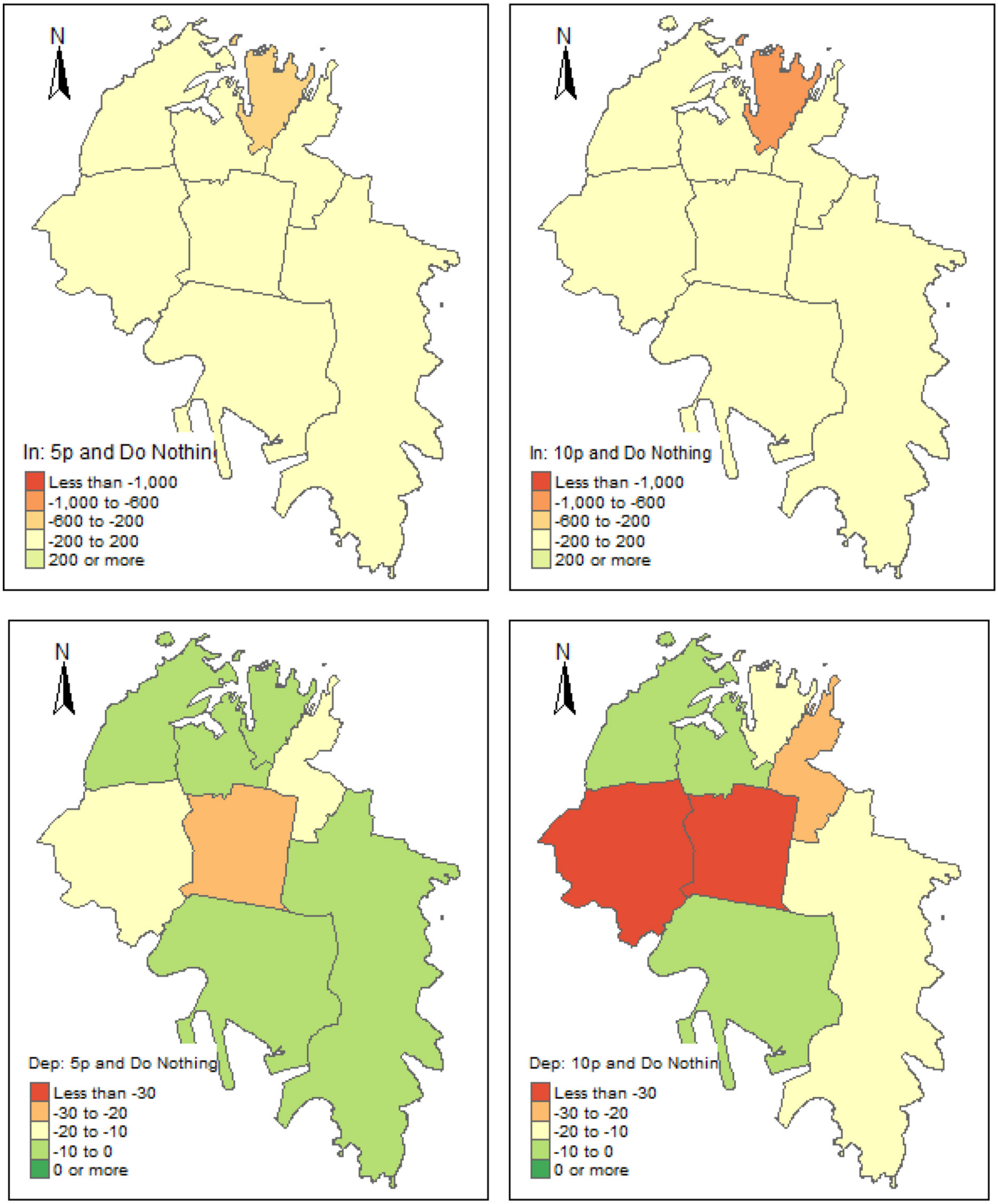

Fig. 6. Incoming and departure train trips forecast in 8 SLAs and the impact of crowding level.

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Appendix A. Sydney toll road network and charge in 2013

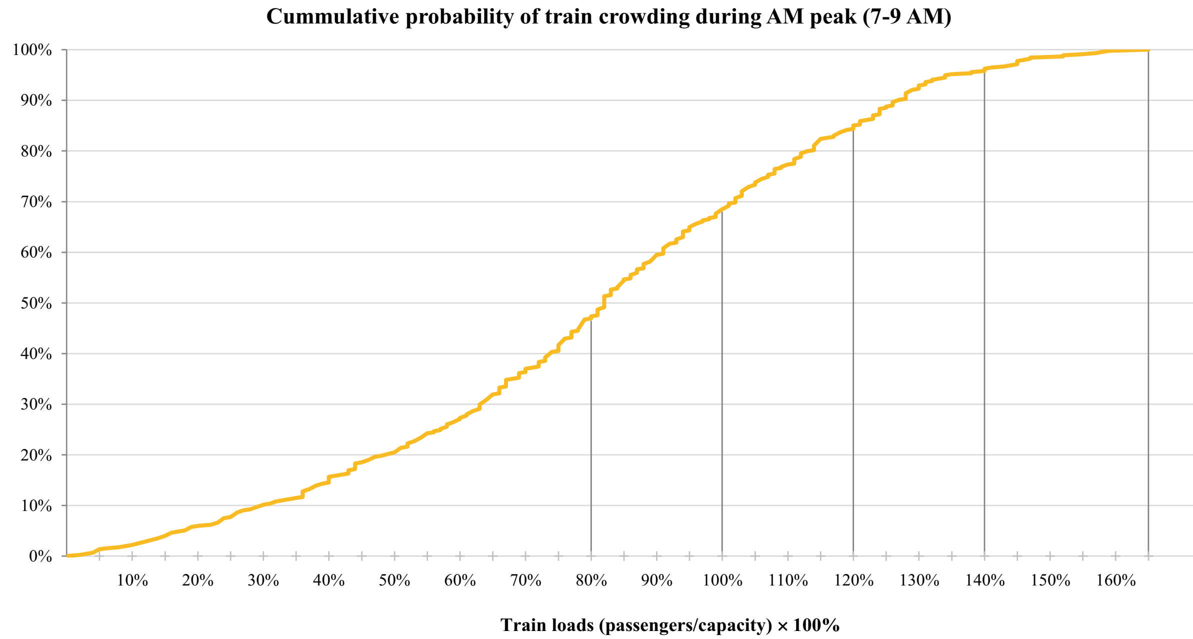
Motorway	Distance	Direction charged	Light vehicles	Heavy vehicles
Sydney Harbour Bridge	1.1 km	Southbound	Time of day tolling, max $4.00	Time of day tolling, max $4.00
Sydney Harbour Tunnel	2.7 km	Southbound	Time of day tolling, max $4.00	Time of day tolling, max $4.00

Eastern Distributor	5.4 km	Northbound	$6.00	$12.00
M5 East Freeway	9.4 km	No toll	Nil	Nil
M5 South-West Motorway	21 km	Each direction	$4.40	$9.30
Westlink M7 Motorway	40 km	Each direction	36.73 cents/km, Capped at $7.35	36.73 cents/km, Capped at $7.35
Hills M2 Motorway	20 km	Each direction	$4.95	$16.50
			$6.05 (North Ryde)	$18.15 (North Ryde)
			$2.98 (Herring and Christie Ramps)	$8.95 (Herring and Christie Ramps)
			$3.15 (Pennant Hills Ramp)	$9.45 (Pennant Hills Ramp)
			$2.11 (Windsor Rd Ramp)	$6.35 (Windsor Rd Ramp)
			$2.76	$8.29
Lane Cove Tunnel	3.6 km	Each direction	$3.01	$6.02
Cross City Tunnel	2.1 km	Each direction	$4.91 (Main tunnel)	$9.82 (Main tunnel)
			$2.32 (Sir John Young Cres)	$4.63 (Sir John Young Cres)
Military Road *E*-Ramp		Each direction	$1.50	$3.01
M4 Western Motorway	40 km	No toll	Nil	Nil

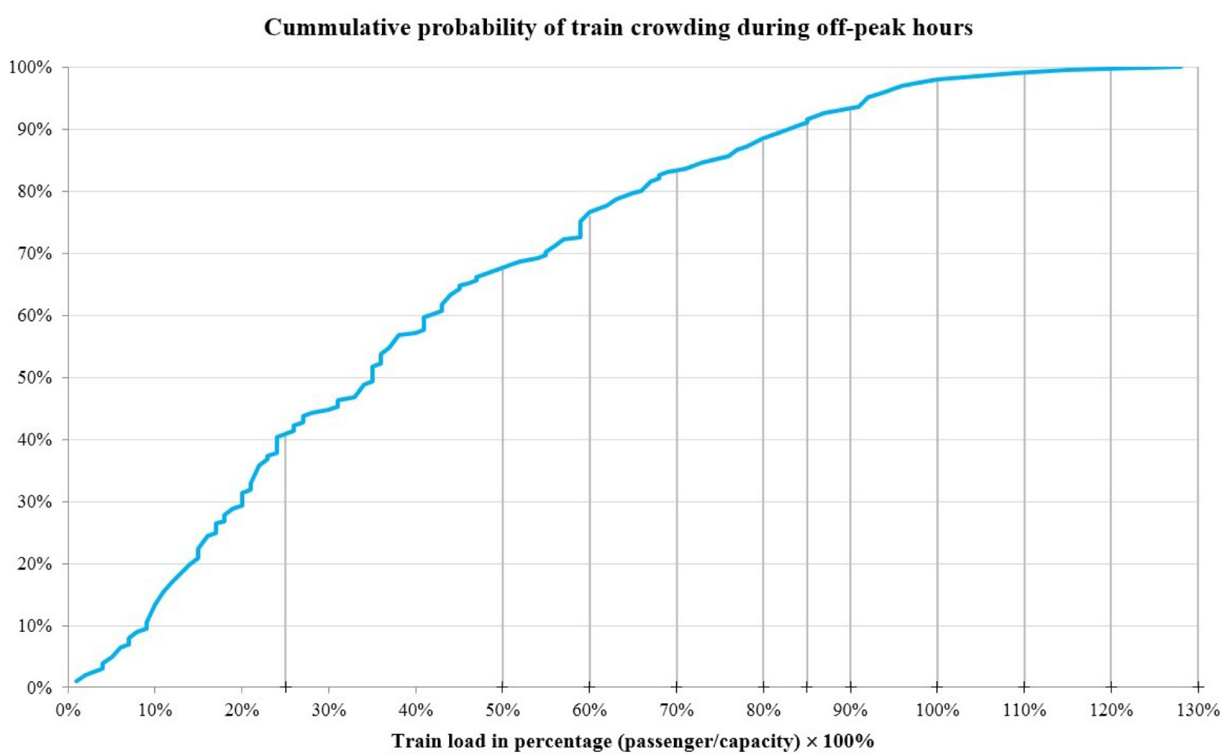
Source: http://www.rta.nsw.gov.au/usingroads/motorwaysandtolling/tolling_tolling.html

Appendix B. Train load in Sydney 2012

(a) AM (7 – 9) peak



(b) Outside the peaks



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