MODELLING PARK-AND-RIDE IN THE WEST MIDLANDS REGION

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1. INTRODUCTION

This paper describes the development of park-and-ride models for PRISM (Policy Responsive Integrated Strategy Model), a new transport model for the West Midlands region of the UK. PRISM consists of a detailed network model covering the highway and public transport (PT) systems which is linked to a disaggregate demand model. The latter models travel behaviour in a number of interacting modules, including car ownership, PT travel pass ownership, tour frequency, destination choice, mode choice (including park-and-ride) and time of day choice.

The West Midlands region, positioned in the heart of England, covers an area of around 13,000 km^2 with over 5 million inhabitants. The main urbanised area consists of a conglomeration of 7 local authorities, of which Birmingham is the largest, containing around 1 million people. The region produces about 8% of the national GDP.

The region's transport problems bear similarities with many other metropolitan areas in Europe: a great reliance on the private car (modal share more than 50%), congestion in the centres at peak times, heavily congested motorways, exacerbated by long distance freight movements, increased lack of reliability for all travel modes, and a growing concern of travellers and business about the impact of transport on health and the economy.

Park-and-ride was identified by model stakeholders as a key policy issue in the region, and can help to alleviate some of the problems listed above. In response to this concern, park-and-ride was explicitly modelled in PRISM by representing two linked choices. Firstly, the choice of access mode to public transport, distinguishing car driver (park-and-ride), car passenger and other access modes (walk, cycle and other PT modes). Secondly, for car access modes, the choice of access station. By summing the predictions of the park-and-ride models across journey purposes, it is possible to obtain forecasts of demand for each park-and-ride site. Thus the model can be used to assess the feasibility of proposed park-and-ride developments, as well as growth in demand at existing sites.

Section 2 of this paper discusses the data available for analysis and model estimation. Section 3 describes the model development process, which followed a two-stage approach, with stand alone park-and-ride models developed first which were then integrated within the overall mode and destination choice structure. Section 4 explains how the models were implemented, and presents validation of the model forecasts. Finally Section 5 presents conclusions.

2. DATA

2.1 Household Interview Data

The main data source for the estimation of the PRISM models was a large Household Interview (HI) survey undertaken in 2001. In the survey, all travel made by household members on the survey day was recorded. Data from 12,000 households across the region was available for model estimation.

The trip data recorded in the HI was formed into home-based tours[1]. In order to do this it was necessary to define mode hierarchies, that define the main and access modes of the tour when multiple modes are recorded. These hierarchies are detailed in Table 1.

Table 1: Mode Hierarchies

	Main Mode	Access Mode
1	Train	Car-Driver
2	Metro	Car-Passenger
3	Bus / Coach	Taxi
4	Car-Driver	Bus / Coach
5	Car-Passenger	Metro
6	Taxi	Train
7	Cycle	Cycle
8	Walk	Walk

These hierarchies maximise the volume of park-and-ride travel recorded, because train and metro lie at the top of the main mode hierarchy, and car-driver and car-passenger lie at the top of the access mode hierarchy.

Despite the large number of households surveyed, and the mode hierarchies adopted, the volume of park-and-ride (P&R) data available for model estimation was low. This is highlighted in Tables 2 and 3, which detail the access modes for public transport (PT) in the HI.

Table 2: Commuting PT Tours in the HI

	Car Driver Access		Car Passenger Access		Other Access		Total	
Train	15	17.2 %	4	4.6 %	68	78.2 %	87	100.0 %
Metro	0	0.0 %	0	0.0 %	8	100.0 %	8	100.0 %
Bus	2	0.3 %	3	0.4 %	721	99.3 %	726	100.0 %
Total	17	2.1 %	7	0.9 %	797	97.1 %	821	100.0 %

1 A (home-based) tour is a series of linked journeys starting and finishing at home.

Table 3: Non-Commuting PT Tours in the HI

	Car Driver Access		Car Passenger Access		Other Access		Total	
Train	4	6.6 %	2	3.3 %	55	90.2 %	61	100.0 %
Metro	2	15.4 %	1	7.7 %	10	76.9 %	13	100.0 %
Bus	5	0.2 %	16	0.7 %	2,333	99.1 %	2,354	100.0 %
Total	11	0.5 %	19	0.8 %	2,398	98.8 %	2,428	100.0 %

Just 2.1% of commuting PT tours use car driver access, and so can be classified as P&R. For train, the proportion is much higher at 17.2% but as the volume of train tours is low the number of observations available for estimation is low at 15. For non-commuting PT tours, the proportion of car driver (i.e. P&R) tours is lower still at just 0.5%. It is noteworthy that the percentage of bus tours which use car access is considerably lower than the percentage of metro and train tours, both for commuting and non-commuting tours.

The low volumes of park-and-ride travel recorded in the HI meant that detailed analysis and modelling of park-and-ride was not possible using the HI data alone. Therefore other data sources were assembled. These are described in the following sections. Park-and-ride remains an important policy issue despite the low volumes of data recorded in the HI. An important consideration is that future P&R policies may result in large increases in demand for P&R services.

2.2 Park-and-Ride Survey Data

2.2.1 Train Data

Train P&R data from 2001 was available from CENTRO, the local PT operator. CENTRO targeted travellers to Birmingham and Wolverhampton city centres. Two surveys were used, one for park-and-ride users, and one for non-users who were surveyed at city centre car parks. Of the 707 surveys, 224 (32%) were from users and 483 (68%) were from non-users.

The journey purposes of respondents are summarised in Table 4.

Table 4: Train P&R Survey Data Journey Purposes

	Train P&R Users		City Centre Car Park Users	
Shopping	21	9.4 %	158	32.7 %
Work	186	83.0 %	255	52.8 %
Leisure	13	5.8 %	26	5.4 %
Education	1	0.4 %	4	0.8 %
Other	3	1.3 %	38	7.9 %
Missing	0	0.0 %	2	0.4 %
Total	224	100.0 %	483	100.0 %

The train P&R users are mostly commuters, whereas a significant proportion of city centre car park users are shoppers.

The personal and household characteristics of users and non-users were also compared. The main difference between the two samples was a higher proportion of females amongst users (64%) than non-users (53%).

2.2.2 Metro Data

Metro P&R surveys were undertaken in 2002 at the four metro sites in the region with P&R facilities. The distribution of forms across sites, and the resulting sample rates, are summarised in Table 5.

Table 5: Metro P&R Survey Form Distributions and Returns

Metro Station	Parking Spaces	Forms Distributed	Forms Returned	Sample Rate
Priestfield	40	47	13	27.7 %
Wednesbury Parkway	143	112	24	21.4 %
Black Lake	83	29	9	31.0 %
The Hawthornes	190	34	4	11.8 %
Total	456	222	50	22.5 %

The journey purposes of respondents are summarised in Table 6.

Table 6: Metro P&R Survey Journey Purposes

Shopping	2	4.1 %
Normal Workplace	43	87.8 %
Work Related Business	3	6.1 %
Personal Business	1	2.0 %
Visiting Friends/Relatives	0	0.0 %
Leisure/Sport/Entertainment	0	0.0 %
School/College/University	0	0.0 %
Other	0	0.0 %
Total	49	100.0 %

Consistent with the train P&R data, the majority of users are commuters. Unlike the train data, the gender split in the sample was approximately 50:50.

Table 7 presents the occupation type distribution for the 46 workers in the sample and compares the distribution to that observed across the 2001 HI sample.

Table 7: Occupation Type Distributions

	2002 Metro P&R Data		2001 HI Data	
Manager/Professional	20	43.5 %	4,842	39.2 %
Other Clerical Non-Manual	22	47.8 %	2,584	20.9 %
Skilled Man./Foreman/Supervisor	2	4.3 %	2,287	18.5 %
Other Manual	0	0.0 %	2,174	17.6 %
Other	2	4.3 %	459	3.7 %
	46	100.0 %	12,346	100.0 %

This comparison suggests that workers who use metro have a different occupation type distribution compared to workers in the 2001 HI data. Unlike the 2001 HI data the 2002 metro P&R sample is comprised predominantly of non-manual workers.

2.2.3 Bus Data

Currently there are only two bus P&R sites in the West Midlands, both located in Coventry. Both of these sites were surveyed in 2002. The journey purposes of respondents are summarised in Table 8.

Table 8: Bus P&R Survey Journey Purposes

Normal Workplace	69	33.7 %
Employer's Business	10	4.9 %
Education	3	1.5 %
Shopping	93	45.4 %
Personal Business	11	5.4 %
Visiting Friends/Relatives	0	0.0 %
Recreation/Leisure	8	3.9 %
Other	11	5.4 %
Total	205	100.0 %

Unlike the train and metro samples, which are dominated by commuters, shopping is the most important purpose for bus P&R trips, and commuters only form one-third of the sample. Females formed 60% of the sample.

2.2.4 Summary

On the basis of the dedicated park-and-ride surveys (which have fairly small sample sizes) it can be seen that train and metro P&R users are mostly commuters, whereas for bus shopping is the most important purpose and commuters only represent one-third of users. For train and bus, the available data suggests females are more likely to be P&R users than males.

While the dedicated P&R data provides useful insight into the characteristics of P&R users, it is not suitable for the development of access mode choice models because non-P&R users are not surveyed. The following section describes a large train survey that includes non-P&R users as well as P&R users.

2.3 Train Survey Data

In 2001, CENTRO surveyed 8,508 train users at a total of 93 stations in the PRISM model area. The journey purposes of these users are summarised in the following table.

Table 9: Train Survey Journey Purposes

Shopping	787	9.3 %
Normal Workplace	5,115	60.1 %
Other Workplace/Meeting	814	9.6 %
Personal Business	180	2.1 %
Visiting Friends/Relatives	250	2.9 %
Sport or Entertainment	151	1.8 %
Other Leisure	206	2.4 %
Education	662	7.8 %
Serve Education Passenger	25	0.3 %
Drop Off Passenger	6	0.1 %
Pick Up Passenger	17	0.2 %
Other	295	3.5 %
Total	8,508	100.0 %

Around 60% of the sample is comprised of commuters. Shopping, business and education are the other significant purposes. Table 10 cross-tabulates the access mode to train with the (aggregated) journey purpose.

Table 10: Access Modes by Journey Purpose

	Car Driver		Car Passenger		Other		Total	
Commute	1,561	33.0 %	623	13.2 %	2,547	53.8 %	4,731	100.0 %
Business	331	44.3 %	113	15.1 %	303	40.6 %	747	100.0 %
Education	93	15.7 %	141	23.7 %	360	60.6 %	594	100.0 %
Shopping	220	31.6 %	45	6.5 %	432	62.0 %	697	100.0 %
Other	243	24.6 %	132	13.3 %	614	62.1 %	989	100.0 %
Total	2,448	31.6 %	1,054	13.6 %	4,256	54.9 %	7,758	100.0 %

Car driver (i.e. P&R) is the access mode for around one-third of train trips, and car passenger is the access mode for around 14% of trips. The car driver access shares are highest for business and lowest for education. The car passenger share is highest for education and lowest for shopping. There is clearly a significant volume of data by each access mode to allow the development of access mode choice models by purpose.

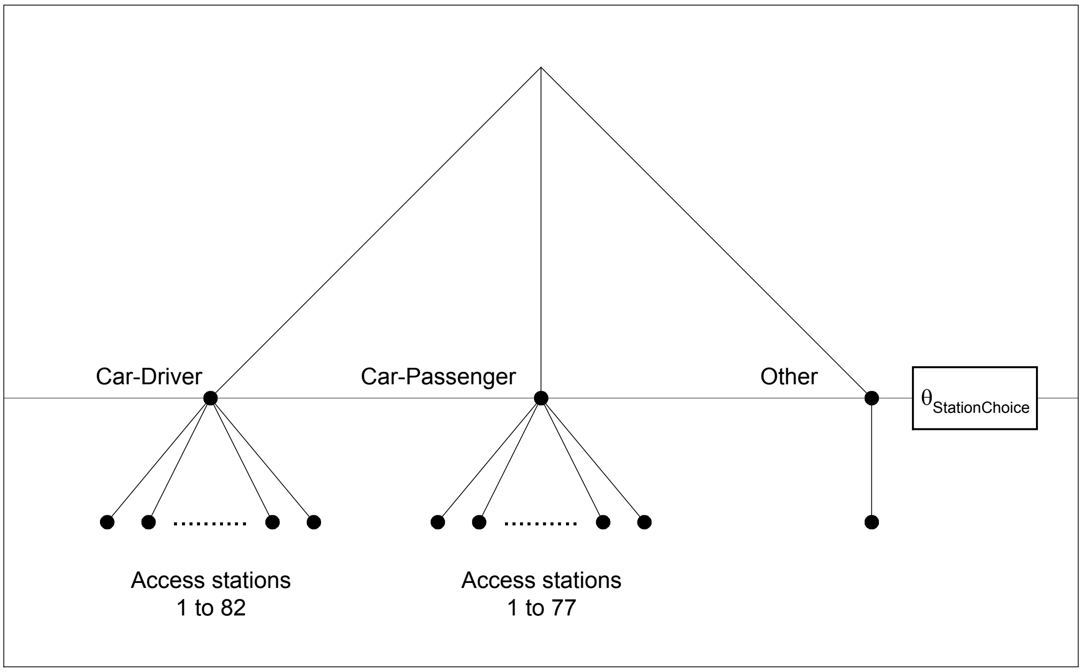
Comparison of the data in Table 10 to that in Tables 2 and 3 demonstrates the car access shares in the train survey data to be significantly higher than those recorded in the 2001 Household Interview data. It is not clear why the car access shares in the 2001 Household Interview data are so low.

3. MODEL ESTIMATION

3.1 Access Mode and Station Choice Models

The first stage in the modelling was to develop models of access mode and station choice from the 2001 train survey data described in Section 2.3. These models represent the choice of access mode to train, with car driver, car passenger and other access modes modelled. The other access mode includes access by slow modes and by other PT modes, for example bus access to train. For car access modes, the models also represented the choice of access station. The model structure used is summarised in the following figure.

Figure 1: Model Structure



The structural parameter $\theta_{StationChoice}$ represents the relative elasticity of access mode and station choice. The car driver alternatives are only available to households with at least one car. There are 82 car driver access station alternatives as car driver access was observed at 82 different stations. Similarly 77 car passenger access was observed at 77 different stations.

The decision to identify the three access listed above is discussed in the following bullets:

- Car driver: identifying the number of car drivers travelling to each station provides forecasts of demand for each P&R facility, which is a key requirement of the model to facilitate assessment of P&R policies.
- Car passenger: such travellers need to be separated from car drivers because they do not create demand for parking at stations. It is noted that this access mode includes both 'kiss-and-ride', where a car passenger is dropped at the station by a vehicle that is then driven

away, as well as cases where car passengers arrive with a vehicle that parks at the station. It was not possible to separate these two types of car passenger access using the available survey data.

- Other: this access mode separates out non-car access travellers, who may use slow modes (walk and/or cycle) and possibly bus and/or metro to access the station. Grouping other access modes together is convenient as it allows the use of conventional PT LOS, which separately identifies walk access and egress time and PT access times.

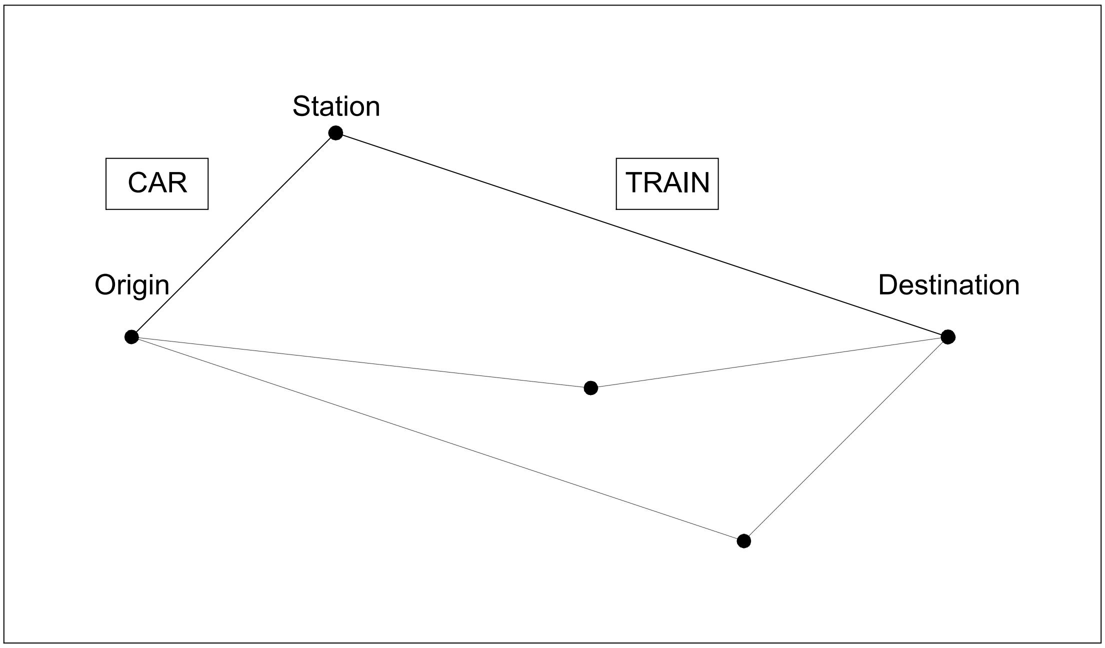
The attractiveness of each access mode and station alternative is represented using a utility measure composed of:

- level-of-service characteristics for the car access leg (where applicable) composed of in-vehicle time and driving cost;
- level-of-service characteristics for the PT leg, composed of fare, in-vehicle time (including any bus egress time), first and other wait time, walk egress time, interchange walk time and the number of transfers;
- socio-economic parameters representing differences in access mode preferences across the population;
- size variables representing the attractiveness of different P&R sites for the car driver alternatives;
- access mode specific constants for the car passenger and other access modes.

Parameters were estimated from the 2001 train survey data to determine the relative importance of these different factors on the utility of access mode and station alternatives.

It should be emphasised that for car access modes, the choice of station for a given OD is also modelled. The level-of-service of both the car access and PT legs is represented, as illustrated in the following figure.

Figure 2: Station Choice



In this example the individual chose a short car access leg and a long train leg. Two alternative stations with longer car access legs, and shorter train legs, were not chosen. The utility terms include a full representation of the PT level-of-service, so that if two stations exist with equal car access and train journey times, the station with the better service (more frequent, fewer transfers etc.) will have a higher utility and thus a higher proportion of the predicted trips.

The terms in the final models are summarised in the following table. All of the parameters in the table are negative, i.e. decrease utility, are significant[2] and have plausible values.

[2] Specifically the ratio of the parameter estimate to its standard error exceeds two.

Table 11: Access Mode and Station Choice Models

	Commute	Shopping	Other
Level-of-service terms			
Linear cost		√	
Log cost	√		√
Car time	√	√	√
PT in-vehicle time	√	√	√
Access & egress time	√	√	√
Wait time	√	√	
Transfers	√		√
Socio-economic terms			
Car driver male	√		
Car driver 16-19	√	√	√
Car driver 20-24	√	√	√
Car driver one car	√	√	√
Car passenger male	√		
Car passenger 35-44	√		
Car passenger zero cars	√	√	√
Car passenger one car			√
Other rail only pass	√		

The level-of-service parameters were expressed relative to PT in-vehicle time to assess their reasonableness. These comparisons demonstrated that car access time was weighted between 4 and 8 times as highly as PT in-vehicle time, implying travellers strongly prefer to minimise their car access leg, i.e. usually drive to their nearest station.

The positive size (attraction) variable in all three models was the number of P&R spaces at the site. Two alternative formulations were for the size variables were tested. The first was total usage at the P&R site in the base year. This model formulation tended to give slightly better results but is problematic for forecasting, because forecasts of usage are the very information the model is supposed to provide. The second formulation was more complex, containing terms for both the number of spaces and the utilisation rate, i.e. current usage divided by the number of spaces. It was not possible to estimate sensible size parameters using this second model formulation.

An interesting finding was that the structural parameter, $\theta_{StationChoice}$ in Figure 1, had a similar value in all three models as shown in Table 12.

Table 12: Structural Parameters

Commute	0.41
Shopping	0.40
Other	0.43

These results suggest that the sensitivity of access mode choice with respect to the modelled variables is around 40% of the sensitivity of station choice, i.e. travellers are more likely to switch station than access mode.

3.2 Integration into Mode-Destination Choice Models

The (main) mode and destination choice models in PRISM were estimated from the 2001 Household Interview data described in Section 2.1. These models represented the choice between eight modes:

- car driver
- car passenger
- train
- metro
- bus
- cycle
- walk
- taxi

A total of 898 destination zones were also represented, giving a total of 7184 mode-destination alternatives, although not all of these alternatives will be available to a given individual.

Before integrating the access mode and station choice model structure described in Section 3.1, analysis was undertaken to investigate whether it was worthwhile to represent access mode and station choice for metro and bus as well as train. Data from three large surveys was collected to determine access mode shares for each PT mode. This data is summarised in the following table.

Table 13: Access Mode Shares

	Train Main Mode		Metro Main Mode		Bus Main Mode	
Car Driver Access	1,951	16.2 %	115	2.7 %	39	0.4 %
Car Passenger Access	1,243	10.8 %	228	5.4 %	119	1.2 %
Other Access	9,988	73.0 %	3853	91.8 %	9,648	98.4 %
Total	13,182	100.0 %	4,196	100.0 %	9,806	100.0 %

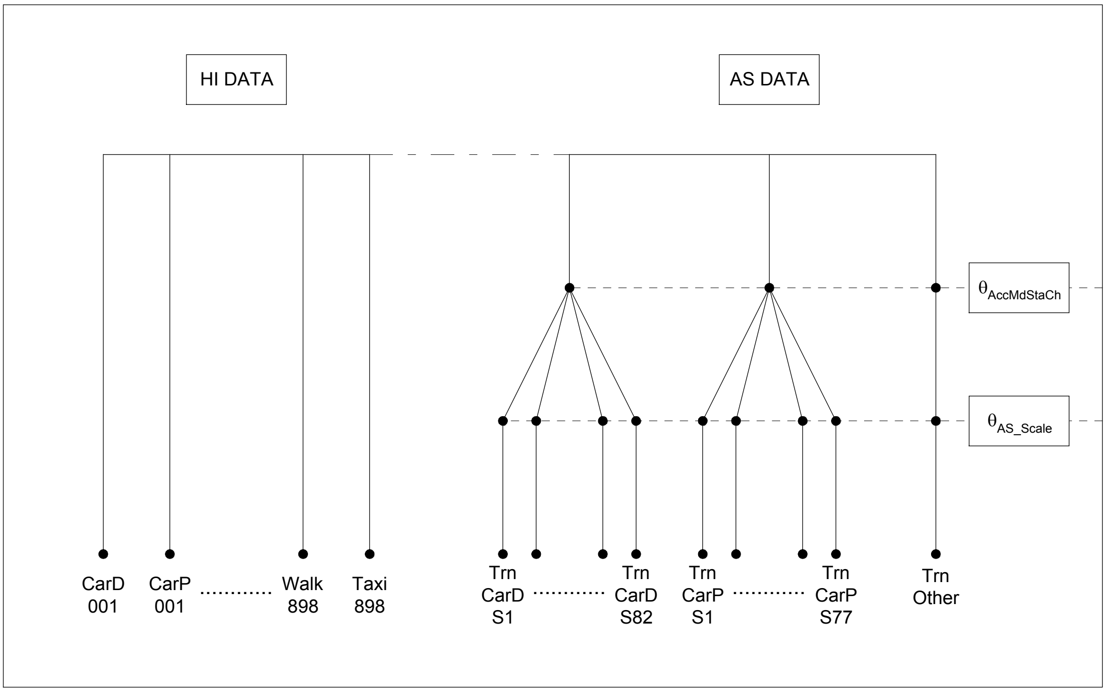
Car access is most significant for train, where it accounts for one-quarter of trips. For metro, the proportion is lower at 8%. Only 2% of bus passengers access by car. Given the low bus access mode share, the lack of data on bus access mode choice, and the fact that there are only two bus P&R sites in the region (both in Coventry) it was decided not to explicitly model bus access mode choice; instead it is assumed all access is made by slow modes. For train and metro the car access shares are significant and so access mode choice has been modelled.

Further analysis demonstrated that car access was not significant for education, and therefore the access mode and station choice models have only been integrated within the commute, shopping and other travel models[3].

[3] The employer's business models in PRISM represent car driver travel only. This is a result of a lack of employer's business data in the 2001 Household Interview data, which meant that car-only road side interview data was used to model employer's business travel.

To integrate the access mode and station choice models within the (main) mode and destination choice structure, a joint estimation approach was employed. Two datasets were used in estimation, the 2001 HI data introduced in section 2.1, used for modelling main mode and destination choice (termed 'MD' data), and the 2001 train survey data introduced in section 2.3, used for modelling access mode and station choice (termed 'AS' data). The MD and AS datasets were treated separately in estimation, but parameters were estimated jointly across the two datasets, and structural parameters were estimated to represent the relative sensitivity of the different choices modelled. The joint estimation structure is illustrated in the following figure.

Figure 3: Joint Estimation Structure



On the left are the 7184 mode-destination alternatives. Note that on the left hand side of the estimation structure, access mode choice is *not* represented for train or metro. Instead it is assumed that all access occurs by slow modes or other PT modes. On the right is the access mode and station choice structure illustrated in Figure 1. The dotted line at the top of the tree highlights that the two sets of alternatives are never available simultaneously; the left hand side alternatives are only available to the MD data, the right hand side alternatives are only available to the AS data. The car driver alternative also has a time-of-day choice structure, this has been omitted from the figure for clarity.

The same cost and level-of-service parameters are used in the utilities for mode-destination choice and the utilities for access mode and station choice. This joint estimation approach improves the significance of the level-of-service parameters, as the volume of PT data is significantly increased by the inclusion of the AS data, and also ensures consistency throughout the model structure.

The $\theta_{AccMdStaCh}$ and θ_{AS_Scale} structural parameters allow the calculation of the relative elasticity of main mode and access mode choice. It is necessary to calculate this parameter to implement the models using a single integrated structure (see the following section).

The car access time parameters are been compared to car (main mode) time and PT in-vehicle time in Table 14.

Table 14: Car Access Time Parameters

	$\beta_{CarAccTime}$ / $\beta_{CarTime}$	$\beta_{CarAccTime}$ / β_{PTTime}
Commuting	1.2	2.9
Shopping	2.5	3.8
Other	2.9	4.3

The car access time parameter ranges from 1.2 to 2.9 times the magnitude of car main mode time, i.e. travellers attach a higher disutility per minute to car access time than to car main mode time. The ratios relative to PT time are higher, ranging from 2.9 to 4.3, which implies that for PT journeys involving car access travellers seek to minimise the car access time relative to PT in-vehicle time as much as possible.

4. MODEL IMPLEMENTATION

4.1 Implementation Structure

In implementation the access mode and station choice structure has been integrated within the overall mode and destination choice structure, as illustrated in Figure 4.

Figure 4: Implementation Structure

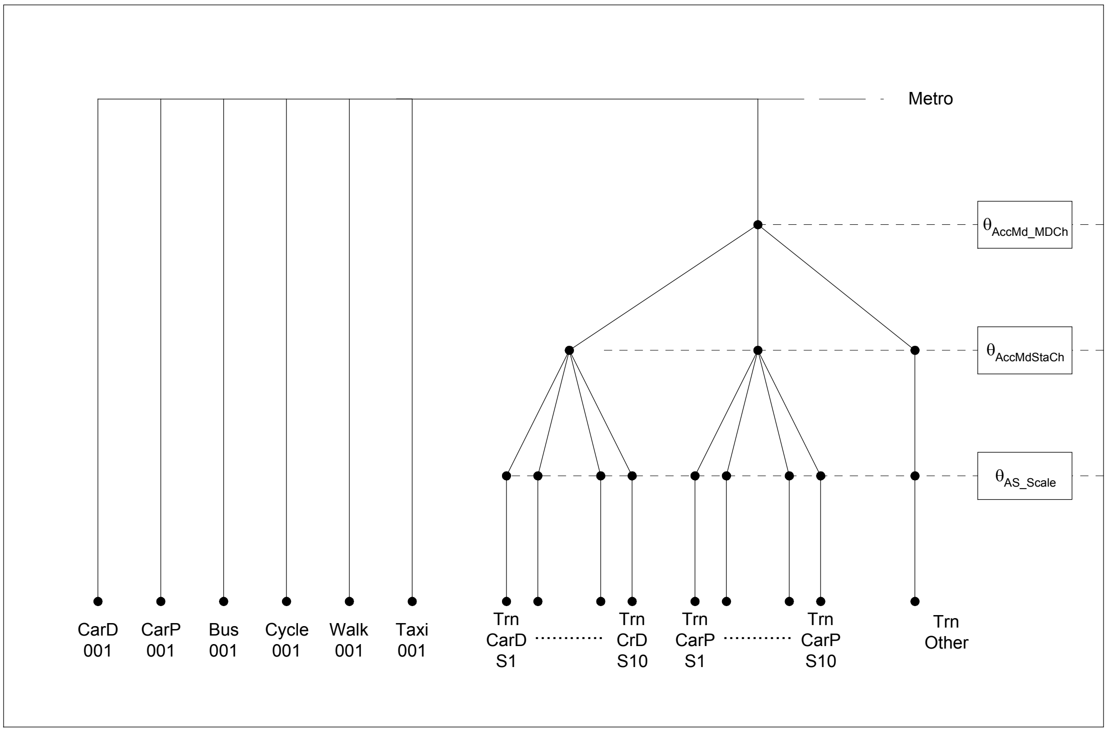


Figure 4 illustrates the alternatives for a single destination. The first six modes are represented without modelling access mode choice. For train, the access mode and station choice structure is represented. An identical structure is used for metro but has been omitted from the figure for clarity. The time-of-day choice structure for car driver has been omitted from the figure for the same reason.

The θ_{AccMd_MDCh} structural parameter represents the relative elasticity of access mode and main mode choice. If mode and destination choice are represented at the same level in the tree for the MD data, then θ_{AccMd_MDCh} can be calculated as follows:

$$\theta_{AccMdStaCh} = \sigma_{ST} / \sigma_{AM}$$
$$\theta_{ASScale} = \sigma_{MD} / \sigma_{ST}$$

where: σ_{MD} is the standard deviation of utility differences between mode-destination alternatives in the HI data

σ_{ST} is the standard deviation of utility differences between station alternatives for a given access mode in the station data

σ_{AM} is the standard deviation of utility differences between access mode alternatives over all stations considered in the station data

$$\theta_{AccMd\_MDCh} = \sigma_{AM} / \sigma_{MD}$$

$$= 1 / (\theta_{AccMdStaCh} * \theta_{ASScale})$$

If mode and destination choice are represented at a different level in the tree then it is necessary to account for the mode destination structural parameter in the calculation of θ_{AccMd_MDCh}.

The following table details the structural parameters estimated for each model. For shopping and other travel, the parameter $\theta_{TR\_D\_M}$ defines the relative sensitivity of destination and mode choice.

Table 15: Estimated Structural Parameters

Purpose	$\theta_{TR\_D\_M}$	θ_{AS_Scale}	$\theta_{AccMdStaCh}$	θ_{AccMd_MDCh}
Commute	n/a	3.071	0.534	0.610
Shopping	0.484	0.569	0.354	2.402
Other Travel	0.490	1.100	0.433	1.029

For the commute and other travel models the parameter θ_{AccMd_MDCh} is less than or approximately equal to one. For shopping the parameter took a value of 2.4. It is not possible to have a structural parameter greater than one and so the parameter was constrained to one and the models re-calibrated accordingly. As a consequence the sensitivity of main mode and access mode choice is approximately equal in the shopping and other travel models implemented[4].

As noted in Section 3.2, the train and metro alternatives in the main mode and destination section of the tree do not represent access mode choice in the joint estimation structure. Consequently the utilities for the train and metro alternatives are different in implementation where the access mode and station choice structure is integrated. Because of these differences, it was necessary to recalibrate the implemented models to ensure consistency with two sets of targets:

- main mode shares from the 2001 Household Interview data[5]
- access mode shares from dedicated train and metro surveys

The models were recalibrated by applying correction factors to modal alternatives in an iterative fashion until the target tours were met closely:

$$c_{i+1} = c_i + \ln(T/P_i) \quad (1)$$

where: c_i is the correction factor ($c_0 = 0$)
i is the iteration number (1 to n)
T is the target number of tours
P_i is the predicted number of tours after iteration i

As noted in Section 3.1 the size (attraction) variable is the number of P&R spaces in the zone. However, the models do not currently contain an accounting mechanism to ensure that the number of parkers does not exceed

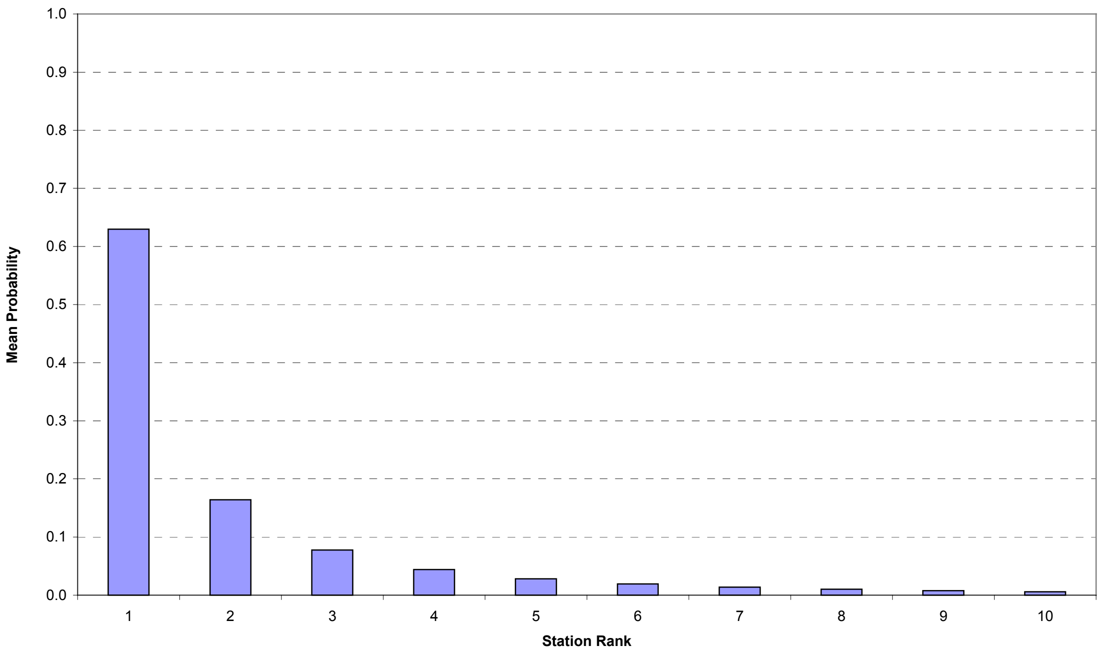
4 Strictly speaking the sensitivity to the modelled variables.
5 These main mode shares have recently been adjusted to boost the share for train and metro, which seem to be under-reported in the 2001 Household Interview data.

the number of spaces. Such a constraint could be implemented by adding a negative constant to over-utilised stations in an iterative fashion. In application the models iterate between supply and demand and so such a constraint could be added without necessitating additional model iterations.

A key issue for implementation is how many station alternatives should be represented for a given origin-destination pair. Because the looping over station alternatives is performed inside loops over origins, destinations and person type segments, the number of station alternatives has a significant impact on model run times. The code used to calculate the utilities of the station alternatives ranks the alternatives by utility (attractiveness) and so the decision was to include the n most attractive stations for a given origin-destination pair. Lower values of n increase run times significantly, but may lead to a loss of accuracy.

Initially a value of 10 was assumed for n, a conservative estimate to ensure accuracy. However this resulted in long run times in implementation, and so possible reductions to n were investigated. Because the model code sorts the output station probabilities by attractiveness, it is possible to examine the variation in mean probability by rank. If the probabilities of higher ranks are low, then it is valid to reduce the n to include only the most attractive station alternatives. The following figure plots the mean station probability by rank.

Figure 5: Mean Station Probability by Rank



The mean probability of the most attractive station is 0.63, i.e. almost two-thirds of demand is predicted to use the most attractive station. By calculating the cumulative probabilities it is possible to determine what proportion of the demand across 10 stations is represented. This calculation is presented in the following table.

Table 16: Means Station Probabilities

Rank	Mean Probability	Cumulative Probability
1	0.6295	0.6295
2	0.1641	0.7937
3	0.0777	0.8714
4	0.0442	0.9155
5	0.0282	0.9438
6	0.0191	0.9629
7	0.0136	0.9765
8	0.0100	0.9866
9	0.0076	0.9942
10	0.0058	1.0000
Sum	1.0000	

On the basis of these results, and bearing in mind the importance of reducing model run times, n was reduced from 10 to 3. The 3 most attractive stations represent 87% of the total demand distributed over the 10 most attractive stations. However it should be emphasised that reducing n does not result in a reduction in the number of P&R trips. Rather, the predicted trips by OD pair are distributed over 3 stations instead of 10. As 87% of demand is predicted to use the 3 most attractive stations anyway, only 13% of demand has to be reallocated from the 7 least attractive stations.

Table 14 also demonstrates that very little demand would be predicted to use stations with a higher rank than 10. Therefore the original decision to include 10 stations did ensure a very high degree of accuracy in terms of including alternatives with a low probability of being chosen.

The following model outputs relate to P&R:

- output files detailing the number of cars predicted to park at each zone with a train station, and at each zone with a metro station (by purpose)
- summary output files which detail the total number of tours by main and access mode (by purpose)
- matrices of train trips for assignment in VISUM – the train legs of car access trips are summed together with other train trips into a single train trip matrix (split by time period)
- matrices of metro trips for assignment in VISUM – the metro legs of car access trips are summed together with other metro trips into a single metro trip matrix (split by time period)
- matrices of car driver trips for assignment in VISUM – the car access legs of PT trips are summed together with trips where car driver is the main mode to form a single car driver matrix (split by purpose and time period)

The inclusion of car access legs to PT tours in the car driver matrix ensures that the impact of P&R choice on congestion is properly represented. P&R trips may cause localised congestion in the vicinity of the station, which could impact upon car driver main mode travellers.

4.2 Model Validation

During the recalibration procedure outlined in the previous section, the model outputs are checked to ensure than main mode and access mode targets are met. However these targets are defined across the model area as a whole and there is no guarantee that the model will validate well at the individual station level.

To provide a more detailed validation, base year model outputs at the zonal level[6] have been compared to observed 2001 data on P&R usage. As noted in the previous section there is no mechanism to constrain P&R usage at a station to available parking capacity and this factor should be borne in mind when assessing the model results.

There are a couple of ways in which the performance of the P&R model could be improved in a future version of PRISM. The first would be to implement a constraint so that the predicted demand at each P&R site does not exceed parking capacity. As discussed in the previous section, this could be achieved by adding a negative correction factor to the utility of over-utilised stations, which would result in excess demand being re-distributed over alternative access modes, main modes and destinations. The capacity correction should take into account the model time period, i.e. that spaces will fill up during the AM-peak and so may become unavailable to all inter-peak travellers.

A second approach would be to *pivot* the predicted trips on the observed data so that the model is used to predict growth in the observed number of trips. This approach could be used in combination with the capacity constraint procedure outlined above.

$$P_z = B_z * S_{fz} / S_{bz} \qquad (2)$$

where: P_z is the predicted (pivoted) number of trips
B_z is the observed usage in the base year
S_{fz} is the future usage forecast by the model
S_{bz} is the base year usage forecast by the model
z is the station zone

For new sites, there is no observed data and so the synthetic forecast would be applied directly:

$$P_z = S_{fz} \qquad (3)$$

It is noted that a more similar pivoting procedure is used in PRISM to forecast predicted demand by the assigned modes (car, train, metro and bus). Special procedures are used to deal with 'extreme growth' cases where the growth in

6 Few zones contain more than one station, so this is almost equivalent to validation at the station level.

synthetic trips is large, and to deal with cases when one or more of the matrices is zero. A full discussion of the issues involved in pivoting can be found in Daly et al (2005).

5. CONCLUSIONS

Park-and-ride is a topical policy issue in the UK, and therefore methodologies for forecasting demand for park-and-ride facilities within a strategic model are valuable. In the West Midlands example, there was insufficient data to analyse and model park-and-ride in the main data source for model estimation, a large Household Interview survey. However methods were developed in this study that allowed park-and-ride models to be developed from existing PT survey data, and therefore no additional data collection was required. Procedures were also developed to jointly estimate models of access mode and station choice (representing park-and-ride) and mode-destination choice. The joint estimation procedure allows PT level-of-service parameters to be jointly estimated across datasets, ensuring more accurate parameter estimates, and also provides estimates of the relative elasticities of the difference choice decisions modelled.

The models developed for this study represented the choice of station for car access to train and metro. This implied a looping over station alternatives within existing loops over origins, destinations and person type segments. Consequently the number of station alternatives represented for a given OD pair has an important impact on model run times.

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