DTO Off-Peak Model

Calibration of the Mode Choice Models

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1 Introduction

1.1 The National Transport Authority (NTA, formerly known as the Dublin Transportation Office DTO) commissioned our team at Steer Davies Gleave in April 2009 to undertake calibration of their transport model for the Off-Peak period. The commission includes calibration of assignment models and development and calibration of a mode choice model for this period.

1.2 The Off-Peak model forms one part of the broader NTA model package. Several updates of the NTA model were undertaken since its first development in 1991 as part of the Dublin Transportation Initiative (DTI) study. However, most of these updates focused on the morning peak only.

1.3 The Off-Peak model at the starting point of this study was still less comprehensive than the morning peak model, and in particular:

- It had not been updated since 2001;
- Demand was not split by journey purpose;
- There was no representation of slow modes; and
- Forecasting was based on absolute logit rather than a more realistic combination of incremental and absolute logit.

1.4 Following a review of the structure and functionality of the full NTA model, which we undertook in 2008, NTA decided that the Off-Peak model should be upgraded to meet similar modelling standards as the morning peak model. Achieving this required a major update of the networks, breakdown by journey purpose, introduction of walking and cycling modes and other changes.

1.5 Note, however, that the scope of this study does not contain creating a time choice model for the Off-Peak; the focus is on traffic during a single Off-Peak hour between 14:00 and 15:00.

1.6 The trip generation and distribution models were upgraded by a team at Minnerva. Our team completed the calibration of the assignment models, and has recently presented this work in a separate report[1]. This report summarises our work to upgrade the mode choice model for the Off-Peak period.

1.7 The remainder of this report is set out as follows. Chapter 2 contains a reminder of the methodology we use for calibrating the mode choice mode, and also demonstrates some key features of the input data. Chapter 3 presents the final calibration of the mode choice model. Chapter 4 presents the summary results of the scenario testing. Finally, Chapter 5 summarises the study and contains some conclusions and recommendations.

1.8 Appendix A provides a brief description of the initial approach to derive the Off-Peak Model choice parameters, including the problems associated with that approach.

[1] DTO Off-Peak Model, Calibration of Assignment Models, December 2009

2 Methodology and Inputs

2.1 This chapter presents an overview of the model estimation approach taken in this study, and also demonstrates some important features of the input data. A brief outline of the model structure is presented in the sections below.

2.2 The Off-Peak model is structured in a manner similar to the AM Peak model, and is a combination of a Saturn based highway modelling suite and a TRIPS based PT modelling suite. As mentioned in Chapter 1, this model is different from the AM Peak model in that only a single Off-Peak hour is modelled and does not include a departure time choice model component as in case of the AM Peak model.

2.3 Similar to the AM Peak model, a set of base year costs are produced for the various journey purpose for both the highway and PT modes from an initial assignment of the highway and PT modules within the model, using the given base year inputs. These base year costs are then passed through an iterative modelling loop to produce the final test year costs. The final test year costs are then used to run a test year highway and a PT assignment, with final outputs segregated by separate journey purposes.

2.4 The model estimation methodology was originally similar to the one used recently for building the mode choice and time choice models for the morning peak. The approach was presented in detail in the report[2] summarising this recent study. However due to data issues discussed later the approach used for the Off-Peak model had to be simplified.

2.5 The approach was also thoroughly described in an article which has recently been circulated among members of the NTA team and DSEG. Since the approach has been discussed extensively in other recent documents, we only include review it here briefly.

2.6 The NTA off peak model distinguishes between six journey purposes and between two levels of car availability (car available, CA, and Car Non-Available, CNA). The purposes are:

- Home Based Work
- Home Based Education
- Home Based Shopping
- Home Based Business
- Home Based Other
- Non Home Based

2.7 We estimated a separate mode choice model for each combination of these. We therefore had 12 mode choice models to build.

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[2] DTO MODEL CALIBRATION, Mode Choice and Time of Travel Choice, Final, August 2009

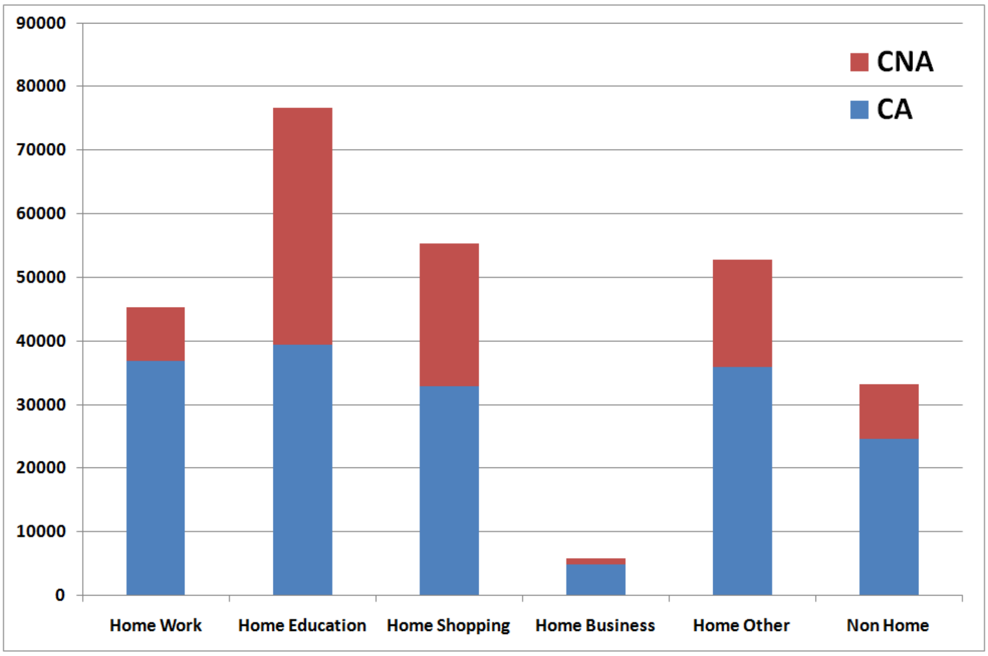
2.8 We initially used multi-objective optimisation to estimate all models. The different objectives used when selecting the best specification of each model are the following.

- Minimise the error of the total number of trips for each alternative. This is measured as the percentage error of the total modelled demand by alternative.
- Minimise the error in the geographical spread of trips across the study area. This is measured using the Chi-Squared test.
- Minimise the difference between the fare elasticity implied by the model and the fare elasticity recommended by U.K. Department for Transport's transport modelling and appraisal guidance, also known as, WebTAG.
- Minimise the difference between the fuel cost elasticity implied by the model and the fuel cost elasticity recommended by WebTAG.
- Minimise the difference between travel time elasticities implied by the model and those recommended by WebTAG.
- Ensure that the proportion of each component of the generalised cost (for each alternative) is within a logical range.
- Ensure that values of time in the model are within a logical range.
- Ensure that alternative-specific constants are within a logical range.

2.9 The inputs for the model estimation work include cost skims for all modes and the total demand for each mode by journey purpose. The estimation process seeks values for the model parameters which would make the model meet the objectives listed above as closely as possible.

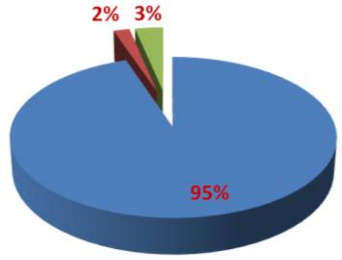
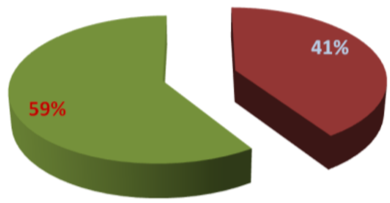
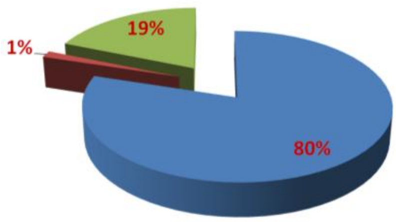
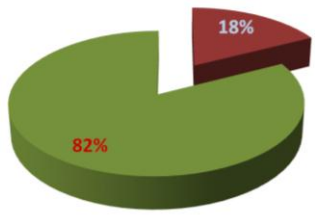
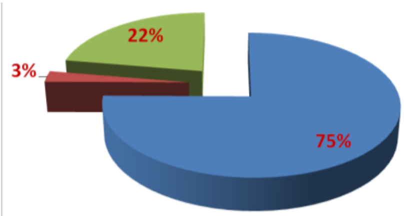
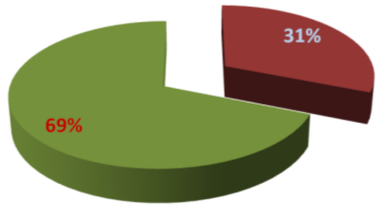
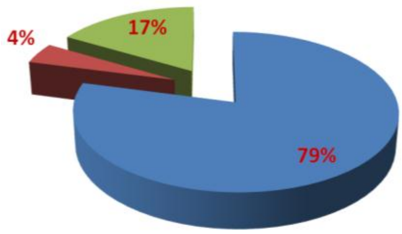
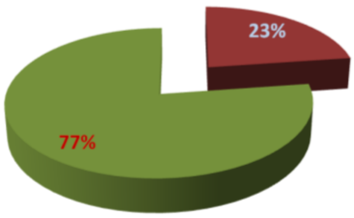
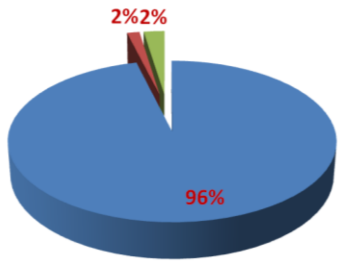
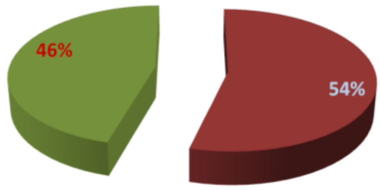
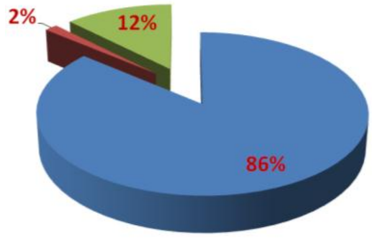
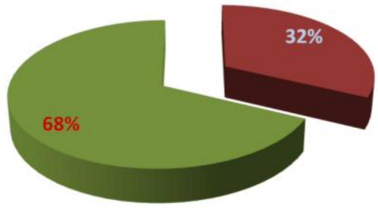
2.10 The total demand that we apply the mode choice model to is presented in figure 2.1. It can be seen that the total demand for the home-to-business purpose is very low. The Car Non-Available (CNA) demand for most purposes (except home-to-education) is low, too. We will return later to this point about the demand segments where the total number of trips is low, because the lower the overall demand, the more difficult it is to identify behavioural patterns that a model can replicate.

Figure 2.1: Total demand by journey purpose and car availability



2.11 Figure 2.2 illustrates how each of the demand categories splits between the available modes of transport. It is easy to observe that travellers with a car available have a very strong tendency to use the car for all types of trips. The proportion of PT users, among travellers with a car, does not exceed 4% for any of the trip purposes.

Figure 2.2: Modal split by journey purpose and car availability

Purpose	Car Available	Car Non-Available
Home to work Highway PT Slow Modes		
Home to shopping Highway PT Slow Modes		
Home to other Highway PT Slow Modes		
Home to education Highway PT Slow Modes		
Home to business Highway PT Slow Modes		
Non-home-based Highway PT Slow Modes		

2.12 The fact that the proportion of travellers using one of the modes of interest is so low turns the estimation of the mode choice model into a serious challenge. When the proportion of PT users is so minor, the entire demand for this mode is smaller than the typical modelling error. A further difficulty lies in the fact that the low share of PT and the slow modes is not a direct result of either poor PT service or excellent performance of the road network. An informal review of the cost skims discloses that car travel in the study area remains most dominant during the Off-Peak period even in cases where travel by alternative modes takes a significantly lower amount of time and costs less.

Yet another difficulty has to do with the typical size of origin-destination flows as per the input demand matrices.

2.13 It was found that most of the travel demand captured in the input matrices comes from cells with demand below one trip. Although small in the base year, this demand cannot be ignored, and we have to include it in all stages of the model calibration work.

2.14 Our multi-objective calibration approach, which was described in detail in separate documents, gives a weight to each of the objectives listed earlier (see paragraph 2.8). Our initial attempts to build mode choice models for the Off-Peak period were based on the standard weights we normally apply this approach for. These weights generally ensure that the importance attached to each one of these objective is more or less similar.

2.15 It is due to the above mentioned reasons that the initial approach to the estimation of the mode choice model involved the introduction of very large mode constants, so as to capture the true reasons for preferring the car. However, this approach resulted in very low and unrealistic demand elasticities.

2.16 The large mode constants, in addition to resulting in an unresponsive model, also caused the model to crash at various stages.

2.17 Therefore, this approach was abandoned and a more pragmatic approach, in keeping with WebTAG Guidance was adopted. This approach is discussed in the next chapter.

3 Alternate Modelling Approach

3.1 As discussed in the previous chapter, it was difficult to find a specification of a mode choice model for the Off-Peak period that would meet all our requirements using our bespoke estimation process. Model specifications that correctly replicated the modal split observed in the data exhibited unlikely levels of sensitivity to changes in fuel cost or public transport fare. This is discussed in detail in Appendix A.

3.2 As per WebTAG Guidance on Variable Demand Modelling, Unit 3.10.4, the section on Realism Testing (Section 1.6, paragraph 1.6.4) states that *"If the model does not behave in accordance with past experience, it should not be used to appraise a transport scheme, unless a convincing case can be made to explain the differences in terms of special local circumstances. Instead, the model parameters and calibration areas should be modified until its responses are plausible"*.

3.3 Following this guidance, it was decided to take the AM model parameters as the starting point and adapt these parameters to the Off-Peak model. The AM model parameters for 0700-0800 were adopted for the Off-Peak as these were considered to be closest representative of the Off-Peak hour.

3.4 The model parameters estimated for travellers with a car available are presented in table 3.1 and those for the travellers with Car Non-Available are presented in table 3.2.

Table 3.1: Models for 'car available' travellers - AM model parameters

	Home-Work	Home-Education	Home-Shopping	Home-Business	Home-Other	Non Home Based Other
Distance (car)	1.180	0.580	2.530	1.060	1.486	5.456
Walk time (PT)	1.203	5.593	4.876	4.453	7.747	4.394
In-vehicle time (PT)	1.000	1.000	1.000	1.000	1.000	1.000
Wait time (PT)	8.763	8.729	4.536	3.894	5.147	4.848
Crowding (PT)	3.01	3.73	1.95	1.37	3.13	1.74
Transfers (PT)	0.274	10.257	6.453	3.733	9.299	5.296
Tolls (car)	1.232	3.031	1.225	2.479	2.802	0.421
Fare (PT)	3.638	3.985	0.413	1.494	1.523	0.676
SM time	4.44	2.72	4.32	3.12	0.5	4.45
Lower level const. (PT)	200.000	50.000	200.000	91.220	150.000	249.881
Upper level const. (car & PT)	-107.761	-120.333	-149.289	-83.108	-150.000	-29.838
General scaling	0.00652	0.01000	0.01100	0.01400	0.01664	0.01600
Car and PT scaling	0.00733	0.01100	0.01100	0.01408	0.01699	0.01600
City centre car dummy	15.9	40.0	38.3	31.2	32.8	20.9

3.5 The following table presents model estimation results for travellers with no car available.

Table 3.2: Models for 'Car Non-Available' travellers - AM model parameters

	Home-Work	Home-Education	Home-Shopping	Home-Business	Home-Other	Non Home Based Other
Walk time (PT)	1.203	5.593	4.876	4.453	7.747	4.394
In-vehicle time (PT)	1.000	1.000	1.000	1.000	1.000	1.000
Wait time (PT)	8.763	8.729	4.536	3.894	5.147	4.848
Crowding (PT)	3.09	0.24	0.25	2.43	2.33	3.49
Transfers (PT)	0.274	10.257	6.453	3.733	9.299	5.296
Fare (PT)	3.638	3.985	0.413	1.494	1.523	0.676
SM time	3.32	3.77	1.45	3.28	2.83	2.98
PT constant	200.000	50.000	-36.069	-46.284	-143.618	374.355
General scaling	0.00388	0.00672	0.02309	0.01101	0.00261	0.00417

Realism Tests

3.6 To test the goodness of fit of the AM model parameters to the Off-Peak model Realism Tests were carried out to test the sensitivity of the model for changes in costs of Highway and PT modes. For PT modes, the Off-Peak model's fares elasticity was evaluated by testing an increase of 10% of the fare. For Highway Modes, the Off-Peak model's fuel price elasticity was evaluated by using a 10% increase in the distance parameter as a proxy for the fuel price.

3.7 One of the issues with the model in its existing state was that the same distance parameter was used for both the Base Year and the Test Year. This functionality was modified slightly so that the Test Year could be modelled separately with an increase of 10% to the base year.

3.8 Starting with the AM peak model parameters, a number of minor adjustments were carried out in the base year mode choice parameters for CA segment models till plausible results were obtained from the elasticity values estimated by the model.

3.9 Based on the above set of Realism Tests, the following elasticities were obtained:

Table 3.3: Elasticities from Realism Tests

MODE	Realism Test	Elasticity
Highway	10% fuel price increase (Using distance parameter as proxy)	-0.26
PT	10% Fare increase	-0.34

3.10 As seen in the table above, the PT fare elasticity is within the WebTAG recommended elasticity range of -0.2 to -0.4. Similarly, the fuel cost elasticity of -0.26 is within the recommended elasticity range of -0.1 to -0.4.

Mode Choice Parameters

3.11 On the basis of the above Realism Tests, the following set of Mode Choice parameters were finalised for the Off-Peak model. The parameters for the Highway Modes are presented in Table 3.4. The Realism Tests showed that the AM model parameters for the hour 0700-0800 were largely appropriate for representing the Off-Peak hour. The only changes that were necessary were to the Distance parameter for the Base Year and the introduction of an additional Distance parameter for the Test Year.

Table 3.4: Models for 'car available' travellers - model parameters

	Home-Work	Home-Education	Home-Shopping	Home-Business	Home-Other	Non Home Based Other
Base Year Distance (car)	5.9	0.58	2.53	1.06	1.486	5.456
Walk time (PT)	1.203	5.593	4.876	4.453	7.747	4.394
In-vehicle time (PT)	1.000	1.000	1.000	1.000	1.000	1.000
Wait time (PT)	8.763	8.729	4.536	3.894	5.147	4.848
Crowding (PT)	3.01	3.73	1.95	1.37	3.13	1.74
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SM time	4.44	2.72	4.32	3.12	0.5	4.45
Lower level const. (PT)	200.000	50.000	200.000	91.220	150.000	249.881
Upper level const. (car & PT)	-107.761	-120.333	-149.289	-83.108	-150.000	-29.838
General scaling	0.00652	0.01000	0.01100	0.01400	0.01664	0.01600
Car and PT scaling	0.00733	0.01100	0.01100	0.01408	0.01699	0.01600
City centre car dummy	15.9	40.0	38.3	31.2	32.8	20.9
Test Year Distance (car)	6.49	0.638	2.783	1.166	1.6346	6.0016

3.12 The Off-Peak model parameters for the PT modes are presented in Table 3.5. As seen from Tables 3.2 and 3.5, these are perfectly identical and no changes were necessary for the travellers with Car Non-Available to represent the Off-Peak hour.

Table 3.5: Models for 'Car Non-Available' travellers - model parameters

	Home-Work	Home-Education	Home-Shopping	Home-Business	Home-Other	Non Home Based Other
Walk time (PT)	1.203	5.593	4.876	4.453	7.747	4.394
In-vehicle time (PT)	1.000	1.000	1.000	1.000	1.000	1.000
Wait time (PT)	8.763	8.729	4.536	3.894	5.147	4.848
Crowding (PT)	3.09	0.24	0.25	2.43	2.33	3.49
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Fare (PT)	3.638	3.985	0.413	1.494	1.523	0.676
SM time	3.32	3.77	1.45	3.28	2.83	2.98
PT constant	200.000	50.000	-36.069	-46.284	-143.618	374.355
General scaling	0.00388	0.00672	0.02309	0.01101	0.00261	0.00417

Mode Shares

3.13 The mode shares on the Highway and PT modes by the various purposes and Car Availability and Car Non-availability for the test year in the base case are shown in Figure 3.1.

3.14 The figure shows that for car available trip, the largest mode shares in the base case are for the highway modes.

3.15 A comparison of the test year mode shares between the base case and the two test cases - Do Economy Plus and Do Environment Plus are provided at the end of Chapter 4 - Scenario Tests.

Figure 3.1: Modal split by journey purpose and car availability

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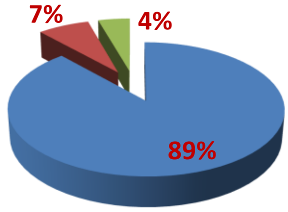
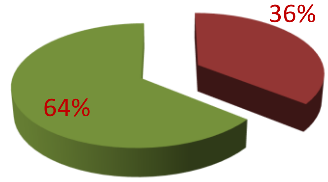
Highway
PT
Slow Modes</td><td>
</td><td>
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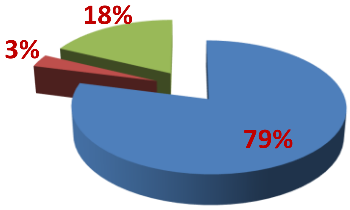
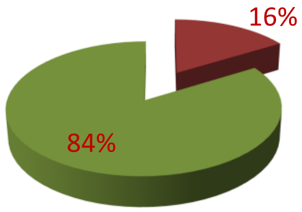
PT
Slow Modes</td><td>
</td><td>
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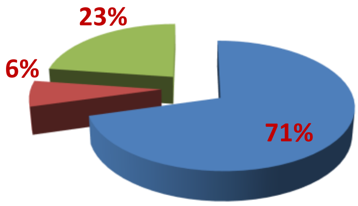
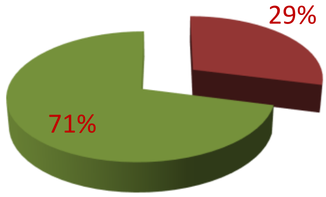
Slow Modes</td><td>
</td><td>
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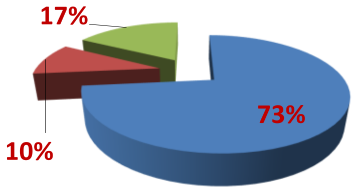
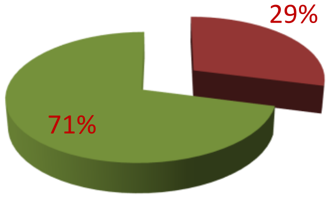
Slow Modes</td><td>
</td><td>
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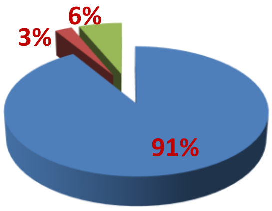
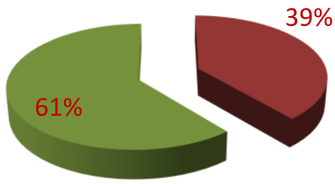
Slow Modes</td><td>
</td><td>
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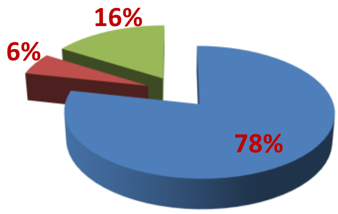
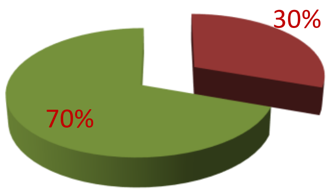
Slow Modes</td><td>
</td><td>
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4 Scenario Tests

4.1 Once the mode choice parameters were finalised based on the Realism Tests, the following sensitivity tests were carried out to test the outcomes of various schemes and provide confidence on the adopted parameters.

4.2 The following two test scenarios were provided by the NTA. These were compared to the Test Year results from the base case scenario.

- DTO Model test 3C: Economy Plus (EconPlus)
- DTO Model test 4C: Environment Plus (EnviroPlus)

4.3 Table 4.1 below gives the overall description of these two scenarios.

Table 4.1: Scenarios Tested

	Road infrastructure	Public Transport
Economy Plus (test 3c)	All major road proposals.	T21 plus Metro West extension to Dundrum, Naas to Sallins Light Rail, Luas extensions to Newcastle (A1 extension), Poolbeg (F and C2 extensions) and Adamstown (F), Bellinstown to Donabate (Metro North Extension), Luas Line E, the line from Tallaght to the City Centre via Kimmage and Luas extension to Meakstown
Environment Plus (test 4c)	Reference case roads only (minor exceptions)	Similar to Economy Plus (test 3c)

4.4 The two scenarios were tested against the test year results of the base case scenario with respect to the PT passenger loadings as obtained from the mode reports of the Trips model.

4.5 Note that since the Base Year for all scenarios is the same, an incremental comparison is done here on the test year results.

4.6 The mode attributes and passenger loadings in the Base Case Test Year are presented in the table 4.1 below.

Table 4.1: Mode Attributes and Passenger Loadings for Base Year Test Case

MODE	Number of Lines	Passenger Loadings
DART	14	5,606
SRAIL	16	5,862
NBUS	215	13,137
BusEInd	109	1,780
LUAS	24	10,577
Total		36,963

4.7 The mode attributes and passenger loadings in the Do EconPlus Test Year are presented in the table 4.2 below.

Table 4.2: Mode Attributes and Passenger Loadings for Do EconPlus Test Case

MODE	Number of Lines	Passenger Loadings
DART	14	3,488
SRAIL	16	5,741
NBUS	209	10,777
BusEInd	132	2,728
LUAS	24	8,375
Total		31,110

4.8 The mode attributes and passenger loadings in the Do EnviroPlus Test Year are presented in the table 4.3 below.

Table 4.3: Mode Attributes and Passenger Loadings for Do EnviroPlus Test Case

MODE	Number of Lines	Passenger Loadings
DART	4	1,280
SRAIL	22	5,760
NBUS	219	15,786
BusEInd	117	3,547
LUAS	8	2,513
Total		28,887

4.9 From the tables 4.1 and 4.2 above, it is seen that the model results are plausible in predicting demand with respect to change in supply. For example, it can be seen that when the number of BusElnd between the base case and the Do Econplus scenario has increased from 109 to 132, the passenger boardings have also gone up by 53%. At the same time, however, boardings on all the other PT modes have gone down, particularly on the rail modes. This is in line with the changes expected due to major highway improvements associated with the Do Econplus scenario.

4.10 Similarly, comparing tables 4.1 and 4.3, it is seen that a decrease in the number of rail based services is accompanied by a subsequent decrease in the number of boardings on that mode. Although in case of the mode SRAIL, even though the number of lines have increased by 22%, the number of boardings have gone down slightly by 2%. This could be due to shift of demand to other PT modes such as NBUS and BusElnd.

4.11 It should be noted that these results are indicative and a detailed examination of these results requires much more detailed analysis beyond the scope of this report.

This is due to the fact that the boardings is not a true indicator of the number of trips carried out, since the TRIPS software on which the PT modes is modelled here, treats multi-legged trips using multiple modes as separate boardings. Hence, if a trip using bus and rail shifts to bus only, this is reported as no change in the number of bus boardings but the number of rail boardings will be treated as one less, even though there is no change to the number of trips between that particular origin-destination pair.

4.12 Also, the documentation provided with the scenarios for testing states the difference between scenario Do Econplus and Do EnviroPlus as only highway related. However, the model results show a decrease in the number of DART and LUAS modes.

4.13 Therefore, the results of these scenario tests are to be considered only for the purposes of testing that the model produces sensible results and it is recommended that a more in depth analysis is to be carried out for any scheme appraisal.

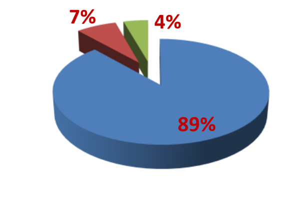
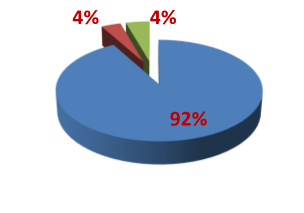
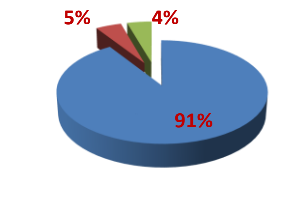
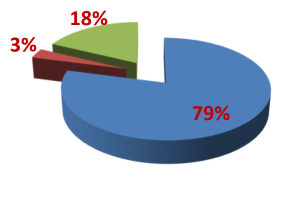
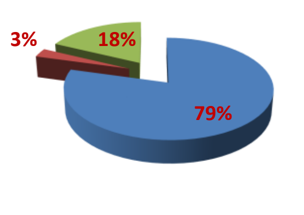
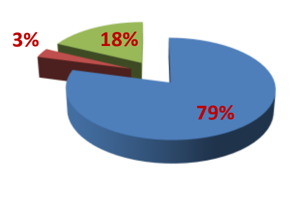
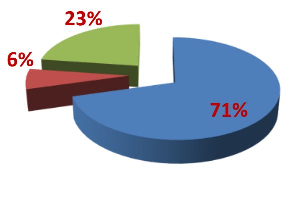
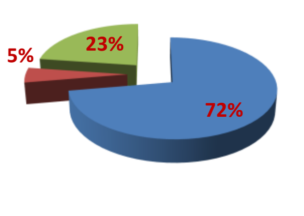
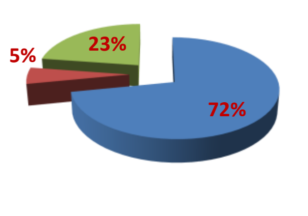
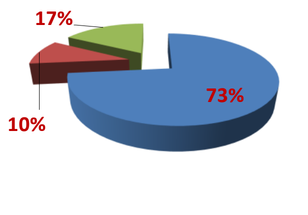
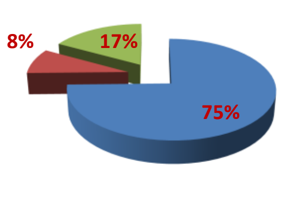
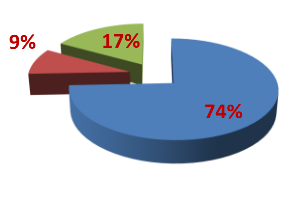
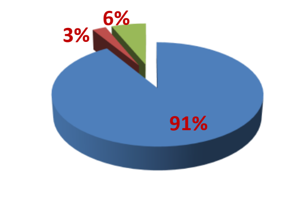
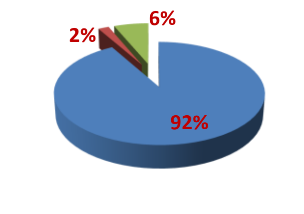
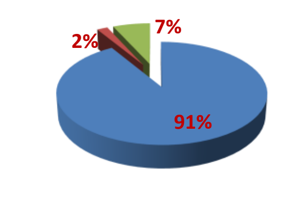
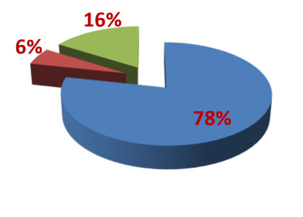
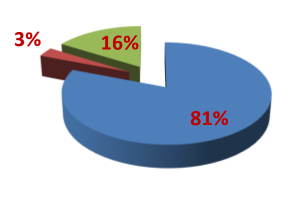
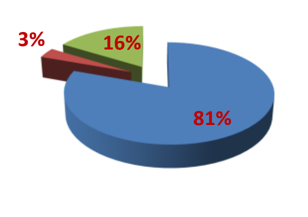
Comparison of Mode Shares

4.14 This section presents the results of the comparison of the mode shares between the test years in the base case and the two test scenarios – Do Economy Plus and the Do Environment Plus.

4.15 Figure 4.1 shows the comparison of the mode shares by the highway and PT modes for the test years in the base case and the scenarios tests. The figure shows that compared to the test year in the base case, the mode shares for the Car Available highway modes have gone up across all the trip purposes, except Home to Shopping purpose. This is accompanied by a decrease in the Car Available PT modes for all trip purposes, with the exception of the Home to Shopping purpose. This change is in line with the improvements to the highway infrastructure associated with the test scenarios.

Figure 4.1: Comparison of Mode Shares between Base Case and Scenario Tests

Purpose

	Car Available - Base Case	Car Available - Do Econ Plus	Car Available - Do Enviro Plus
Home to work Highway PT Slow Modes			
Home to shopping Highway PT Slow Modes			
Home to other Highway PT Slow Modes			
Home to education Highway PT Slow Modes			
Home to business Highway PT Slow Modes			
Non-home-based Highway PT Slow Modes			

4.16 From the mode shares in Figure 4.1, it cannot be inferred what effect the highway improvements have had within the PT modes itself. For this analysis, the mode shares of the road-based and rail-based PT modes are compared in Table 4.4.

Table 4.4: Comparison of PT Mode Shares between Base Case and Scenario Tests

Mode	Test Year - Base Case	Test Year - Do EconPlus	Test Year - Do EnviroPlus
DART	15%	11%	4%
SRAIL	16%	18%	20%
NBus	36%	35%	55%
BusElnd	5%	9%	12%
LUAS	29%	27%	9%

4.17 Table 4.4 shows that the mode shares on the road based modes increase significantly in the scenario tests compared to the base case, while the rail based mode shares decrease. The exception is NBus in the Do Econplus scenario, but this is due to a decrease in the number of lines from 215 in the base case to 209 in the Do Econplus scenario. However, it is to be mentioned that there might be shifts within rail based modes too. For example, the share of SRAIL increases in the test scenarios. This is possibly due to shift from other competing rail based modes.

4.18 From Figure 4.1 and Table 4.4, it can therefore be concluded that the share of highway based modes increases in the test scenarios compared to the base case. This is in line with the changes to the network – enhancements to the highway infrastructure.

5 Conclusions and Recommendations

5.1 Estimating a mode choice model for the Off-Peak period in the Greater Dublin Area is a challenging task, due to a number of reasons:

- The proportion of PT trips is very low, particularly for Car Available demand segment
- Mode choices cannot be intuitively explained by differences in travel conditions or levels of service
- In the available demand matrices, a very high proportion of the demand comes from origin-destination flows with a tiny number of trips.

5.2 Out initial approach to estimate a mode choice model that meet the standard set of criteria using extremely high mode constants that replicated observed demand had to be abandoned due to the model being made insensitive to cost changes

5.3 We do believe that the mode choice model presented here forms a step change compared to the previous versions of the Off-Peak mode choice model, which was not based on segmentation by journey purpose. The new model has stronger behavioural foundations and is therefore more credible as a tool for forecasting.

5.4 The model presented here performs well, in terms of being sensitive to cost changes and produces elasticities within the ranges recommended by WebTAG. However, as a best practice, it is recommended that more in depth analysis is carried out at an individual scheme level for business case development using this model.

APPENDIX A

INITIAL APPROACH

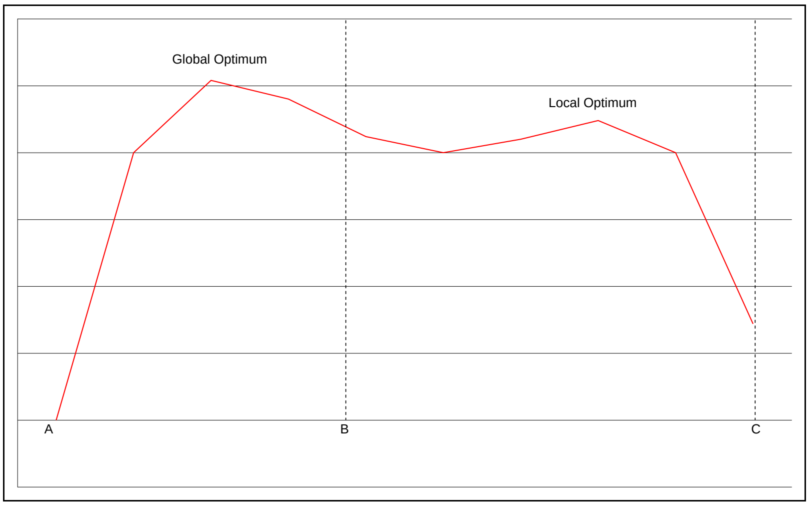
A1. Initial Approach used for Model Estimation

A1.1 This section provides a brief description of the initial approach to calibrate the Off-peak DTO model, explaining the approach that was used and the reasons why this was found to be unsuitable to the task.

Initial Approach

A1.2 When estimating discrete choice models it is common practice to determine the values of the model parameters by maximising the log-likelihood function. This approach picks the values of the model parameters in such a way as to make the modelled data 'more likely' (to that which is observed) than would be the case with any other set of parameter values. This is a powerful approach, and the set of parameter values it renders as the solution of the estimation problem is often the global optimum (i.e. the highest value within a given domain. Other approaches exist which do not always find the highest value overall but rather the highest value within just a part of the domain – commonly termed a local optimum). An illustration of the two types of optimum is shown in Figure A.1.

FIGURE A.1 ILLUSTRATION OF LOCAL AND GLOBAL OPTIMA



A1.3 In the above diagram, the domain is AC and the global optimum is the maximum turning point in the sub-domain AB. Some estimation approaches may begin in the sub-region BC and may only find the local optimum without going on to find the global optimum which would represent the best solution.

A1.4 Solving the estimation problem using a maximum likelihood approach is also very robust in the sense that it lets us test the significance of each model parameter separately, using statistics such as the t-test. These allow us to examine not only the goodness-of-fit of the entire model but also the adequacy of each individual parameter.

A1.5 For the purposes of travel demand forecasting we are often willing to compromise on a set of parameter values that forms a local optimum of the model estimation problem, so long as this solution passes some pre-defined validation tests. We are not aware of software tools that can do this through maximum likelihood model optimisation so therefore continued with the model estimation process using an alternative approach.

Market Simulation Experiment

A1.6 The model presented in this initial approach were estimated using a multi-objective market simulation tool with an automated solution search algorithm.

A1.7 By stating that this is a multi-objective tool we mean that the choice of the best set of parameters for the Mode Choice model is done by combining several objective functions, rather than one function as in a likelihood maximising process. We use one expression, which we call the meta-error, to combine all objectives, and try to minimise the value of this meta-error.

A1.8 By stating that this is a market simulation tool we mean that for each candidate set of parameter values, we generate a full set of mode/time of travel, share estimates for each origin-destination pair, based on the dataset with the components of the generalised cost. We then use the different objective functions mentioned above to test to what extent these estimates meet our needs. We do this repeatedly with different possible parameter sets.

A1.9 By stating that we use an automated solution search algorithm we mean that instead of adopting a trial-and-error approach for examining possible solutions, we use a more systematic technique. It helps us make an intelligent guess of what parameter set has a good chance of performing well, based on what we know on the performance of parameter sets we have already examined. This technique is based on the Downhill Simplex Method which we describe in the next section of this chapter. The algorithm was programmed in a statistical analysis package called STATA and the process is fully automated via the use of “For Loops” that continuously iterate in search for parameter values that further improve (minimise) the value of the meta-error.

A1.10 As explained earlier, the process we describe here is dominated by difficulties related to the high correlation between the different components of the generalised cost functions. This high correlation means that when we try to determine the value of each parameter, there seem to be too many degrees of freedom, i.e. too many combinations of parameter values seem equally likely to be the sought solution.

A1.11 The standard procedure when estimating models is to go through a calibration process first, and then use some validation tests (or ‘realism tests’) to verify that the solution chosen in the calibration process is satisfactory. But if a procedure where calibration precedes validation is used to solve a problem with too many degrees of freedom, the validation test is rarely satisfied, and there is a need to loop over the process of calibration and validations repeatedly.

A1.12 We therefore embark here on a model estimation procedure in which calibration and realism testing are undertaken simultaneously. We define several different objectives; some of them are measures of goodness-of-fit like those used in calibration processes, and some others are typical validation tests. We examine the performance of each candidate set of model parameters based on all these objectives; namely, validation is done at each stage of the calibration process rather than after calibration is complete.

A1.13 As explained above, what we practically try to minimise is a meta-error, that is, a weighted average of the values of all objectives. To calculate the meta-error we assign a weight to each objective before the process is run. This weight is determined so that the meta-error is not dominated by any of the objectives; so that once some of the objectives reach plausible values, the meta-error is always more affected by the objectives that have not reached plausible values yet.

A1.14 Setting the values of the weights required some preliminary experiments and was based on our judgement of the sensitivities of the different objectives, because an improvement of 0.1 in one objective is not equally important as an improvement of a similar size in another objective. We refrain from presenting the weights used because they do not have a straightforward meaning, and were subject to continuous refinement throughout the model estimation process. We did this, for example, if we found a solution for the model estimation problem that satisfied all objectives but one; we then increased the weight of the remaining objective, resumed the process with the revised weights, and so on.

A1.15 The different objective functions that we used in the combined calibration/validation process are described in paragraphs that follow.

Objective 1: Minimise error in total trips of each alternative.

A1.16 The difference between the observed (i.e. from the input data) and estimated (i.e. from the model output) total number of trips is calculated for each alternative as a proportion of the observed number of trips. The target value for this objective is zero.

Objective 2: Minimise error in the geographical dispersion of demand of each alternative.

A1.17 Similar totals of observed and modelled demand do not mean that the model correctly replicates the distribution of this demand across different origin-destination pairs. To examine this spatial distribution we use the RMSWE measure, which stands for Root Mean Squared Weighted Error. It is calculated as follows:

$$\sqrt{\frac{1}{\sum y_i} \cdot \sum \left(\frac{x_i - y_i}{y_i} \right)^2 \cdot y_i} \qquad \text{(Equation 1)}$$

A1.18 In equation 1, x_i represents the modelled flow for a specific alternative for a specific origin-destination pair i, and y_i represents the observed flow for the same alternative and origin-destination pair. The term within the bracket is simply the error for a single i, i.e. the normalised difference between the observed and modelled flows. It is squared so that errors of different signs do not cancel each other out, and also in order to give larger errors a bigger weight. The multiplication by y_i gives larger flows a greater influence. The ideal value of the RMSWE is zero.

Objective 3: Ensure that fuel cost elasticity in the model is within the range recommended in WegTAG.

A1.19 This is, in fact, a constraint rather than an objective function, but it is converted into an objective function by defining an expression (that we wish to minimise) that includes a high penalty if the fuel cost elasticity implied by the model is outside the range specified in WebTAG. The market simulation tool calculates, for each origin-destination pair and for each candidate set of parameters, how modal shares would change if fuel cost increased by 10%. The difference between this and the case without cost increase is summarised across the study area to derive the arc elasticity of demand to fuel cost.

Objective 4: Ensure that public transport fare elasticity in the model is within the range recommended in WebTAG.

A1.20 This is implemented in a similar way to the one described for objective 3.

Objective 5: Ensure that the proportion of each components of the public transport generalised cost is within a logical range.

A1.21 The market simulation tool contains a module that calculates, for each candidate parameter set, the contribution of each variable to the public transport total generalised cost. For a specific origin-destination pair, the contribution of variable K is calculated as the parameter weight of K multiplied by the value of K, divided by the total generalised cost. The equation below serves as an illustration, where K in this case is the variable In Vehicle Time (IVT) for public Transport:

Contribution of IVT to PT Gen Cost = ([IVT]*[IVT Parameter weight])/PT Gen Cost

A1.22 This is summarised across all origins and destinations, and the demand in each pair is used as a weight. The idea in this calculation is to ensure that the automated model estimation process does not let the relativities between the components of the generalised public transport costs contradict our intuitive judgement. Thus, the objective here is to minimise an expression that includes a high penalty for parameter sets that make the In-Vehicle-Time constitute more than half of the total generalised cost; for parameter sets where the public transport constant is above 25% of the generalised cost; and so on.

The Downhill Simplex Method

A1.23 The search for a solution for the model estimation problem used an algorithm we programmed based on the Downhill Simplex Method. This method is suitable for optimising objective functions that do not have a closed form. In our case the meta-error does not have a closed form because it depends on the parameters we estimate in an indirect way. In other words the parameters are used in a logit model to estimate modal shares for many origin-destination pairs, and the results of this estimation are aggregated in several different ways to calculate the objective values; the objective is not an explicit function of the parameters.

A1.24 The Downhill Simplex Method is not a particularly efficient optimisation technique in terms of the number of iterations required to get to an optimal solution. It is also does not guarantee convergence to the global optimum. In the context of building travel demand models, a further disadvantage is that when we use this method we cannot present the statistical measures which the readers may be more familiar with, such as the Rho-squared for the full model or t-test for individual attributes.

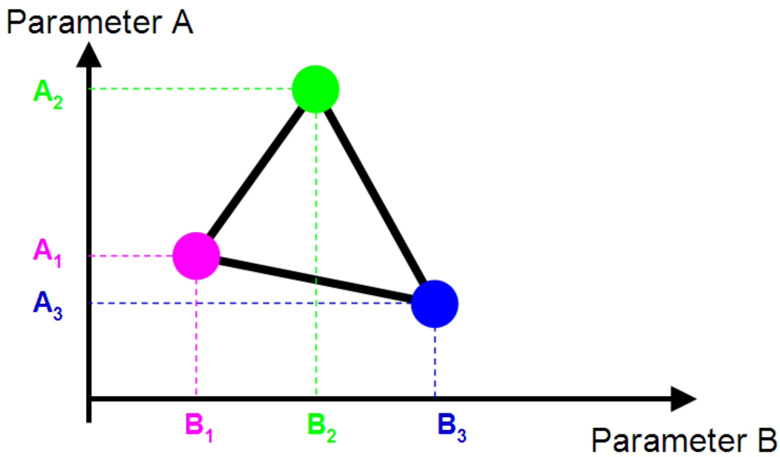
A1.25 Nevertheless, this method is very powerful in that it is suitable for any type of objective function or problem, including the problem that could not be solved using a maximum likelihood approach. The Downhill Simplex Method also guarantees continuous improvement of the objective as long as we continue to allow it to run. For our current needs, using this technique appears the most robust approach available, because the alternative would be a manual trial-and-error process (which is not uncommon among practitioners).

A1.26 We now describe the basics of this approach. A simplex is a geometrical shape in a multi-dimensional space. For example, a simplex in a two-dimensional space is a triangle, and a simplex in a three-dimensional space is a pyramid, but there can be simplexes in spaces of any dimension.

A1.27 At each corner of a simplex there is a vertex; in a N-dimensional simplex there are N+1 vertices. When we use the Downhill Simplex Method to optimise the values of N parameters we use an N-dimensional simplex with N+1 vertices; each dimension represents one parameter and each vertex is one candidate set of values of all the parameters. The simplex at each stage of the process is the best group of candidate solutions we are aware of at that point.

A1.28 A simple case, where we want to estimate a model with two parameters, is illustrated in Figure A.2. Since there are two parameters, this is a two-dimensional problem and the simplex is a triangle. Each of the three vertices of the triangle is a possible solution of the problem. The coordinates of vertex 1, B1 and A1, are the respective values of parameters B and A according to solution 1; the same goes for vertices 2 and 3.

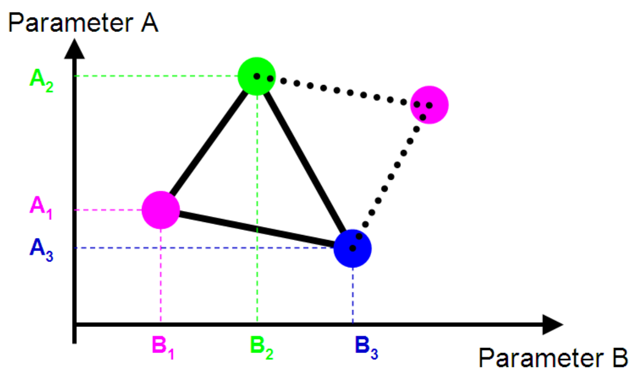
FIGURE A.2 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



A1.29 The fact that each vertex is a possible solution of the model estimation problem means that each vertex is in fact a Mode Choice model for which we can calculate the values of the different objectives and the meta-error. At the first stage of the Downhill Simplex algorithm we calculate the objective values for all vertices. After the first stage, we start an iterative loop, and in most iterations throughout the process the number of times we need to calculate the objective value per iteration is much smaller.

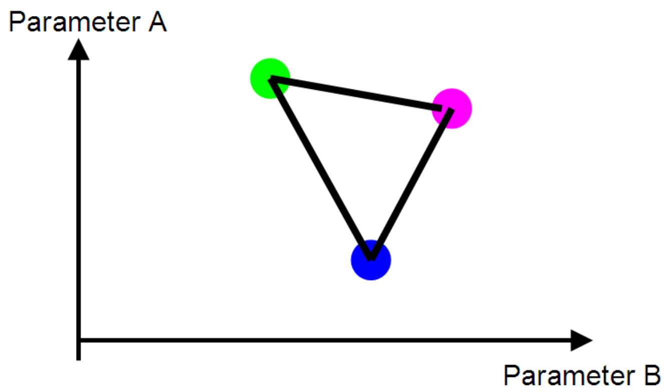
A1.30 The core iterative process works as follows. Since we know the objective value (i.e. the meta-error) for each vertex, we can identify the vertex that has the worst (i.e. highest) value. We deem this "the worst vertex" and the other vertices (the remaining two, in the triangle example) "the base of the vertex". In order to get rid of the worst vertex, and replace it with a better solution of our problem, we undertake a reflection manoeuvre. Namely, we replace the worst vertex with a point in space that lies at the same distance from the base of the simplex as the worst vertex, but on the opposite side of the base. If vertex 1 in Figure A.2 was the worst vertex, Figure A.3 demonstrates how we undertake a reflection manoeuvre.

FIGURE A.3 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



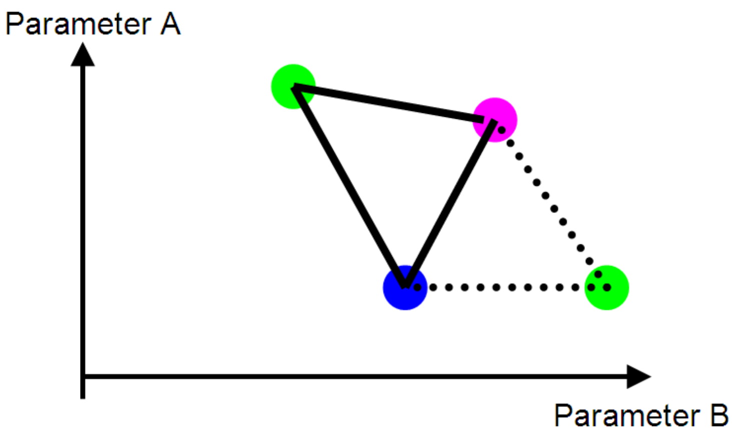
A1.31 It is merely a guess that the new vertex, with the implied new values of the parameters, would have a better value of the objective; but this is an intelligent guess which often works well. If the objective in the new location is indeed better than the worst objective value in the original simplex, we complete this manoeuvre and we now have a new simplex, as described in Figure A.4.

FIGURE A.4 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



A1.32 Like any simplex, one of the vertices in the new simplex is “the worst vertex”, and with it we can start a new iteration. Figure A.5 illustrates what the next reflection might be like. We can do this repetitively until we are satisfied with the objective value we reach. It is worth noting that although in each iteration we improve the worst vertex of the simplex, when we decided to halt this process it is sensible to use the best vertex.

FIGURE A.5 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



A1.33 The reflection manoeuvre does not work well in every iteration. If a simple reflection does not lead to an improved objective value, some alternative types of reflection are investigated. We avoid a full description of all technical aspects of this process here, but these are available from our team, or in the optimisation literature, if necessary.

A1.34 The model estimation discussed in this report has more parameters than in the example above, and therefore the solution is not as graphically intuitive. Nevertheless, the principles of the process as the same. We have run this algorithm separately with the commuting trips dataset and with the dataset of other journeys, and in each of these we reached a set of parameter values from which it appeared that no further improvement of the meta-error was possible.

Problems Encountered with the Initial Method

A1.35 The initial approach of calibrating the off peak model discussed above resulted in reasonably correct representation of observed mode splits but exhibited unlikely levels of sensitivity to changes in fuel cost or public transport fares. Therefore, it was decided to waive some of the initial requirements to focus on what was believed to be the more critical requirements. A new version was developed with higher weights attached to the objective functions in order to produce elasticities within the ranges recommended by WebTAG. The following tables show the mode choice parameters for Car Available and Car Non-Available travellers respectively.

Table A1: Mode Choice Parameters for "Car Available" Travellers

	Home-Work	Home-Education	Home-Shopping	Home-Business	Home-Other	Non Home Based Other
Distance (car)	6.89	22.11	5.07	10.47	6.09	8.85
Walk time (PT)	1.24	2.94	1.84	2.18	2.97	1.86
In-vehicle time (PT)	1.00	1.00	1.00	1.00	1.00	1.00
Wait time (PT)	1.76	2.64	1.10	2.43	1.29	1.80
Crowding (PT)	3.01	3.73	1.95	1.74	1.37	3.13
Transfers (PT)	2.54	3.06	1.46	1.94	2.00	2.51
Tolls (car)	10.7	16.6	54.6	28.1	33.1	44.2
Fare (PT)	14.2	2.3	7.4	5.2	9.3	12.9
SM time	4.44	2.72	4.32	4.45	3.12	0.50
Lower level const. (PT)	18.1	-3.90	2.03	9.80	21.0	-30.0
Upper level const. (car & PT)	-19.3	20.6	7.5	5.3	11.9	-1.2
General scaling	0.32	0.02	0.50	0.19	0.41	0.60
Car and PT scaling	0.35	0.67	0.89	0.30	0.85	0.85
City centre car dummy	15.9	40.0	38.3	20.9	31.2	32.8

A1.36 Table A2 below shows the mode choice parameters for the Car Non-Available travellers.

Table A2: Mode Choice Parameters for "Car Non-Available" Travellers

	Home-Work	Home-Education	Home-Shopping	Home-Business	Home-Other	Non Home Based Other
Walk time (PT)	2.71	2.59	1.00	2.34	2.79	2.69
In-vehicle time (PT)	1.00	1.00	1.00	1.00	1.00	1.00
Wait time (PT)	1.63	3.10	0.93	3.17	3.65	1.96
Crowding (PT)	3.09	0.24	0.25	3.49	2.43	2.33
Transfers (PT)	2.15	3.28	2.11	1.62	3.14	2.90
Fare (PT)	10.00	3.15	9.99	10.72	9.60	8.08
SM time	3.32	3.77	1.45	2.98	3.28	2.83
PT constant	-1.24	-8.35	-3.32	-9.70	0.62	-1.81
General scaling	0.25	0.03	0.08	0.06	0.20	0.53

A1.37 A comparison with the mode choice parameters in Chapter 3 (para 3.11 onwards) shows that the parameters in this initial approach are very different from the parameters finally used.

A1.38 A key problem with using the process described above was that it relied on having a good spread of costs and mode shares for various demand segments to be able to estimate a robust set of parameters. However for off-peak period with relatively low levels of demand for several demand segments and relatively less variation in costs the parameters being estimated by the process were being impacted more by the constraints provided than the input data (costs and demand) itself.

A1.39 Therefore, some of the main problems associated with this approach, which resulted in finally abandoning this approach for a more refined one, are as follows:

- The estimation process was getting complicated and produced implausible model parameters
- Resulted in significant difference between observed and modelled demand particularly for car-available demand segments
- Resulted in elasticities that were beyond acceptable ranges, especially PT fare elasticities
- In addition, and quite importantly, the above parameters caused the model to crash repeatedly due to the implausibility of the estimated parameters.

A1.40 Due to the above mentioned reasons, it was decided not to proceed using this approach but to start with the AM model mode choice parameters and adapt these to the off-peak model.

CONTROL SHEET

Project/Proposal Name	DTO Off-Peak Model
Document Title	Calibration of the Mode Choice Model
SDG Project/Proposal No.	221210-01

ISSUE HISTORY

Issue No.	**Date**	**Details**
1	November 2009	First draft before DSEG presentation
2	December 2009	Full draft incorporating updated models
3	December 2010	Full draft with alternate modelling approach

REVIEW

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