CRANFIELD UNIVERSITY
LIBRARY

Cranfield University

Romano Italo Pagliari

Estimating the Monetary Value of Airport Runway Departure Slots

Supervisor: Ian Black

School of Management

Centre of Logistics and Transportation

October 1996

PhD Thesis

ProQuest Number: 10820903

All rights reserved

INFORMATION TO ALL USERS
The quality of this reproduction is dependent upon the quality of the copy submitted.

In the unlikely event that the author did not send a complete manuscript
and there are missing pages, these will be noted. Also, if material had to be removed,
a note will indicate the deletion.

ProQuest 10820903

Published by ProQuest LLC (2019). Copyright of the Dissertation is held by Cranfield University.

All rights reserved.
This work is protected against unauthorized copying under Title 17, United States Code
Microform Edition © ProQuest LLC.

ProQuest LLC.
789 East Eisenhower Parkway
P.O. Box 1346
Ann Arbor, MI 48106 – 1346

ABSTRACT

Slot allocation is one of the most contentious and keenly debated topics within the air transport industry. The issue of pricing access to airport slots, as a means of relieving congestion, has received increased attention in recent years. However, little attempt has been made to determine how airlines value access to slots, or to measure the impact quantitatively of introducing the pricing mechanism into slot allocation.

It is the objective of this thesis to establish a process whereby the potential value of a slot can be determined. Since the value of a slot is ultimately a function of the how highly passengers value travelling at different times of the day, the research problem is initially approached from the passenger's perspective.

Analysis focused initially on the use of stated preference methods, to derive parameters which measure how highly passengers value different departure times. These parameters were then calibrated on a departure time choice model, which estimates, given assumptions on the distribution of ideal departure times on a given route, how passengers select flights scheduled at different times.

Decision-rules governing the scheduling of profitable flights were developed. These rules determine the conditions necessary for the scheduling of profitable flights and the setting of fares.

Combining both passenger and flight scheduling decision-rules within a simulation model it was then possible to generate, given various assumptions on aircraft size and total demand, a set of equilibrium flights scheduled at different departure times, associated with a level of passenger demand and equilibrium fare. From these simulations, slot value estimates were derived.

Within the context of the thesis objective, analysis focused on a wide range of issues. These were: stated preference experimental design and parameter estimation, how passengers value departing at different times of the day, competition for slots, time of day pricing, and estimating potential slot values for different aircraft types.

CRANFIELD UNIVERSITY LIBRARY

This thesis has contributed to existing literature on slot allocation through firstly, outlining a method to estimate slot values, secondly, providing a more thorough analysis of passenger departure time preferences in air transportation, and thirdly, a further demonstration of the application of stated preference techniques within an aviation context.

ACKNOWLEDGEMENTS

I would like to thank my parents, family and friends for their support during the development of this thesis.

A special thanks to: my supervisor Mr Ian Black, for his guidance and constructive criticism, all the staff and students at the Cranfield Centre for Logistics and Transportation, Cranfield Air Transport Group, Mrs Val Singh and Mrs Barbara Birtles for their patience and kind help over the last five years.

In developing the research approach and methodology, I would like to thank the following individuals and institutions for their help and advice: Dr Mohammed Yeahya, Dr Fariba Alamdari, Dr Marco Caldas, Mr John Sheldon, and Manchester Airport Ltd

CONTENTS

CHAPTER 1: INTRODUCTION	Page
1.1 Research problem	**1**
1.2 Research rationale	**2**
1.3 Research approach	**3**
1.4 Research aims and objectives	**5**
1.5 Thesis structure	**5**
CHAPTER 2: SLOT ALLOCATION AND PRICING	
2.1 Introduction	**7**
2.2 Slots and airline operating efficiency	**7**
2.3 The current I.A.T.A method for allocating slots	**8**
2.4 Administrative regulation	**12**
2.5 Slot pricing	**17**
2.5.1 Basic principles	17
2.5.2 Slot auctions	18
2.5.3 Slot trading	22
2.5.4 Airline operations in a slot priced environment	24
2.5.5 Measuring the value of a slot	25
2.6 Summary and conclusions	**29**
CHAPTER 3: PASSENGERS CHOICE OF DEPARTURE TIME	
3.1 Introduction	**31**
3.2 Theories of passenger choice	**31**
3.2.1 Deterministic choice theory	31
3.2.2 Probabilistic choice theory	33
3.3 Probabilistic choice theory behavioural models	**34**
3.3.1 Probit model	34
3.3.2 Logit model	35
3.3.3 Choice of model	37
3.4 Schedule delay time	**39**
3.4.1 Definition	39
3.4.2 Schedule delay time in urban transportation	39
3.4.3 Schedule delay time in air transportation	41

3.5 The money value of schedule delay time **46**
3.6 Choice of analytical technique **47**
3.6.1 Revealed preference analysis 47
3.6.2 Stated preference analysis 49
3.6.3 Choice of analytical technique 50
3.7 Summary and conclusion **54**

CHAPTER 4: STATED PREFERENCE EXPERIMENTAL DESIGN
4.1 Introduction **55**
4.2 Issues in experimental design **55**
4.2.1 Choice of travel context 55
4.2.2 Choice of product attributes 58
4.2.3 Theoretical framework 60
4.2.4 Attribute levels 62
4.3 Measuring responses **66**
4.3.1 Discrete choice 66
4.3.2 Ranking 66
4.3.3 Rating 67
4.3.4 Choice of response measurement scale 68
4.4 Choice set design **70**
4.4.1 Boundary values 70
4.4.2 Boundary values versus orthogonality 74
4.5 Response simulation **76**
4.5.1 Method 76
4.5.2 Orthogonal and non-orthogonal design features 79
4.5.3 Analysis of simulation results 82
4.6 Summary and conclusion **89**

CHAPTER 5: ANALYSIS OF STATED PREFERENCE RESULTS
5.1 Introduction **91**
5.2 Experimental conditions **91**
5.2.1 Interview technique and sampling strategy 91
5.2.2 Questionnaire design 92
5.3 Sample characteristics **94**
5.4 Estimation method **96**

5.4.1 Introduction 96
5.4.2 Linear regression versus Logit and Probit 98
5.4.3 Results sensitivity to variation in dependent variable scale 102
5.5 Analysis of results 106
5.5.1 All respondents 106
5.5.2 Business and non-business respondents 111
5.6 Lexicographic Analysis 113
5.6.1 Non-trading respondents 113
5.6.2 Illogical responses 114
5.6.3 Results summary 118
5.7 Estimation of β^0 121
5.7.1 Method 121
5.7.2 Results 124
5.8 Summary and conclusion 131

CHAPTER 6: SLOT VALUE SIMULATION MODEL

6.1 Introduction 133
6.2 Passenger departure time choice model 133
6.3 Operator choice of slot decision-rules 136
6.4 Simulation model 138
6.4.1 Basic assumptions 138
6.4.2 Model structure 142
6.4.3 Model limitations 151
6.5 Summary and conclusion 155

CHAPTER 7: SLOT VALUE SIMULATION MODEL RESULTS

7.1 Introduction 156
7.2 Data and analytical assumptions 156
7.3 Patterns of flight scheduling with demand = 100, 200, 300, 400 and fares fixed at £55 by aircraft type 157
7.3.1 65-seat turboprop 157
7.3.2 100-seat jet 160
7.3.3 37-seat turboprop 163
7.3.4 Frequency, passenger generalised costs and average profits per aircraft type 165

7.4 Slot value model analysis assumptions **170**
7.5 Slot value model results **171**
7.5.1 100-seat jet 171
7.5.2 65-seat turboprop 177
7.5.3 37-seat turboprop 183
7.6 Validation of simulation model results **187**
7.7 Sensitivity analysis **194**
7.7.1 Assumptions 194
7.7.2 Sensitivity Test 1: doubling the magnitude of β^0 and β^{se} 194
7.7.3 Sensitivity Test 2: uniform distribution of ideal departure times 198
7.7.4 Sensitivity Test 3: 150-seat aircraft and total demand = 1,400 201
7.8 Policy implications **204**
7.9 Summary and conclusions **206**

CHAPTER 8: SUMMARY AND CONCLUSIONS
8.1 Introduction **209**
8.2 Summary of the findings **209**
8.3 Contribution to knowledge **213**
8.4 Weaknesses and deficiencies **216**
8.5 Suggestions for further research **220**

REFERENCES **221**

APPENDICES
Appendix A: Full factorial design A-1
Appendix B: Full factorial design boundary values B-1
Appendix C: Orthogonal and non-orthogonal designs C-1/C-2
Appendix D: Stated preference design simulation results D-1/D-3
Appendix E: Late departure time questionnaire E-1/E-6
Appendix F: Early departure time questionnaire F-1/F-6
Appendix G: Scale parameter derivation simulation results G-1/G-3
Appendix H: Operating cost model H-1/H-3
Appendix I: Aircraft operating cost data I-1
Appendix J: Sensitivity analysis results data J-1/J-3

TABLES

4.1	Product attribute levels	65
4.2	Response measurement scale	69
4.3	Sample choice sets	72
4.4	Response measurement scale and generalised cost values	78
4.5	Non-orthogonal design correlation matrix	80
4.6	Simulation input values of time	82
4.7	Average coefficient t-ratio performance by stated preference design	89
5.1	Correlation matrix: ideal and actual departure times	95
5.2	Parameter estimates by estimation method based on five-point scale	98
5.3	Ratio of parameter estimates to in-flight time coefficient by estimation method	99
5.4	Parameter estimates by dependent variable scale specification based on ordered Logit	104
5.5	Ratio of parameter estimates to in-flight time coefficient by response scale	105
5.6	Model results: all respondents	106
5.7	Values of in-flight time and schedule delay time from past research	110
5.8	Model results: business and non-business respondents	111
5.9	Model results: trading respondents only	113
5.10	Model results: rational respondents only	117
5.11	Model results: R^2 and t-ratio's (three samples)	119
5.12	Model simulation results	125
5.13	Interval of σ_ε^2 point of intersection	130
7.1	Total costs per departure by aircraft type	157
7.2	Equilibrium demand and fare per flight by change in fare ∂f: 100-seat jet	172
7.3	Equilibrium profit per flight by level of ∂f: 100-seat jet	174
7.4	Equilibrium demand and fare per flight by change in fare ∂f: 65-seat turboprop	178
7.5	Equilibrium profit per flight by level of ∂f: 65-seat turboprop	180
7.6	Equilibrium demand and fare per flight by change in fare ∂f: 37-seat turboprop	184
7.7	Equilibrium profit per flight by level of ∂f: 37-seat turboprop	185
7.8	Sensitivity test 3 model input assumptions	202

FIGURES

1.1	Thesis analytical approach	4
2.1	Demand for slots and capacity at London Heathrow: August 1994	10
2.2	Distribution of passengers ideal departure times and flight scheduling	28
3.1	Time of day departure preference distribution for a short haul market	43
4.1	The choice process	65
4.2	Sample choice set boundary values	72
4.3	Design simulation flow-diagram	79
4.4	Non-orthogonal design boundary value map	80
4.5	Orthogonal design boundary value map	81
4.6	Mean simulated R^2 performance by stated preference design	83
4.7	Percentage variation between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £15 and α^{t} = £10	84
4.8	Percentage variation between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £20 and α^{t} = £20	85
4.9	Percentage variation between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £10 and α^{t} = £25	86
4.10	Percentage variation between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £30 and α^{t} = £40	87
4.11	Percentage variation between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £35 and α^{t} = £15	88
5.1	Rate of substitution between schedule delay time and fare	109
5.2	Irrational choice example	115
5.3	Values of time: all respondents, trading respondents only, consistent respondents only	118
5.4	Simulation method flow-diagram	122
5.5	% variation between input and simulated parameters	126
5.6	Simulated schedule delay late parameter	127
5.7	Simulated fare parameter	127
5.8	Simulated in-flight time parameter	128
5.9	Simulated schedule delay early parameter	128

6.1 Passenger demand by time of day: 400 passenger trips 134

6.2 Required simulation model input parameters 142

6.3 Computer model flow-diagram: first iteration 143

6.4 Example of flight scheduling and demand per flight in one iteration 145

6.5 Computer model flow-diagram: second and subsequent iterations 146

7.1 Flight time scheduling and passenger load per flight when demand = 100, 200, 300, 400, and $\partial f = 0$: 65-seat turboprop 159

7.2 Flight time scheduling and passenger load per flight when demand = 100, 200, 300, 400, and $\partial f = 0$: 100-seat 161

7.3 Disequilibrium passenger load per flight: demand =200 and $\partial f=0$: 100-seat jet 162

7.4 Equilibrium passenger load per flight: demand =200 and $\partial f \neq 0$: 100-seat jet 162

7.5 Flight time scheduling and passenger load per flight when demand = 100, 200, 300, 400, and $\partial f = 0$: 37-seat turboprop 164

7.6 Daily service frequency against total demand by aircraft type 165

7.7 Average generalised cost per passenger against total demand by aircraft type 167

7.8 Average profit per flight against total demand by aircraft type 169

7.9 Average profit per flight against ∂f, (total demand = 400) : 100-seat jet 175

7.10 Slot values and maximum equilibrium fares by departure slot, (total demand = 400) : 100-seat jet 176

7.11 Average profit per flight against ∂f, (total demand = 400) : 65-seat turboprop 181

7.12 Slot values and maximum equilibrium fares by departure slot, (total demand = 400) : 65-seat turboprop 182

7.13 Average profit per flight against ∂f, (total demand = 400) : 37-seat turboprop 186

7.14 Slot values and maximum equilibrium fares by departure slot, demand = 400: : 37-seat turboprop 187

7.15 Slot values and % distribution of passenger ideal departure times: 100-seat jet. 189

7.16 Passenger choice probabilities generated by empirically derived and sensitivity test 1 parameters 195

7.17 Sensitivity test 1 slot values and maximum equilibrium fares by departure slot: 65-seat turboprop 196

7.18 Difference in slot values between model and sensitivity test 1 results 197

by departure slot: 65-seat turboprop

7.19 Difference in equilibrium fares between model and sensitivity test 1 results by departure slot: 65-seat turboprop 197

7.20 Sensitivity test 2 slot values and maximum equilibrium fare by departure slot: 65-seat turboprop 199

7.21 Difference in slot values between model and sensitivity test 2 results by departure slot: 65-seat turboprop 200

7.22 Difference in equilibrium fares between model and sensitivity test 2 results by departure slots: 65-seat turboprop 200

7.23 Sensitivity test 3 slot values and maximum equilibrium fare by departure slots: 150-seat jet 202

7.24 Difference in slot values by departure slot between 100-seat jet and Sensitivity test 3 150-seat jet 203

CHAPTER 1

Introduction

1.1 Research problem

Airlines, airports, governments, regulators, and aviation industry organisations have identified airport congestion as one of the most important issues facing the European air transport industry. The International Air Transport Association (I.A.T.A), in a special infrastructure needs report, published in 1990, predicted that by 1995, 22 out of 46 major European airports would face acute shortages of runway capacity (Donne 1991). Given recent polices designed to remove barriers to increased competition in European airline markets, national governments and regulatory authorities have been seeking methods to tackle the problem of slot congestion. They have come to recognise that unless the problem of slot congestion is resolved, the expectation of increased competition and greater choices for passengers which their policies are intended to facilitate, may not in fact materialise.

Increased demand for air travel, during the 1980s, prompted the selective introduction of short-term policies designed to alleviate the problem. Examples include various technical measures such as, reduced vortex wake separation distances between aircraft and the implementation of airport pricing policies designed to discourage inefficient aircraft operations during busy periods of the day. Although these policies have had some effect, longer term solutions must inevitably focus on developing a more efficient method of allocating take-off and landing slots at busy hub airports. The current method of allocating slots, which was formulated during the 1960s when the industry was still heavily regulated, may no longer be suited to the different economic and regulatory environment which exists today. Based on the principle of historic precedence, this method of allocation effectively acts as a barrier to enhancing those opportunities which liberalisation is seeking to promote. Despite the implementation of successive measures to deregulate airline markets in Europe since 1987, larger airlines, who have benefited from the present system, still retain a significant degree of market power. The inability of the I.A.T.A slot allocation guidelines to

accommodate both the growth in air traffic and regulatory change has prompted the search for alternatives.

Some proposals involve allocation based on the price mechanism as a more efficient means of rationing scarce runway slots. Doganis (1992) argues, for example, that by introducing some form of slot pricing, those airlines who value the scarce resource most would gain access to it. This is in contrast to the present system which relies heavily on the privilege of historic precedence, irrespective of whether the slot is being utilised in the most efficient way. Secondly, infrastructure needs assessments, can become more refined by using information generated from a slot auction as a guide to the need for future investment. From the airport's perspective there are obvious attractions to such a policy. However, airlines, particularly small regional operators, argue that slot pricing, given the cost implications, would eliminate many small carriers that currently benefit from access to busy hub airports. Auctioning slots at an airport as suggested by some authors such as Doganis (1992) and Hulet (1991), could involve airlines placing a sealed bid to the auctioneer for the right to take-off-off and land at an airport at a specific time of day for a whole season. The auctioneer or scheduling committee could then perhaps allocate on the basis of the highest value bid, therefore rationing slots to those users that value them most. Although it is not the intention or aim of this thesis to evaluate the direct impact of slot pricing on the structure of the air transport industry or on any vulnerable sector, these issues are discussed in greater detail in Chapter two.

Given that slot pricing is being actively considered by policy-makers as a potential solution to the problem, the aim of this research is to establish a method of determining the monetary value of a slot. It is assumed that the value of a slot is a function of how highly passengers value departing at different times of the day. The research problem is initially approached from the passenger perspective.

1.2 Research rationale

The justification for undertaking this research is based on a belief that the issue of slot allocation is one of the most important facing the air transport industry. Past research on slot allocation, restricted, in the main, to papers published during the 1980s and

early 1990s, focused primarily on deriving qualitative judgements on the likely impact of different methods on the air transport industry. Whilst their conclusions may indeed be correct, little effort has been made to construct an empirically rigorous analysis of slot pricing. Establishing a method whereby the value of slots can be measured, would make a significant contribution to existing research on airport slot allocation. Furthermore, an examination of how highly passengers value travelling at different times of the day would also make a contribution to understanding passenger choice decision-making in the airline industry, a topic often neglected by researchers.

1.3 Research approach

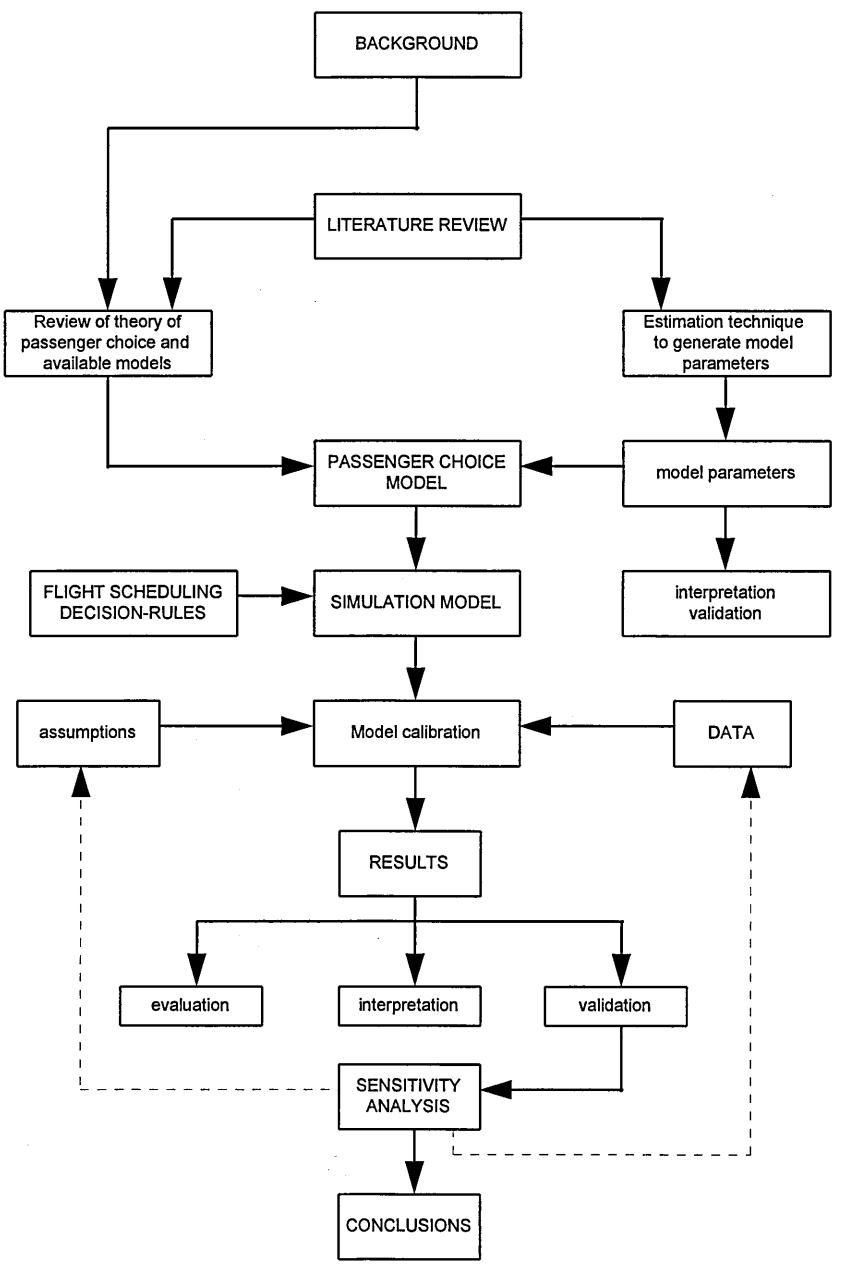
In setting an analytical context, it is necessary to define what precisely is being estimated. This research provides a method whereby the value of a slot can be quantitatively measured. A slot is defined as the right to either take-off or land at an airport, at a specific time, on a specific day. The value of any given slot is assumed to be a function of the maximum profit that could be potentially generated at each departure slot over a period of time. This value will be strongly influenced by how highly passengers value departing at different times of the day.

The research approach therefore, consists of two key components. Firstly, estimating the value passengers attach to travelling at different times of the day, and secondly using this information to determine how this influences the profitability of slots.

In defining the context and scope of the analysis, it is necessary to establish whether to model these processes on a network-wide or on a city-pair context. The analysis focuses on applying the method to a given city-pair market. Given the computational complexities involved in modelling the profitability of slots on a network-wide basis, and the fact that the passenger choice estimates will be derived from a sample route, a decision was made to focus within a city-pair context. In doing so, a number of assumptions had to be made regarding passenger choice behaviour and operator scheduling within this city-pair market. Inevitably, restrictive assumptions apply since supply-side issues such as network-wide aircraft scheduling requirements are not considered. These limitations are discussed when developing the method and when validating the results. However, it is not specifically the intention to generate

slot prices specific to a certain time or a specific airport or airline. Rather, using data and assumptions that are as realistic as possible, the primary aim is establish a methodology for estimating slot values, and to apply this methodology to passenger choice and airline operating data in order to derive slot value estimates. The following sub-section outlines the aims and objectives of this thesis. The flow-diagram in Figure 1.1 illustrates the sequence of steps involved in approaching the problem.

Figure 1.1: Thesis analytical approach



1.4 Research aims and objectives

The aim of this thesis is to develop a method whereby the monetary value of slots can be estimated. Within this overall framework there are four key objectives:

- To select and apply a method to estimate the value passengers place on departing at different times of the day.
- To establish behavioural decision-rules which define how passengers choose at what time to travel and how operators schedule flights and price their services at different departure slots.
- To use both sets of decision-rules to build a simulation model which can generate a set of flight departure times with their passenger demands and fares
- To generate slot values by using the simulation model on a specific route with a given level of demand, and with different aircraft types.

1.5 Thesis structure

The thesis consists of eight chapters organised as follows.

Chapter two focuses on a review of past literature on slot allocation, examining the mechanics, advantages and disadvantages of the present system. This is followed by an appraisal of some suggested alternatives within the context of a review of previous studies.

The third chapter examines the issue of modelling passenger choice in general and more specifically choice of departure time. An overview of available behavioural choice models is provided, with an appraisal of their strengths and weaknesses. Since there are a number of methods available to estimate the model parameters, a discussion of available analytical techniques will also be provided.

Having identified the options, chapter four examines the methodology selected from the previous chapter to estimate the relevant model parameters. This involves an evaluation of the various steps involved in estimating choice model parameters.

Chapter five evaluates and interprets the results generated from applying the method described in Chapter four. This includes a discussion of the validity of the estimation

technique, followed by a detailed examination of these results in light of any *a priori* expectations and in light of model results produced by similar studies.

Having generated the passenger choice model estimates, chapter six covers the precise specification of those decision-rules which govern both passenger and operator choice of departure times. These decision-rules are then combined to develop a simulation model. This model will aim to generate equilibrium flight departures, passenger demand levels on each flight and equilibrium fares from which the slot value estimates will be derived. Assumptions used to operationalise the model will be fully specified as will any weaknesses or limitations.

Using the model formulated in Chapter six, Chapter seven examines and evaluates results generated from the model calibrated on the basis of assumed levels of aircraft type, costs, intervals of demand and pricing behaviour to generate a set of slot value estimates. The validity of these results generated by the model will also be examined, and in light of any conclusions drawn, this is followed by a sensitivity analysis which will determine the transferability of the model to different model input assumptions. The chapter concludes with a consideration of any policy implications that arise from these results.

Finally, chapter eight provides a summary of the main findings of the research. Contributions to knowledge, weaknesses and deficiencies in the results and in the methodology applied will also be considered. Chapter eight concludes with an examination of future research possibilities.

CHAPTER 2

Slot Allocation and Pricing

2.1 Introduction

Since the orderly use of airports is critical to the efficient operations of a scheduled airline, the method of allocating scarce runway capacity has become one of the most keenly debated topics in aviation. As congestion becomes increasingly more acute at Europe's main airports, governments, air transport regulators and airlines, will have to come to terms with at least two important issues. Firstly, when demand exceeds supply, how does one allocate or ration scarce runway slots? Secondly, given the increasing liberalisation of air services, how does one ensure that the benefits of increased competition are not undermined by monopolistic or oligopolistic control of runway slots by a small number of operators at the world's busiest airports ?

Bearing in mind that the objective of this research is to establish a method which enables the value of slots to be estimated, it is nevertheless important to provide an understanding of the issue of slot allocation in general. Chapter two aims to provide the reader with an overview of current slot allocation procedures and suggested alternatives within the context of a literature review. Within this framework, the chapter is divided into four sections. The first section briefly attempts to define a slot and to provide an explanation as to the crucial importance of obtaining slots from an airline scheduling perspective. Section 2.3 describes the features of the present system of allocating slots currently in operation at congested airports throughout the world. This is followed by two sections which examine alternative proposals based on administrative regulation and pricing mechanisms respectively. Chapter two concludes with an examination of the issues involved developing a model capable of estimating the monetary value of runway departure slots.

2.2 Slots and airline operating efficiency

In advance of examining the features and effectiveness of various slot allocation procedures, it is necessary to establish how and within what context one defines an airport slot. Both Hamzawi (1992) and Borenstein (1988), define a slot as a license to operate to and from an airport at a given time. The European Commission is

somewhat more specific in defining a slot as: "the scheduled time of arrival or departure available or allocated to an aircraft movement on a specific date at an airport during periods which are co-ordinated" (CEC 1991). In the United States, regulatory authorities also incorporate access to gates, apron positions and check-in facilities when defining a slot. In light of these differences, it appears, as Grethner et al (1981) suggests, that defining a slot has increasingly become a matter of conjecture. For the purposes of this research, and in order to simplify the analysis, a slot is defined as the right to take-off or land at an airport at a specific time of day for a specified period.

To operate commercially viable services, an airline needs to obtain an appropriate quantity of slots at an airport in accordance with it's proposed scale of operations. For example, to provide three daily round trips between airports A and B, an operator needs to obtain 6 slots (three departures and three arrivals) at each airport. Moreover, for the vast majority of air carriers, the timing of these slots is extremely important. The airline, in scheduling it's departure times, needs to align the timing of it's slots with passenger departure time preferences within a particular market. In addition, choice of slots must also be evaluated within the context of various supply-side considerations, such as the need to optimise aircraft utilisation. However, scheduling becomes even more complex when an airline has to firstly, consider slot timing at an airport within the context of it's entire network structure and secondly, slot acquisition strategies within competitive markets.

2.3 Current IATA method for allocating slots

In the early days of air transport, airlines devised schedules taking for granted the availability of runway capacity. However, as congestion emerged during the late nineteen sixties and early nineteen seventies, airports and regulatory authorities were forced to consider measures designed to co-ordinate and regulate the allocation of runway slots. The International Air Transport Association (I.A.T.A) eventually introduced slot allocation guidelines for capacity constrained airports throughout the world. I.A.T.A believed that the allocation of slots would be best served by handing the powers of regulation to airlines through scheduling committees. The mechanics of this self-regulatory procedure approach, involved two stages: firstly, the overall world-wide co-ordination of schedules at biannual IATA conferences and secondly,

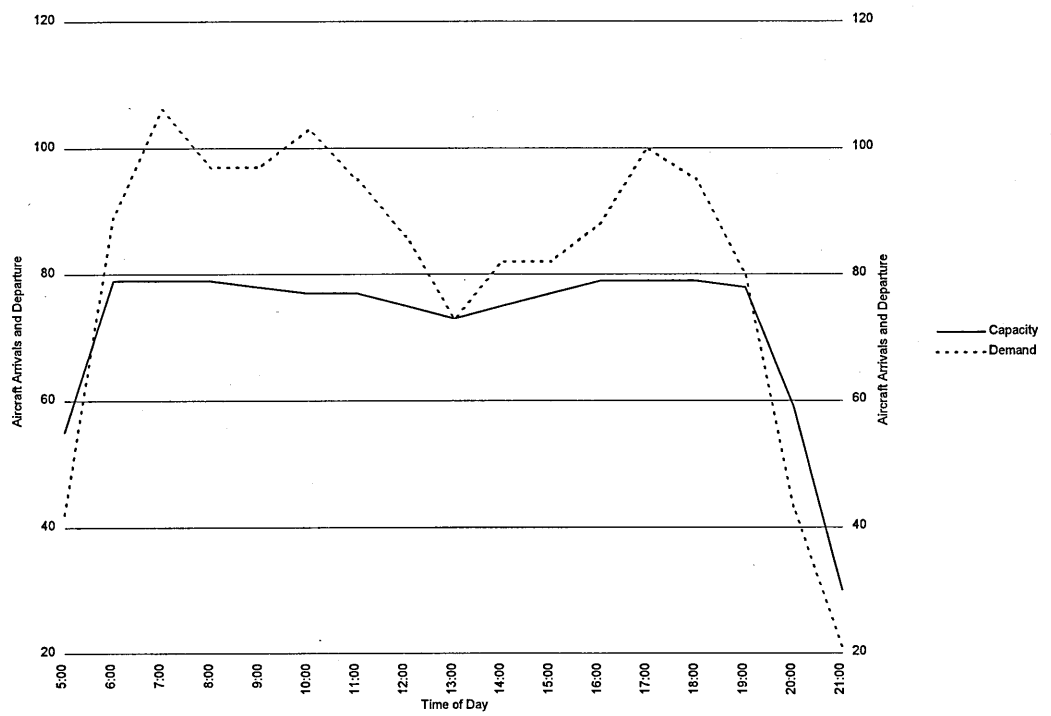
local co-ordination at individual airports through scheduling committees. The standard working arrangements of these committees are: firstly, to provide a forum for the reaching of a consensus on schedule adjustments necessary to conform to airport capacity constraints; secondly, to optimise interline connections, and thirdly, to allow for the co-ordination of schedules where interline handling takes place (I.A.T.A 1991).

At the level of an individual airport, the scheduling committee appoints a slot co-ordinator, usually a representative of the largest resident airline. At London Heathrow, for example, this function was, until recently, performed by British Airways. The co-ordinator is supposed to act in accordance with the following slot allocation guidelines established by I.A.T.A. Firstly, airlines are entitled to keep slots granted to them in the previous season provided they use it at least 65% of the prescribed time. This is known as the principle of historic precedence or "grandfather right". Secondly, an airline which intended to use the slot for a longer duration i.e. year long as opposed to seasonal, is given priority. Thirdly, scheduled passenger services and programmed charter flights are given preference over irregular aircraft operations. Having allocated slots on the basis of these basic principles, airlines are granted the freedom to exchange slots between themselves, while unclaimed slots are distributed to new entrants based on duration and type of service priority rules. Both Doganis (1992) and Hulet (1991) recognise the benefits associated with such a system. By allocating slots on the principle of historic precedence, the level of professional consensus and required integration of airline schedules enables operational programmes to be planned and disputes resolved which, to a large extent, satisfies all within the industry.

However, whilst this system may have benefited the air transport industry, it has, in recent years, been heavily criticised. These criticisms focus on it's widely perceived anti-competitive characteristics. Barret (1992) claims that grandfather rights are a major obstacle to ensuring a contestable aviation sector, since it sustains the oligopolistic control of airport access by a few airlines. Likewise, Borenstein (1988) describes the principle of historic precedence as inherently inefficient and unfair to new entrant carriers. Blore (1992) highlights a recurring criticism in that the

"grandfather right" principle ensures that the most commercially attractive slots are sewn up year in year out, leaving only marginal slots associated with unattractive times and therefore, of little commercial benefit available to new entrant airlines. Figure 2.1 below, illustrates the problem faced by many airlines seeking access to London Heathrow.

Figure 2.1: Demand for slots and capacity at London Heathrow: August 1994.



Source: UK CAA paper *Slot Allocation: a proposal for Europe's airports* (CAP 644) 1994

From 06:00 to 19:00 the demand for slots exceeds available supply. However, before 06:00 and between 19:00 and 21:00, take-off and landing slots are available, but are not being requested on the same scale as those slots associated with peak departure times. Apart from those carriers that operate services to long-haul destinations, these slots are associated with commercially unattractive departure times, particularly for those flights to and from medium-haul destinations.

The I.A.T.A system effectively ensures that commercially attractive slot times are rarely available to new entrant carriers, thus sustaining oligopolistic control of access at major airports throughout Europe. Access with regard to other airports, such as Frankfurt and Milan, is even more restrictive where long-established airlines, usually subsidised by their governments, have managed to obtain virtual monopoly control of

runway slots. Under these circumstances, potential new entrants have difficulty in obtaining slots of a sufficient quantity and quality to mount an effective competitive challenge against incumbent airlines. However, one frequently cited criticism focuses on the effectiveness of the I.A.T.A slot allocation procedures, when measured against economic efficiency criteria. Grethner et al (1981), Borenstein (1988), Brander et al (1989), and Doganis (1992) recognise two fundamental weaknesses associated with the present system. Firstly, under conditions of resource scarcity, efficient allocation is achieved by granting the landing right to the operator who values it most. Allocation based on historic precedence, which amounts to a barrier to entry, effectively prevents potential new entrants from making more efficient use of a slot than an incumbent carrier. For example, consider the case of a regional airline operating a domestic service using a 50-seat aircraft during a peak period. This operator is denying this slot to a potential new entrant who proposes to operate a more profitable international service using a 250-seat jet, in which the passengers might be prepared to pay more in terms of higher fare to depart at that particular slot time. Indeed, looking at the issue of efficiency from the airline scheduling perspective, one can also claim that under conditions of resource scarcity, airlines themselves are operating schedules that are to a large extent inefficient from an airport's perspective. Hamzawi (1992), for example, found that many airlines, who for marketing reasons, are maintaining high frequency levels on busy routes, tend to operate flights with a substantial proportion of empty seats. During 1991, on services from London Heathrow to Paris Charles de Gaulle, British Midland, British Airways and Air France scheduled a combined total of thirty departures each day. However, both Air France and British Midland could only manage average passenger load factors of only 58% and 49% respectively [1]. This illustrates the fact this scale of competition can, in many cases, lead to over-capacity in which aircraft operate with a substantial proportion of empty seats at a time when runway capacity is in extremely short supply. Furthermore, from the airports perspective, the present system based on historic precedence does not according to Doganis (1992) and Jones et al (1994), provide a guide to the need for future investment in new or improved runway facilities, since

[1] Load factors are defined as the proportion of seats occupied by passengers on an aircraft. The level at which load factors are commercially viable is generally deemed to be between 60% and 65%

there is no indication of how much airlines would be prepared to pay in order to obtain an additional slot or retain existing slots.

As demand for limited capacity grows and deregulation spreads, the I.A.T.A system will appear increasingly anti-competitive. Potential new entrants will find it very difficult or in many cases, almost impossible to obtain the number of slots at the most commercially desirable times to mount a competitive challenge against those airlines who have exploited the privilege of historic precedence. However, two alternatives have been considered: the administrative regulation of existing capacity and the introduction of some form of pricing mechanism in order to seek a more efficient allocation of slots.

2.4 Administrative regulation

In order to achieve a more competitive air transport environment, both governments and regulatory authorities may decide to intervene in the slot allocation process in order to facilitate a more efficient utilisation. Within this context, restrictions or priorities could be established at a congested airport with regard to specific categories of traffic. For example, a government or relevant airport authority could give priority to scheduled passenger services at certain airports, and at the same time, restricting those aviation operations that place inordinate time demands on runway use, such as general aviation and short-haul regional airline services. Furthermore, within the context of a national strategy, more efficient use could be made of airports which are under-utilised. This could encourage both general aviation and regional aircraft operations to relocate services to nearby airfields within the same metropolitan district. In the United Kingdom, a series of traffic distribution rules have been implemented over the last twenty years designed to make better use of existing runway and air traffic facilities. For example, in 1977, the Civil Aviation Authority issued a regulation denying access to new entrants seeking to obtain slots at Heathrow. In order to make greater use of spare airport capacity elsewhere within the south-east of England, new entrants were encouraged to operate services from London Gatwick [2]. Doganis et al (1988) argues, in an analysis of strategies designed to

[2] Restrictions lifted by UK Secretary of State February 1991 followed by British Airways decision to transfer African operations from London Heathrow to London Gatwick between 1995 and 1996.

alleviate congestion, that significant progress can be made through either relocating traffic or by rescheduling flights to less convenient departure times in order to make greater use of off-peak capacity. For example, regional airlines operating out of London Heathrow or Gatwick, though limited in number, could be encouraged to transfer operations to either Stansted or London City airport. However, given the limited capacity of both airports to accommodate similar volumes of traffic, and the absence of a comparable range of connecting international services, they cannot be considered as effective substitutes to either London Heathrow or Gatwick.

Charter services, argues Hamzawi (1992) can similarly be either restricted to operating at certain times of the day or be encouraged to relocate to other airports. This argument is based on the assumption that charter passengers are largely indifferent to quality of service attributes such as departure times and airport origin. However, this ignores the fact that many airports derive a large proportion of their concession income from charter passengers, who on average, spend more time in airport terminals compared to business travellers, and are therefore more likely to use the airport's retail facilities. Furthermore, the ability of charter operators to relocate operations to other airports is also constrained by various capacity limitations in operation at these airfields. For example, the UK's largest charter airline, Britannia Airways outlined, in a recent submission to the Manchester Airport second runway enquiry, three reasons why relocation to Liverpool airport could not be considered as a commercially viable substitute to Manchester airport. Firstly, it's limited runway length could not accommodate the airline's fleet of Boeing 767s. Secondly, previous attempts to operate out of Liverpool during the early nineteen seventies failed to succeed because of a poor response from tour operators, and thirdly, night-time restrictions at Liverpool precluded charter airlines from operating significant schedules (Manchester Airport 1994). Given the reluctance of charter airlines to relocate operations, and in order to make greater use of off-peak capacity, airports could restrict charter airlines to operating at certain times of the day, such as early morning, mid afternoon and late in the evening. However, many charter airlines would find it increasingly difficult to maintain operating efficiency and aircraft utilisation under such a restrictive schedule. Charter airlines, for example, operating between the UK and the Mediterranean, are required to maintain at minimum three

daily aircraft rotations to optimise aircraft utilisation. Assuming four aircraft rotations within twenty-four hours, a flying time of two hours to the Mediterranean, the first departure at 0700 and a turnround time of 1 hour at each airport, a charter airline would need to obtain landing rights at Manchester at 07:00, 13:00 and 19:00 and 01:00 to achieve four aircraft rotations with the last flight arriving back in Manchester at 0600. In addition, charter airlines also have to cope with night-time restrictions currently in operation at many airports in Southern Europe.

In the absence of regulatory controls, airports are increasingly restricting those activities that generate few financial benefits. Since the early nineteen seventies, for example, general aviation has all but disappeared from BAA plc-managed London airports, while small scheduled passenger aircraft operations at both London Heathrow and London Gatwick have declined from 8% and 14% in 1985 to 4% and 9% in 1991 respectively (CAA 1993a). In general, airlines, especially within the charter and short-haul scheduled sectors, remain hostile to proposals which aim to restrict their operations at major airports

However, alternative measures designed to seek a more efficient use of existing capacity could be achieved through administrative regulation of air carrier frequency levels on high density routes. It has already been suggested that airline competitive strategies in a number of city-pair markets have generated significant excess capacity in the provision of services. Doganis (1992), suggests that frequency capping on high density routes could release a sufficient number of slots for either additional competitors or for services to new destinations. By limiting frequency, scheduling efficiency would improve, as excess capacity is gradually eliminated in airline markets. However, while there are strong and persuasive arguments in support of frequency capping, the airline industry will almost certainly resist the implementation of such a measure. Indeed, many would argue, as the UK Civil Aviation Authority does, that attempts to restrict airline scheduling would be both unwelcome and would violate the spirit of deregulation currently prevailing within Europe (CAA 1989).

Hulet (1991) in submitting proposals to the UK Department of Transport on alternative slot allocation procedures, examines the viability of four different methods. In the case of each alternative proposal considered, the principle of historic

precedence is retained. One of these options involves airlines being required to relinquish a percentage of slots each year. In order to avoid the dumping of marginal slots, the airport co-ordinator would ensure that sacrificed slots would enable new entrants to provide commercially viable services. These slots would then be distributed through a lottery system, ring fenced within certain categories, with slots reserved for scheduled domestic services, international services and charter flights. For such a system to operate, however, these slots would have to be arranged in such a way as to be capable of providing an acceptable package for the provision of commercially viable services and in addition, the percentage of slots sacrificed would have to strike a balance between on the one hand, ensuring that only a small percentage of slots were surrendered in order to minimise disruption, while on the other hand, providing a sufficient quantity and quality of slots to enable new entrants to operate commercially viable services. Recognising the potential long-term implications for runway capacity and the need to encourage increased competition, the European Commission drafted a proposal in 1991 to modify existing slot allocation rules. The new procedures were based on the following guidelines:

- The commission proposed that the scheduling committees appoint an airport co-ordinator who would be independent of the airlines.
- Existing priority rules maintained the principle of historic precedence in allocation.
- Newly created slots, unused slots, abandoned slots, and those used for less than 65% of the allocated period would be collected and placed into a slot pool.
- At least 50% of slots in the pool would be allocated to new entrants carriers who are defined as those airlines with less than three slots a day or less than 30% of slots a day, but is seeking to operate on a route where there are only one or two carriers.
- If slots for new entrants are not available, then they could be reclaimed from those airlines operating more than six slots on routes which new entrants wish to provide services; these slots would be reclaimed on a priority basis from those services which operate aircraft of less than 200 seats.

An amended version of these proposals was eventually adopted in a council regulation implemented in 1993 (CEC 1993). The priority rules with respect to airlines operating aircraft with less than 200 seats was dropped, while new guidelines designed to encourage greater transparency in the workings of the scheduling committee and provisions for the protection of regional routes were introduced. As far as allocation was concerned, the principle of historic precedence was retained. Although the regulation was an improvement on the I.A.T.A system, it fell short of the radical changes needed to confront the problem of new entrant access. Frequency capping, which is generally considered to be an effective means of increasing the supply of available slots was not considered in the council regulation. Frequency capping would firstly, encourage competition, and secondly, ensure a more efficient utilisation of airport capacity through encouraging airlines to operate large aircraft. For example, according to Barret (1992), if all general aviation, cargo and small domestic service aircraft movements were converted into passenger numbers at one hundred passengers per aircraft, then in 1984, capacity could have been increased by just over two million extra passengers. In addition Fawcett and Fawcett (1988) recognise some of the advantages associated with re-regulation in order to alleviate capacity problems at congested airports. However, many airlines have remained hostile to any form of regulation as some fear, as they did in the United States, that re-regulation would decrease service / price options currently available to passengers.

However, despite it's many positive features, administrative regulation, retains elements of anti-competitive characteristics such as the principle of historic precedence. Furthermore, the EC regulation or any other reform is unlikely to ensure that scarce runway slots are used by those who value them most, nor will they provide an adequate guide to future investment requirements given the absence of any pricing element. Nevertheless, in recent years a quantity of literature has emerged which focuses on the issue of pricing runway slots. The remainder of this chapter will deal with these suggested alternatives.

2.5 Slot pricing

2.5.1 Basic principles

Given inherent inefficiencies associated with both administrative and self-regulatory forms of slot allocation, a body of opinion has emerged in recent years which advocates the introduction of the pricing mechanism as a more effective method of allocating slots at capacity constrained airports. Levine (1969), Grethner et al (1981), Rassenti et al (1988), Brander et al (1989), Hulet (1991), Barret (1992), Hamzawi (1992) and Jones et al (1994) share the view that a competitive market-based allocation of slots would lead to a more efficient utilisation of scarce runway capacity. An economic approach, according to Doganis (1992), would have two key aims; firstly, to ensure that those airlines who derive the most benefit from scarce resources i.e. those who value it most, obtain access to it, and secondly, to use the pricing mechanism as a guide to the need for future investment or disinvestment. In theory, it is argued that market forces would determine the true cost of a slot, based on how highly operators value access at any given time. Scarce slots would thus be allocated to those who valued them most, and it then follows that airlines would seek to put those slots to their most profitable use. For example, existing airport charges, levied at BAA-managed London airports, do not fully reflect the scale of resource scarcity at these congested airports. As a consequence they have had only a limited effect in transferring demand to off-peak periods. There are two reasons for this: firstly airport managers at some airports in the UK, can only set airport charges within a limit prescribed by regulatory authorities, and secondly higher peak time charges are not passed directly on to peak passengers and therefore have no effect on the demand to travel at those particular times. Furthermore, as Blore (1992) points out, the present level of traffic charges at many congested airports do not recover from the airlines and passengers the actual costs of operating these airports. As a consequence, large hidden subsidies in the form of monopoly rents are generated by the current system to incumbent airlines. A form of economic rent, in this case, reflects the difference between what the operator is willing to pay for access to peak landing slots and what he actually pays in terms of landing charges, air traffic control fees and apron parking costs. In light of this, many economists argue that a slot allocation system based on

the price mechanism would eliminate economic rent and would ensure that those airlines who value operating at peak times, should pay the scarcity value of the slot.

In recent years, a limited quantity of literature has emerged on alternative market-based methods of allocating scarce capacity. These methods tend to fall into two categories; slot auctioning and slot trading.

2.5.2 Slot auctions

Auctioning slots could, in theory, provide a means of determining how highly operators value access to congested airports. This method of competitive bidding for scarce landing rights could ensure that the operator with the highest value bid price obtains the slot. Although it has been a frequently cited alternative to the inherent inefficiencies of the present system, many economists argue that the concept of slot auctioning, is fraught with numerous difficulties in terms of the potential effect on the competitive structure of the air transport industry and complexities relating to the mechanics of actually operating a competitive auction of this sort.

Given that airlines have inherently different cost and production functions, it stands to reason that those operators, that are financially stronger, will be in a more favourable position to bid for scarce landing rights. As Barret (1992) and Doganis (1992) recognise, small regional carriers would, in many cases, be unable to match bids by large airlines who operate in relatively more profitable international markets. Indeed, far from creating a more competitive environment, slot auctioning could accentuate monopolistic and oligopolistic control of landing rights. This is because, a few large airlines, given their financial strength, would be able to secure a majority of slots at capacity constrained airports. Hulet (1991) offers a solution to this problem whereby slots are effectively ring-fenced within specific categories such as: short-haul domestic, short-haul international, and long-haul etc. Competitive bidding therefore, could be confined to individual markets ensuring the survival of short-haul domestic services, which could otherwise be threatened by unrestricted slot auctioning. However, this still does not ensure that level playing fields exist within each slot market, because little could prevent large airlines with ample financial resources from bidding for slots in a short-haul market. Clearly, in this instance, an airport or regulatory authority would have to specify which airlines would be permitted to bid

within particular slot markets. Given that unrestricted slot auction may generate undesirable market developments, regulation would be required to ensure that potential predatory or monopolistic abuses are avoided.

Jones et al (1994) argues, that slot auctioning would cause major disruption within the air transport industry. Given that airlines plan schedules well in advance, failure to secure the appropriate slots through the auction could leave an airline short of the appropriate number and timing of slots necessary to provide commercially viable services. Grethner et al (1989) suggested that this problem can be overcome by auctioning packages or combinations of slots which can match the scheduling requirements of an airline on a given route. For example, an airport could offer 6 slots (three landings and three take-offs) to provide an airline with three daily round trips for a given route. However, further complications arise because, in order to operate a service, an airline needs to obtain slots at both airports. Therefore, before engaging in a competitive auction, an airline would have to take into account the availability of appropriate landing rights at other airports, which would be determined by type of aircraft and the flying time between both points. Indeed, since various aircraft types place different time demands on the runway, slots would have to be categorised according to aircraft type. Therefore an airport, having ring-fenced slots, would have to categorise each slot not only by time of day but by type of aircraft, since the airport's facilities may not accommodate significant volumes of large aircraft movements. For example, consider the case where two airlines submit bids for a long-haul international slot at 0900. Airline A proposes to operate a Boeing 747 whilst Airline B proposes to schedule an Airbus 340. Given the higher passenger load and lower unit costs, Airline A offers a higher bid. However, in light of the physical capacities of the terminal and apron space, the airport auctioneer could be forced to accept Airline B's lower bid price. Thus, an airport operator in either accepting or rejecting bids would have to take into account the physical capacities of runway, terminal and apron facilities.

The complexities associated with auctioning and the potential disruption it could cause to the air transport industry is well documented. Governments, airlines, airports and regulatory authorities, aware of these deficiencies and the practical difficulties

associated with such a system, have been increasingly reluctant to consider slot auctioning as a solution to the present capacity crisis facing the industry. In the United Kingdom, the Civil Aviation Authority (CAA) has consistently ruled out auctioning on the grounds that competition would not take place on a level playing field. The CAA points out, that charter operators at London Gatwick and domestic carriers at London Heathrow engaged in a competitive market would be competing for slots against international carriers operating in an environment of limited frequency, monopolistic pricing practices, pooling agreements, code-share agreements and alliances. "It is open to question whether, under these circumstances, use of the price mechanism can produce an allocation of resources which could be rationally described as being efficient" (CAA 1985). Furthermore, Borenstein (1988) challenges the traditional allocative efficiency argument by claiming that while a slot auction can produce an allocation of scarce resources that can be theoretically described as being more efficient than the current system, the outcome would still be significantly sub-optimal. The author's measure of efficiency focuses on the need to ensure a high level of correlation between an airlines willingness to pay for a scarce resource and society's valuation of the carriers new services. A market based system, it is argued, would probably yield too many flights on high density routes, and consequently, a sub-optimal service on routes that can only support one or two operators. However, one is unable to test these theoretical assumptions, since slot auctioning has not been implemented either in the United States or in Europe.

Nevertheless, several attempts have been made to simulate an auction process under laboratory conditions. In an analysis of alternative methods for allocating slots, Grethner et al (1989) develops a mechanism based initially on a primary auction in which airlines submit sealed bids for combinations of slots, followed by a computerised secondary market which allows carriers to purchase freely and sell primary market slots to each other. In addition, special provisions for services to small communities were incorporated and supplemented by sanctions against non-use and other abuses of market power. The author further proposed that the system be phased in gradually and funds generated by the auction would be used to expand capacity. However, a method of estimating slot values remains curiously absent from this research and as a consequence, any slot prices generated from the laboratory

experiment, lack the necessary elements of realism and statistical validity. Similarly, work by Rassenti et al (1988) which attempts to simulate a competitive auction using a computer algorithm and set under similar laboratory conditions, fails to provide an adequate methodology to determine bid prices which are ultimately derived by the operator's value of the slot.

Given inherent complexities associated with slot auctioning and the potential implications in terms of the probable disruption to airline operations, governments and regulatory authorities have ruled out implementation at least in the short to medium term. However, given the disadvantages of a straightforward auctioning system, an intermediate approach might be to introduce some form of slot trading

2.5.3 Slot trading

Slot trading, argues Doganis (1992), could offer a less disruptive mechanism for allocating scarce capacity by integrating elements of the existing system with a form of slot pricing. Operators would retain "grandfather rights", but a market for slots would exist where airlines would be free to buy and sell slots at times when demand exceeds supply. Unlike slot auctioning, examples of slot trading can be found which can assist in an evaluation of the effectiveness of this method. In 1986, the Federal Aviation Authority introduced a form of slot trading at four airports in the United States (Chicago O'Hare, New York John F Kennedy, New York La Guardia, Washington National) after the scheduling committees had been unable to reach agreement the previous year and the pressure on demand had become much more intense as a result of increased competition between airlines.

The trading system introduced in the United States allocated 95% of slots to existing carriers operating within four traffic categories: domestic, commuter, international and essential air service traffic. A residual 5% was allocated by lottery with priority rights for new entrant carriers. A secondary market was established whereby, within domestic and commuter markets, any organisation was permitted to buy, sell or lease landing rights. Because of various bilateral agreements and public interest obligations, both international and essential air service traffic were exempt from the buy-sell rule. Transactions were regulated by an airline reservation and reporting system, accountable to the Federal Aviation Authority, which possessed powers to

requisition slots for international and essential air service operations. Each slot allocated to domestic and commuter carriers, possessed a random withdrawal sequence number. Those slots with the highest withdrawal numbers, had a greater chance of being possessed by the regulator to supplement the international and essential air service pools. In order to avoid potential anti-competitive practices, various safeguards were introduced. Firstly, airlines had to use their slots at least 65% of the time within a two month period, and secondly, the regulator had to be notified of all transactions, and thirdly, slots could not be transferred from one category to an other.

In theory, slot trading can be a viable alternative to both the existing system and unrestricted slot auctioning. Indeed, a method based on the F.A.A buy-sell rule can achieve, to a greater degree than the existing system, the pursuit of allocative efficiency, by permitting airlines to either buy or sell runway slots. Doganis (1992) illustrates the benefits of such a system by providing an example of an airline in possession of a slot valued at $700,000. This figure would be based on the financial benefits it would generate from operating the slot and it's withdrawal sequence number. However, another airline could value this slot at $800,000 or $1,000,000, because it could make a more profitable use of it. Slot trading therefore, potentially, could achieve increased efficiency in the allocation of scarce runway capacity and would provide the necessary pricing information required to guide future airport investment decisions. In addition, provisions against anti-competitive behaviour through the 65% use it or lose it rule, slot ring-fencing and the fact that transactions are brokered through an independent agency, could ensure that oligopolistic collusion does not undermine the system. However, as Fawcett and Fawcett (1988) point out, slot trading, whilst maintaining to a certain degree the inequities of the present system, cannot in itself prevent large carriers from outbidding smaller airlines, since the buy-sell provisions do not sufficiently protect the interests of small communities and new entrant carriers. Indeed, the scope for significant new entry is further reduced by the fact that large airlines could temporarily lease slots they do not use to other incumbents thereby denying access to new entrants. To test these hypotheses one would need to refer to the effects of slot trading in the United States to identify the extent to which these authors arguments have been vindicated.

According to Starkie (1991,1994) in a report to the European Commission, the buy-sell rule facilitated a significant number of transactions within the first year whilst in addition, the author provides evidence that trading did allow airlines to fine tune their schedules and generally improve their efficiency. Indeed by 1988, the total annual turnover of slots, including one-for-one trades, was equivalent to more than 50% of the daily carrier and commuter slots available at the four airports (Starkie 1994). One significant development was the fact that commuter airlines were more inclined to engage in outright buying and selling, whereas on the other hand, domestic trunk carriers tended to lease slots. However, evidence suggests that the trading mechanism failed to secure the level of new entry required to achieve competitive market conditions. Basically, retention of the principle of historic precedence in the initial allocation effectively prevented large scale entry. Indeed, in order to achieve entry at a magnitude designed to ensure that the carrier is able to provide commercially valuable services, at least 6 six slots needed to be obtained. Furthermore, in the United States, airlines face an additional hurdle of obtaining access to restricted gate facilities which is not normally the case in Europe. This may partly explain why commuter carriers have been able to achieve higher levels of entry, since they require less sophisticated facilities, as gate access and certain items of ground handling provision are not essential for small aircraft operations. However, one could argue, as Starkie (1994) does, that because transactions have declined, this may indicate that equilibrium has been achieved and that all profitable opportunities have been fully exploited. In his recommendations to the European Commission, the author concluded that slot trading, despite some difficulties, has had a beneficial effect in securing a more efficient allocation of limited runway capacity at the four high-density airports. As far as a slot trading within a European context is concerned, any attempt to introduce such a system would obviously have to take into account different operating conditions that prevail. Firstly, the distribution of slots at many of Europe's major airports is more concentrated amongst a few large carriers, which effectively creates a significant imbalance to the disadvantage of new entrants. Secondly, a trading mechanism would first, have to deal with jealously guarded control by national governments of flag carrier airlines and access to slots at major airports.

Slot pricing has been analysed at a strategic level. However, in order to understand it's detailed mechanics, one would need to focus on the effect of such a method on airline operations at the microeconomic level.

2.5.4 Airline operations in a slot priced environment

The modelling of aircraft operations within the context of slot allocation is both very recent and relatively scarce. Research in air transportation modelling has tended to focus on issues such as, air passenger choice analysis and aircraft scheduling and routing problems. However, there have been attempts, though few, to estimate the effect of slot pricing on airline operations.

There has been two conventional approaches to modelling airline operations within a slot allocation context. Firstly, to estimate the effects at the level of an airline's entire network and secondly to model operations on a route by route approach. Zacca (1991) sought to develop a model which could estimate the effects of slot pricing on airline operating costs, and to examine how the pricing of runway slots would affect route profitability and airline competition. This research approach focused on testing the effects of implementing two alternative slot allocation methods developed by Hulet (1991), on six Intra-European routes flown by twenty-eight different aircraft types. The author sought to estimate the extent to which implementation of a market hybrid slot pricing mechanism affected route profitability. Results showed that airline schedules operating aircraft with less than 150 seats were found to be vulnerable to slot pricing. This is not surprising since any uniform increase in airport turnround costs will have a disproportionate effect on small-sized aircraft, since the cost burden is spread over fewer seats. The author's analysis is substantially weakened by mistakenly assuming peak and off-peak slot charges of £250,000 and £150,000 respectively without any theoretical or empirical validation. These figures are based on estimates derived by Hulet (1991) who in turn, generates values for both domestic and international slots at London Heathrow. These values are £500 for a domestic slot and between £6,000 and £14,000 for an international slot. Basically any attempt to quantify the value of a slot has to supported by credible empirical evidence.

Blore (1992) incorporates passengers' choice of airport within an overall evaluation of the potential effects of slot pricing on the network structure of a major European

airline. His research attempts to estimate the commercial viability of transferring British Airways European operations to Birmingham Airport as a result of the introduction of slot pricing at London Heathrow. Within this framework, the author derives estimates of slot values on a variety of Intra-European routes. The slot values are determined by the maximum amount the operator would be willing to pay before it would be financially favourable to transfer flights to Birmingham. The bid prices are then passed on to passengers in higher fares, who within the context of an airport choice model, decide whether to continue flying out of Heathrow at a higher fare, or to accept cheaper fares in the absence of slot pricing at Birmingham airport. Within the context of this scenario, a model was developed which aimed to determine the optimal strategic response in terms of route restructuring to the introduction of slot pricing at London Heathrow. The study found that each route possessed it's own critical slot charge where it would be financially advantageous to relocate operations to Birmingham. The highest slot charge being £7,100 per slot on the Heathrow-Paris route, illustrating the comparatively low price-elasticity of demand for services out of Heathrow with respect to the implementation of slot pricing. However, the research is weakened by a rather simplistic approach to deriving slot charge estimates. The author, through ignoring substantial differences in slot values on routes throughout the operating day, neglects to provide accurate estimates of slot values for each individual flight and the fact that choice of departure time is an extremely important factor in determining a passenger's choice of airline or airport. Whilst the conclusions reached by Blore (1992) and Zacca (1991) appear to be theoretically valid, in their narrow and simplistic perspective, both authors have neglected to consider, in more detail, the numerous complexities associated with establishing how airlines can estimate the value of a slot. In light of the limitations of previous studies, the author believes that there is sufficient justification for further research into deriving a method which can measure the monetary value of a slot.

2.5.5 Measuring the value of a slot

Logically, the value of a slot would be determined by the maximum amount an airline is willing to pay. Yance (1969), Hulet (1991), Doganis (1992), and Blore (1992) recognise that this figure must be a function of the net economic benefit or

profitability of operating a service at a specific time of the day. The amount that a carrier actually pays, would depend on the precise mechanics devised by the airport authority to allocate slots. Grethner et al (1989) proposed that in order to minimise the potential cost burden, the highest bidder obtains the slot and pays the second highest bid price. Under these circumstances, however, since there is likely to be a difference between what an operator is willing to pay and the amount that is actually paid, this form of slot pricing will generate hidden subsidies in the form of monopoly rents, one of the fundamental inequities of the present I.A.T.A system. Hulet (1991), in a submission of alternative proposals to the UK Department of Transport, offered a system whereby within the context of slot pools or ring fences, the highest bidder pays the full market value of the slot. The author proposed that slots would be auctioned as medium term leases payable in the form of an annual rent, depending on the duration of the lease. For example, an airline having established a schedule with appropriate departure times and aircraft types, would submit a bid for a five year lease based on the likely profit generated over the period which is say £1,000,000. The airline would submit payments each year of £200,000 for the slot. This figure would, as Blore (1992) suggests, be recouped through passenger fare increases. In attempting to estimate the value of a slot, an airline will have to take into consideration the terms and conditions attached to it's use. Therefore, in the case of a medium term lease of say five years, the operator would have to judge, firstly, whether the slot would be used on the same route for the duration of the lease, secondly, whether the airline would be free to deploy alternative aircraft types on the slot, and thirdly, the operator would have to evaluate the extent to which potential competition would affect the profitability of this particular slot. Clearly, a wide range of complex factors would have to be taken into consideration. However, given these complexities, should market conditions say after two years of a five year lease change dramatically then the airline would be free to sub-let or change the terms and conditions attached to it's use with the airport operator.

Whilst there are a number of issues to be taken into consideration, it is beyond the scope of this research to evaluate, in detail, the precise mechanics of a slot allocation system. The purpose of this thesis is to establish a methodology to estimate the value of departure slots. Given that the value of a slot associated with a city-pair market is

likely to closely correspond to the profitability of operating a service at a particular time of the day, one can assume then that the value of a slot will be a function of it's estimated profitability.

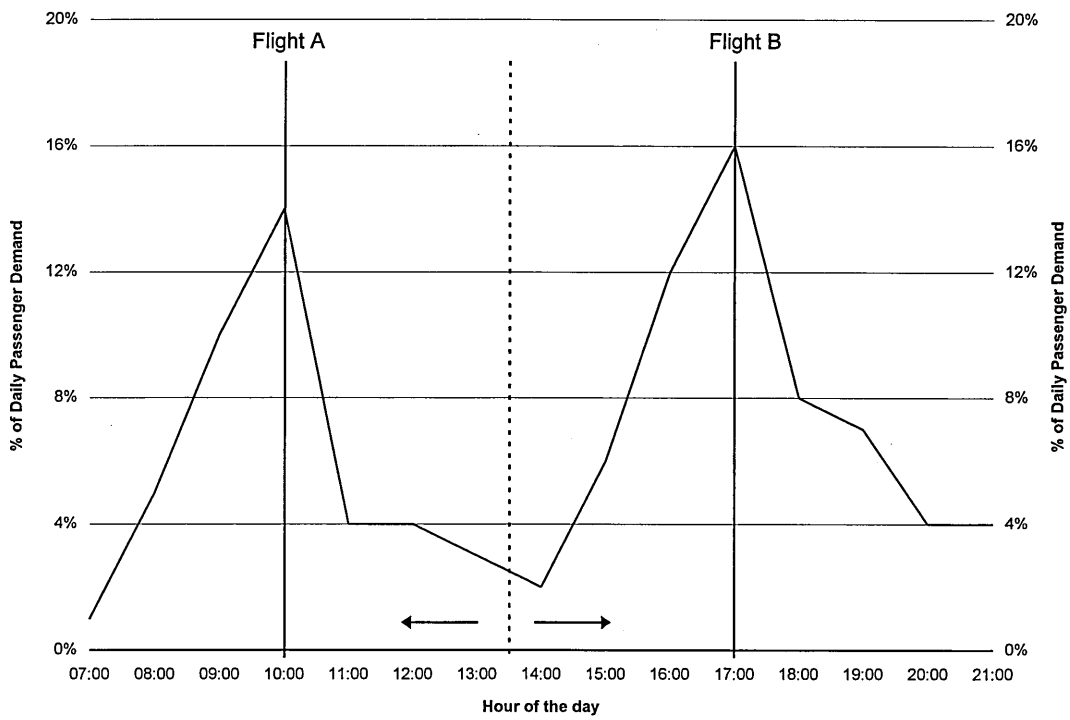
The profitability of a slot is, in turn, determined by the revenues generated and costs accrued by operating services at that particular time of the day. Costs are largely determined by factors both endogenous and exogenous to the operator. Endogenous factors include those costs that can, to a significant extent, be controlled, such as: aircraft operating expenses, and to a smaller extent, fuel prices and ground handling fees. However, those costs that are exogenous tend to be largely beyond the control of the airline. These are landing and apron parking fees and air traffic control charges which are set by either the airport or regulatory authority.

An airline's revenue function is determined by the passenger load and the level of fares set. The number of passengers on a flight departing at a specific time of the day is, to a large extent, determined by how highly those passengers find this departure time convenient. Given a range of flights to choose from throughout the operating day, and assuming all quality of service attributes such as travel time and fare are identical across the schedule, then passengers will select the flight that is scheduled in closest proximity to their own ideal time of departure.

Therefore, the value of a slot will be ultimately determined by the extent to which passengers, within a particular market, desire to travel at that specific time. A profit maximising operator will, within operating constraints, schedule flights at those departure times favoured by passengers. In many airline city-pair markets, passenger departure time preferences tend to follow a particular daily distribution, depending on demand characteristics prevalent within each market. Figure 2.2, below, illustrates a typical distribution of ideal departure times on a fictitious domestic short-haul route. The distinguishing feature of this distribution is the variation in demand density, characterised by two peaks in passenger preferences during mid-morning and early evening. This conforms generally to existing patterns of demand associated with many low density short-haul routes. The pronounced peaking in demand is primarily driven by business travel departure time preferences. Leaving aside more complex scheduling issues, a profit maximising airline will schedule flights at those times

guaranteed to maximise load factor. Given the preference distribution illustrated in Figure 2.2, the operator decides to schedule two flights: A and B at 10.00 and at 17.00 respectively.

Figure 2.2: Distribution of passengers ideal departure times and flight scheduling



Those passengers who desire to travel at both 10:00 and 17:00 are assumed to travel at those times. Passengers, who prefer to depart at other times must, therefore, choose between Flights A and B. Their decision will rest on the difference between their preferred departure time and the actual departure time supplied by the airline, a concept referred to as "schedule delay time". In choosing between A and B, and assuming that fares, aircraft size and other quality of service attributes are identical, for each flight, passengers will choose the departure time which incurs minimal schedule delay time. Therefore, those passengers who prefer to depart at times later than 13.30 will select Flight B whilst those who prefer to depart earlier will choose Flight A.

This is a rather simplistic assumption which will be challenged in the following chapters but, nevertheless, offers a straight forward starting point in which to examine the issue of estimating slot values. Schedule delay or choice of departure time is central to estimating the value of a slot. This is determined, to a large degree, by

the extent to which departure times are convenient or attractive to passengers within a particular market. In seeking to build a model which estimates how highly passengers value travelling at different times of the day, the following chapter focuses initially on an examination of those theories of passenger choice behaviour before suggesting a number of methods and model parameter estimation techniques that can be used.

2.6 Summary and Conclusion

Chapter two has sought to provide the reader with an understanding of slot allocation as a major policy issue facing the air transport industry, an examination of the issues behind the allocation of scarce runway capacity and within this context, a review of existing literature on this subject. The key points from Chapter two are summarised below:

- Amongst policy-makers and airport economists, there is general agreement that, in order to accommodate increased demand for air travel and to achieve a more efficient utilisation of scarce runway capacity, consideration must be given to reform of the existing method of allocating slots at congested airports.
- Given the inadequacies of the existing method, policy-makers and economists have investigated various alternatives designed to fulfil specific policy objectives, or in more general terms, to achieve a more efficient allocation of slots
- The most favoured option regarded by governments, aviation authorities and airlines is gradual evolutionary reform of the existing system through the introduction of more rigorous and transparent administrative and allocative procedures. Governments and regulatory bodies are constrained in the extent to which they can change the existing system by political considerations which implies that they must balance the interests of the various players within the air transport industry.
- Radical reform, focuses on the introduction of the pricing mechanism into the allocative process. Despite the relatively successful experiment with slot trading in the United States, the European air transportation industry has not sufficiently embraced or appreciated the idea of slot pricing to warrant it's implementation. Nevertheless, it is the opinion of the author that, given demand and supply

conditions at many of Europe's airports, it is inevitable that slot pricing will be introduced in some form within the next ten to twenty years.

- This present hostility to the market mechanism, in so far as slot allocation is concerned, stems from a belief that slot pricing would precipitate a period of widespread disruption at a time when the industry is already undergoing fundamental change through the liberalisation of air services and airline and re-organisation.
- Past literature on the subject of slot allocation has tended to focus on either the efficiency of various allocation procedures or on the effects of various allocation systems on airline operations using rather simplistic and narrow assumptions regarding how the value of a slot is derived.
- The value of a slot is a function of the profits generated by operating a flight at a specific departure time. This in turn, a function of passenger departure preferences.

The following chapter examines the concept of schedule delay time which is fundamental to an understanding of how passengers value slots.

CHAPTER 3

Passengers Choice of Departure Time

3.1 Introduction

In estimating passenger's choice of departure time, it is necessary to examine those models capable of simulating these decision making processes. Chapter three seeks to provide an understanding of the various concepts which form the basis for estimating passenger choice decisions within the context of an airline's flight timings. This chapter consists of five sections. Section 3.2 focuses on an exposition of the theoretical framework underlying appropriate choice models, followed by a more detailed examination of these choice models and their associated statistical properties. Section three examines the issue of schedule delay time within the context of a review of past research. This is followed by a discussion in Sections 3.5 and 3.6 on statistical estimation techniques available to generate choice model parameters.

3.2 Theories of passenger choice

3.2.1 Deterministic choice theory

Choice is a fundamental component of a trip decision making process, since in many instances, passengers usually have the freedom to choose between alternative and competing travel arrangements. For example, air travellers can choose between different airports to begin their journey or between competing airlines with each alternative offering distinct product and service characteristics. The extent to which each option appeals to the traveller depends on the level of satisfaction or utility one expects to derive from such a choice alternative. Utility, therefore, is a measure of the level of satisfaction yielded from consumption of a specific product and is dependent on firstly, the socio-economic characteristics of the individual decision-maker (disposable income, gender, tastes, geographic location), and secondly, the attributes attached to each competing alternative (travel cost, flight timing, level of service frequency etc.). In order to predict various decision-making outcomes or to identify these factors that influence choice, econometric models need to be developed which are theoretically valid and capable of accurately modelling behaviour. According to

Ben-Akiva and Lerman (1985), these models should be based on choice theories that are, descriptive, in the sense that they should postulate how human beings behave and not how they should behave, abstract, meaning they can be formalised in terms that are not specific to particular circumstances, and operational, in the sense that they can easily and accurately estimate parameters. In measuring the precise relationship between behavioural intentions and product attributes, utility can be expressed as an objective function which represents the attractiveness of an alternative in terms of its product attributes. Although various assumptions can be made regarding the appropriate form of utility construct, the most common tends to be additive and linear in the combination of variables.

$$V_{in} = \sum \beta x_{in} \tag{3.1}$$

Where the utility experienced by individual n with respect to alternative i is measured by V_{in} which is a function of the vector of unknown parameters β associated with product attributes x_{jn} where $i \in C_n$.

The magnitude of each coefficient β measures the importance of each variable within the utility function, and may vary between individuals, depending on personal characteristics such as income and taste. Assuming that an individual n is faced with a set of alternative travel arrangements C_n, the logical decision rule is to select the option that yields the highest utility relative to other alternatives within the choice set.

$$V_{in} > V_{jn} \qquad i, j \in C_n \tag{3.2}$$

The fundamental assumption underlying this theory is that individual decision makers are both rational and consistent in choices they make. Where passengers are assumed to possess complete knowledge of all travel options and their associated product attributes, choice, under these circumstances, is said to be rational or deterministic. This concept may seem intuitively logical. However, understanding choice behaviour on the basis of purely rational thought processes and actions is both a simplistic and misleading assumption to make, since there is a complete absence of error, which is inherent in real-life choice decision-making. A model based on these assumptions will assign all individuals to the alternative that yields the highest relative utility. This is generally known as the "all or nothing rule". However, in the

majority of cases, travellers are not always aware of all possible alternatives, and in many instances may incorrectly perceive product attribute levels. Teodorovic (1988) suggests, that within the context of air transport, where deficiencies exist in the supply of information, passengers may not necessarily choose the most logical alternative. Firstly, because they may be unaware of all travel options, and secondly, because they may incorrectly perceive the value of specific product attributes. For example, choice will be theoretically sub-optimal, particularly in cases where passengers within highly competitive markets are not fully aware of cheaper or more convenient alternative travelling arrangements. In light of these deficiencies, the theory of deterministic choice is limited in the extent to which it can form the basis for developing accurate and robust decision-making models.

3.2.2 Probabilistic Choice Theory

Developed initially by Luce (1959), probabilistic choice theory offers a solution to the problem of incorporating random and irrational influences in the modelling of individual choices. Ben-Akiva and Lerman (1985) identify three sources of error. Firstly, inconsistency on the part of the individual such as incorrect perception of product attributes, secondly, deficiencies in the supply of transport information and thirdly, a failure on the part of the analyst to either include important variables or to include those attributes that cannot be easily identified or measured. Probabilistic choice theory, therefore, defines the decision rule as the probability of selecting an alternative as opposed the assumption of all or nothing allocation as in deterministic theory.

The utility associated with the purchase of a product or consumption of a service, under probabilistic theoretical assumptions, is therefore a function of two individual components: a deterministic element V which represents all the measurable and observable characteristics of the traveller, and the product attributes of each alternative, and a random function which incorporates a measure of error in individual choice decision-making.

$$U_{in} = V_{in} + \varepsilon_{in}$$
$$U_{jn} = V_{jn} + \varepsilon_{jn} \qquad (3.3)$$

From equations 3.3 above, the utility associated with alternatives U_i and U_j function as random variables with deterministic elements V_i and V_j and error terms ε_i and ε_j, The error components represent all random elements, such as those attributes that cannot be quantified or identified. Therefore, the probability that an individual *n* will choose option *i* is derived by the following empirical relationship.

$$\begin{aligned} P_n(i) &= \text{Prob}\left[U_{in} \geq U_{jn}\right] \\ &= \text{Prob}\left[\left(V_{in} + \varepsilon_{in}\right) - \left(V_{jn} + \varepsilon_{jn}\right)\right] \\ &= \text{Prob}\left[\left(V_{in} - V_{jn}\right) + \varepsilon_{jn} - \varepsilon_{in}\right] \end{aligned} \tag{3.4}$$

In order to operationalise this theory into a predictive model, an understanding of the nature, specification and distribution of the error terms ε_i and ε_j is required. One approach suggested by Ben-Akiva and Lerman (1985) is to treat the deterministic element *V* as a mean of the overall utility *U*. This implies, therefore, that the random terms represent some disturbance or more specifically a standard deviation from this mean. Empirical observation of the error term requires that an individuals' actions are recorded on repeated occasions under experimentally controlled conditions to measure any variability in perception or behaviour. However, in order to short-cut this rather tedious procedure, statistical assumptions are made regarding the distributional nature of the error terms. Different assumptions underlying the nature and distribution of the error terms ε_i and ε_j will inevitably produce different probabilistic choice models which are distinct in their statistical properties and in their application to real life choice decision-making scenarios. Both the probit and logit models are derived from probabilistic choice theory and are used to estimate choice probabilities based on specifications of *V* and statistical distributions of the random component terms.

3.3 Probabilistic choice theory behavioural models

3.3.1 Probit model

The probit model was developed initially by Daganzo (1979) and is primarily based on the assumption that the random components associated with each utility are independently and normally distributed. The error terms ε_i and ε_j are distributed according to a joint density function, and are both based on the multivariate normal

distribution associated with a mean = 0, variances σ_i^2 and σ_j^2, and covariance σ_{ij}. The MVN distribution of error components is characterised by a vector of means and a covariance matrix, which includes the variance associated with the random components and the covariance between them. The probit model is shown below.

$$P_n(i) = \phi \frac{V_{jn} - V_{in}}{\sigma} \tag{3.5}$$

However, given the properties of the cumulative distribution function ϕ, the probit models choice probabilities cannot be expressed in closed form i.e. between 0 and 1. Indeed, whilst the underlying assumptions regarding the nature and distribution of the error terms may be theoretically valid, the probit model is limited in its applicability to choice scenarios involving more than two alternatives. Basically, as the number of alternatives increases, probit analysis begins to lose its relative computational simplicity. Calibration effectively becomes more complex especially when estimating a vast array of error variance estimates σ associated with each travel option and the covariance between each alternative error term. Attempts have been made by Daganzo (1979) and Horowitz (1983) to extend probit analysis into a multinomial dimension. However, given the computational complexity associated with such a task, applications of the probit model have tended to focus on binomial choice situations, examples of which include research by Lisco (1967). Within the context of air transport demand analysis, economists have tended to avoid the probit model. This is understandable, given the complexities associated with such a choice decision-making process, particularly in relation to airline choice and the numerous sources of inconsistency and error that may emerge. As a consequence, researchers within this field have tended toward use of what is known as the logit model both for analytical convenience and for computational simplicity.

3.3.2 Logit model

The logit model is one of the most widely known and most extensively used choice models in the field of transportation demand analysis. Common uses include estimating choice probabilities within the context of mode and route choice problems in urban transportation. In air transport, the logit model has been utilised both to

determine which factors influence choices and to estimate probabilities in a wide variety of scenarios. For example, studies by Kanafani and Ghobrial (1985), and Hansen (1990) on air passengers choice of route, research by Alamdari (1989) and Milan (1992) on rail-air competition, and work by Ashford and Benchemam (1987) and Caves (1992) on airport choice behaviour are a few examples of the application of logit modelling to choice analysis within the field of air transportation.

The theoretical framework that underlies the logit model is derived from statistical assumptions regarding the distribution of the random terms ε. Thinking in terms of the differences in the random components as opposed to each element separately, logit analysis assumes that these elements which contain a variety of unobserved factors affecting choice, are logistically distributed. This is equivalent to assuming that the random terms are identically independently and gumbel distributed. The logistic or Gumbel distribution is used for analytical convenience as it represents a close approximation to the normal distribution. Therefore the choice probability for alternative *i* can be expressed as follows.

$$P_n(i) = P\left[U_{in} \geq U_{jn}\right] \tag{3.6}$$

$$= \frac{1}{1+\sum_{j=1}^{n} exp^{-\beta\left(V_{in}-V_{jn}\right)}} \tag{3.7}$$

Since it is not within the scope of this research to provide a detailed explanation of the mathematics of logit model formulation, an exposition of the precise steps between equations 3.6 and 3.7 is described in Ben-Akiva and Lerman (1985). Multiplying the right hand side of equation 3.7 by ε_i yields the following transformation

$$P_n(i) = \frac{exp^{-\beta V_{in}}}{\sum_{j=1}^{n} exp^{-\beta V_{in}}} \tag{3.8}$$

The choice probability P_n *(i)* is derived by imputing values of deterministic components V. These values will depend on *a priori* specification of the variables and the values of those variables including estimates of the unknown parameters a. The difference in error terms ε_i and ε_j are assumed to have a mean 0 and standard

deviation σ^2. The scale parameter β re-scales the objective function in order to take into account the variance associated with the error terms. The β parameter can be estimated from the following equation

$$\beta = \frac{\pi^2}{\sqrt{6}\sigma^2} \tag{3.9}$$

However, the assumption that the disturbance terms are independently and identically distributed constrains all the error terms to have the same β . This implies that the variances of the random components are identical across alternatives. However, there are two limiting cases associated with the logit model and both involve extreme values of β As $\beta \rightarrow \infty$, the deterministic component assumes increasing weight and, as a consequence, the level of randomness within the model is reduced. Therefore, the choice probability associated with alternative *i* becomes.

$$P_n(i) = \begin{cases} 1 & if \quad V_{in} - V_{jn} > 0 \\ 0 & if \quad V_{in} - V_{jn} < 0 \end{cases} \tag{3.10}$$

However, on the other hand, as $\beta \rightarrow 0$ the choice process is subject to the increasing influence of random effects, to such an extent that despite utility differences, there is an equal chance of any alternative being selected.

3.3.3 Choice of model

In deciding whether the probit or logit model is the most appropriate form of behavioural model, choice rests on, firstly, the extent to which distributional assumptions underlying the error terms are realistic and appropriate to the choice context, secondly, which of the models are analytically and computationally more convenient. In relation to error term distributions, the logit model is based on the disturbance terms being independently and identically distributed. This means that the statistical distribution is independent in the sense that all the utilities associated with each alternative are mutually exclusive and identical in the sense that each disturbance term is distributed across the sample of individuals according to a density function based on the Gumbel or Weibul distribution. This distribution represents a close approximation to the normal distribution according to Ben-Akiva and Lerman

(1985). The assumption of independence may in fact be difficult to defend. The independence from irrelevant alternatives assumption states that the ratio of probabilities between two alternatives is unaffected by the introduction or the presence of a third alternative. Considering the case of choosing between air rail or bus, the introduction of bus services into the market will reduce the market shares or choice probabilities of both air and rail but not their joint probability ratio. However, this is a difficult assumption to defend unless all choices are mutually exclusive in terms of their product attributes. The introduction of bus services will probably have more of an effect on rail services as opposed to the airline alternative. The probit model, on the other hand, assumes that the disturbance terms are distributed according to the multivariate normal distribution. Therefore, probit analysis, unlike the logit alternative, can handle circumstances where alternatives are not mutually exclusive and do overlap exhibiting in some cases strong correlation between random terms. This is a more realistic assumption on which to base a choice model and is indeed one of the probit models most appealing features. However, in terms of computational simplicity and analytical convenience, the probit mode has several weaknesses. Firstly, choice probabilities cannot be estimated in closed form, secondly, the probit model can only be realistically applied in situations involving only two choices.

As far as estimation capabilities are concerned, there is no evidence to suggest that the probit model produces statistically significant or more efficient estimates than the logit model. Indeed, in an example provided by Kanafani (1983), choice probabilities derived from probit and logit techniques were more or less identical. Moreover, the logit model particularly in multinomial choice situations can derive choice elasticities which is more or less impossible with multinomial extensions of the probit model.

Whilst various assumptions underlying the logit models theoretical framework may be considered unrealistic or invalid, for computational simplicity and analytical convenience, the logit model has been selected as the choice technique which will be applied to this particular problem. This follows well established practice in the field of air transportation choice analysis, where the consensus of opinion suggests that despite several weaknesses, the logit model for reasons of analytical convenience, remains the most popular probabilistic choice modelling technique. Within the

context of estimating passengers choice of departure time, logit analysis appears reasonably suitable given the need to estimate choice probabilities from a set of departure times. The independence assumption therefore, is suitable for this particular choice context in the sense that each departure time can be considered mutually exclusive. Having identified the appropriate behavioural choice modelling framework for estimating passenger's choice of departure time, a variable measuring the utility or disutility of alternative flight timings must be specified.

3.4 Schedule delay time

3.4.1 Definition

One measure of departure time convenience is conventionally known as schedule delay time. This measures the difference between a passenger's ideal departure time and the scheduled departure time offered by the air transport operator. This measure can then be incorporated into the logit model (equation 3.8) as the one of several variables included in the objective function V. However, past research in passenger choice analysis within aviation, has tended to neglect to either consider or incorporate in detail this important variable. Schedule delay time measures the convenience of an airline schedule to the passenger. In an idealised world an airline would schedule flights to match each individual's ideal departure time, but because of the need to schedule profitable flights, not all departure time preferences will be satisfied. As a consequence, passengers, depending on the proximity of their preferred times to the departure times offered by the airline, will have to endure additional units of disutility in selecting alternative flights. Schedule delay time, therefore, measures the disutility associated with the inconvenience of a schedule.

3.4.2 Schedule delay time in urban transportation

The application of schedule delay time to passenger choice analysis has received more attention in the field of urban transportation economics, specifically within the context of analysing commuters choice of departure time. In response to escalating road congestion, a body of research emerged which sought primarily to understand and identify factors that were influencing commuters choice of departure time. Examples include work by Mannering and Hamed (1990) on investigating commuters' decision

to delay their departure from work to home in an effort to avoid peak-time congestion, and research by Small (1992) on estimating choice probabilities associated with twelve possible five minute intervals for work arrival time, using a sample of auto commuters from the San Francisco area. This work involved defining schedule delay as the difference between the scheduled arrival time and the official work start time. Similar work was undertaken by Hendrickson and Plank (1984) on departure time flexibility within the context of modal choice, where commuters had a choice of drive alone auto, shared transit with walk access, and transit with auto access. Their research concluded that departure time choice was significantly more elastic compared to choice with respect to mode. From a different perspective, Mannering and Hamed (1990) focus their research on an investigation of commuters decision to delay their departure from work to home in an effort to avoid congestion. The commuter, in this particular instance, is assumed to have a choice of either not delaying their departure, delaying their departure time and undertaking a work activity, or delaying their departure and undertaking a non-work activity such as shopping. Results showed that traffic system characteristics dominate delay choice followed by socio-economic factors such as household size, income and activity opportunities at work.

However, in seeking to incorporate the concept of schedule delay time to research problems in air transport, it is important to remember that direct comparisons between the application of schedule delay time to commuter choices and air passenger choices can be misleading. Firstly, automobile commuters are essentially providers of their own transport service, whereas air travellers are restricted to schedules supplied by the airline. Secondly, the commuter's trip purpose tends to be more homogenous in the sense that journey purpose is almost invariably travel to work. On the other hand, given the degree of market segmentation associated with air travel, trip purpose can be one of four possible journeys: business, leisure, inclusive tour holiday and visiting friends and relatives. Thirdly, trips involving air travel consist of several components: access time to the airport, check-in time, waiting time, in-flight time and egress time from the arrival airport to the destination activity. Given the relatively unpredictable nature of this journey and the potentially large transit times involved, the business passenger is likely to select a journey that minimises travel time, is associated with

flight departure times that closely correspond to his or her ideal preference and an arrival time which is in turn, dependent on the trip purpose and the precise timing and nature of the destination activity.

In incorporating the concept of schedule delay time to air passenger choice analysis, one important factor to consider is the issue of asymmetrical disutility between earlier and later departure times. Small (1992), in his analysis of commuter choice behaviour, differentiates between the disutility associated with early and late arrival. In air transport, schedule delay time can similarly be treated as two individual components, one measuring the inconvenience of those flights scheduled earlier than one's desired departure time and the other measuring the inconvenience of flights scheduled later than one's desired departure time. The magnitude of disutility will ultimately depend on the journey purpose and the nature and timing of the destination activity. For example, corporate travellers, restricted by fairly tight trip and destination activity schedules will, in order to complete a round trip within one day, be increasingly averse to later departure times and more inclined to accept earlier options. Conversely returning passengers completing a one-day round trip, may prefer later departure times in order to minimise trip and activity constraints. Leisure travellers, on the other hand, because of the absence of similar trip restrictions will, in theory, and up to a point, experience less and possibly equal disutility between late and earlier flights.

3.4.3 Schedule delay time in air transportation

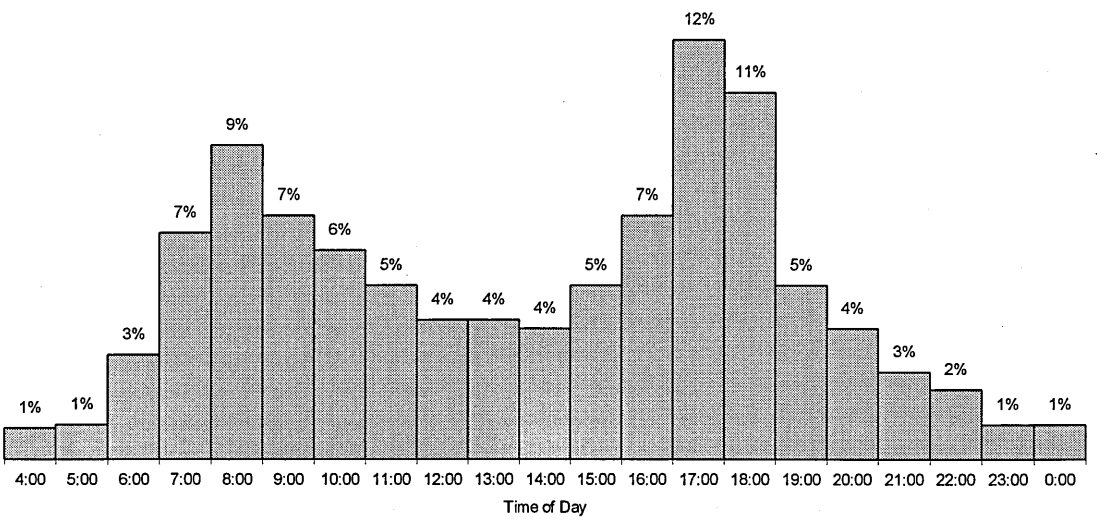
Past research on passenger choice behaviour in air transportation has however, tended to neglect to consider or incorporate the concept of schedule delay time. Applications of the logit model to passenger choice analysis by Douglas and Miller (1974), Kanafani and Ghobrial (1985), Ashford and Benchemam (1987), Harvey (1987), Hansen and Kanafani (1988), Hansen (1990), Thompson and Caves (1992), Ghobrial (1993), and Brooke et al (1994), support evidence which suggests that in competitive aviation markets, frequency of service is the most important product attribute that influences passenger choice behaviour. This research also validates the S-curve non-linear relationship between market share and service frequency, where a rise in service frequency offered by an airline leads initially to a disproportionate increase in its share

of the market. The importance of frequency is evident in a wide variety of markets. For example, in identifying the factors that influence passengers' choice of airport in the North of England, Thompson and Caves (1992) concluded that service frequency measured by the magnitude and statistical significance of its coefficient estimate is one of the most important variables, in addition to access time that influences passenger choice behaviour. However, what is perhaps neglected, is a consideration of the precise timing and convenience of these frequencies. Basically, past literature validates the rationale behind the need for airlines operating in competitive markets to maximise frequency and hence obtain a large proportion of origin-destination demand. By providing a high level of departure times subject to economic and operational constraints, airlines can ensure that they are providing a sufficient range of flights throughout the day in order to align those departure times as closely as possible to passenger trip preferences. While the volume of service frequency has generally been used to measure the convenience of an airline schedule, this measure is inappropriate when aiming to estimate how highly passengers value alternative departure times.

In measuring schedule delay time, it is necessary to obtain information on the distribution of passenger ideal departure times on any day. Airlines do not possess knowledge of the precise distribution of ideal departure times within a given market. Therefore, aircraft time of day scheduling remains highly conjectural and even reactive, in the sense that departure time choice is driven by competitor strategies and supply-side inelasticities. In competitive markets, a new entrant airline may assume that the current incumbent is operating flights that closely correspond to ideal departure times, and will therefore schedule flights accordingly. This is called "bracketing", where airlines schedule flights as closely as possible to other competitor airline flight times. Indeed, observation of departure time schedules on existing high-density city-pair markets, reveals a pattern where competing airlines are scheduling flights at around the same time as each other. For example, the daily flight schedules of British Airways, Air France and British Midland on the London Heathrow-Paris Charles de Gaulle route clearly illustrates the effect of bracketing (ABC, 1994a). For example, flights tend to be scheduled by each airline at the same departure time. However in order to ascertain a precise ideal departure time distribution, this method

is largely ineffective, since scheduling is also a function of the availability of slots and the operational and network-wide characteristics of the airline. Jessiman et al (1970) nevertheless provides a complete set of time of day departure preference functions for various market segments within the United States.

Figure 3.1: Time of day departure preference distribution for a short-haul market.



Source: CAB passenger survey in Jessiman et al (1970)

These functions were obtained from a survey of 10% of daily passengers within the relevant markets. Passengers within this sample, were asked to identify departure time preferences assuming they had to undertake a trip to the destination. Clearly, the distribution of preferences will ultimately depend on the nature of the destination activity. Business passengers operating within fairly tight time schedules will aim to complete a round trip between airports within one day. For example, by departing in early to mid-morning, the business traveller seeks to complete his or her activity in order to return by the same evening. Obviously, this depends on the length of the route. Indeed, in short haul sectors, driven by business travel patterns, the daily distribution of ideal departure times is usually characterised by two peaks. However, in predominantly leisure or discretionary markets, given that passengers are generally less time-sensitive, then any daily peaks are usually less pronounced.

In long-haul intercontinental markets, given significant journey times and time zone changes, it could be argued that arrival time assumes more importance relative to departure time. Indeed, most carriers operating in long-haul markets ensure that arrival times are convenient to both transfer and terminating passengers. Therefore, the air operator, because of significant journey times involved, is very much restricted in the choice of departure time. For example, observation of the daily distribution of flights on services between London Heathrow and Sydney illustrates the fact that because of significant journey times and time zone changes, flights are scheduled to leave Heathrow between 12.00 and 13.00 and 21.00 and 22.00 to ensure convenient arrival times in Sydney. Although these carriers do not have precise knowledge of ideal arrival times within the London-Sydney market, they will schedule flights given various network-wide considerations to what they consider to be the most convenient set of arrival times.

Basically, insufficient data and research into ideal departure time preference distributions is probably one of the main reasons why economists have given insufficient attention to the issue of schedule delay time. In the past, assumptions have generally been made regarding the distribution of ideal departure times. Anderson and Kraus (1980) incorporated a variable measuring schedule delay into a model of air transport demand. A frequency delay function was derived from assumptions on desired departure times by Douglas and Miller (1974). This delay function was obtained by computing average frequency delay on the basis of absolute differentials between desired and nearest offered departure times. This approach assumes a very high correlation between the actual flight times and the desired flight times in a market. Therefore, one assumption that is frequently made is that the distribution of flight times is a close approximation to ideal departure time preferences within any market. This is indeed true for high density shuttle routes, where passengers are offered flights on the hour. One can obtain a clear but maybe crude indication of ideal departure time preferences. However on routes associated with limited frequency such as: short-haul regional services or long-haul international flights, the distribution of flights is such that little information can be gained on precise departure time preferences. Morrison and Winston (1985) in an analysis of the

demand for inter-city passenger transportation, incorporate a schedule delay variable based on similar assumptions from work undertaken by Douglas and Miller (1974). In this instance, a nested logit model is used to estimate choice of destination, choice of mode to the destination, and finally, the choice of whether to rent a car or not to rent a car. Within this context, schedule delay is computed from existing schedules and is derived from the total time between scheduled departures associated with the air transport alternative and for bus service schedules. In this instance, the time between departures is treated as a proxy for schedule delay time. This implies that ideal departure time preferences are uniformly distributed throughout the day. Similar assumptions underlie research into an examination of airline strategic behaviour in competitive markets under deregulation by Alamdari (1989). The author assumes that departure time preferences are uniformly distributed throughout the day and that travellers have no particular preference for either later or earlier departure times i.e. both schedule delay components are utility symmetrical. However, markets characterised by corporate travel patterns, with passengers more sensitive to additional units of late schedule delay time relative to early schedule delay time, implies that symmetrical disutility cannot easily be held as a valid assumption to make when estimating departure time choice behaviour.

In the absence of precise data on ideal departure time preferences, load factor ratios on individual shuttle flights on a given high density market could provide an indication as to the relative attractiveness of a particular departure time. However, given the commercial sensitivity associated with load-factor data, airlines or regulatory authorities would be unlikely to assist in providing such data. Research on schedule convenience, therefore has been handicapped by the fact that rather restrictive and somewhat unrealistic assumptions have had to be made regarding passengers ideal departure times and their preferences for earlier or later flights.

The concept of schedule delay time has also been introduced into research on aircraft scheduling problems. Work by Dobson and Lederer (1993) incorporated a logit choice analysis into a linear programming model designed to simulate an aircraft scheduling and routing outcome within a hub and spoke network system. Their utility function contains variables measuring schedule delay time, total in-flight time and

fare. Unlike previous research, the authors do not assume a uniform distribution of ideal departure times, but a density of preferences that varies throughout the day, with the disutility associated with alternative flights similarly varying throughout the day. However, in general, analysis of schedule delay time within the context of logit analysis has not received sufficient attention. Research, initially developed in the United States on aircraft scheduling problems, whilst incorporating the concept of schedule delay time, tend to omit assumptions relevant to probabilistic choice theory as discussed in section 3.2. Work by Miller (1972), Gagnon (1967), Gordon and De Neufville (1973) develop passenger choice models that are deterministic in nature in that passengers' select their most convenient flight without any consideration of possible random influences.

3.5 The money value of schedule delay time

The value of time is one of the most important qualities inferred from travel demand models and represents the money values that people place on saving various forms of travel time. The value of time, expressed in money terms, measures the marginal rate of substitution between time and cost. In order to obtain value of time estimates, a variable representing travel cost would need to incorporated into the utility function *V*. The value of schedule delay time, therefore can measure the level of fare reduction required to induce a passenger to accept an additional unit of schedule delay time. Using one of several statistical estimation techniques such as linear regression or maximum likelihood techniques, relevant journey cost and schedule delay time coefficients can be obtained for a specific city-pair market or segment of demand. Provided the signs are correct, and assuming that the coefficients are statistically significant at the 99% level, the value of schedule delay time can be derived by taking the ratio of the time and cost parameters as shown below.

$$\alpha^{sd} = \frac{\beta^{sd}}{\beta^{f}} \tag{3.11}$$

The value of time will depend on the magnitude of the fare and scheduled delay coefficients β^{f} and β^{sd}. A high value of schedule delay time suggests that passengers, because of the time sensitive nature of their journey, will be partial to additional units

of schedule delay time, and therefore, unlikely to be responsive to marginal reductions in fare. Given the segmented nature of air transport demand in terms of trip purpose, values of schedule delay time will inevitably differ between passengers within a given market. For example, business travellers, because of the time-restrictive nature of their journey, would be less responsive to cheaper fares and more responsive to increases in schedule delay time. Leisure passengers, conversely, will have lower values of schedule delay time, because they are generally more sensitive to journey cost: firstly, because they usually pay their own fares and secondly, because their trips are not as time-restrictive as those associated with business travel.

Past research in value of time estimation in air transport confirms that significant variation can exist between business and non-business passengers within a given market. For example, in an analysis of air travellers' choice of departure airport and destination, Furuichi and Koppelman (1994) generated values of access time of US$76 per hour and US$ 41 per hour for business and leisure passengers respectively.

Values of schedule delay time may also differ from an individual passenger's perspective between earlier and later departure times. For example, those travellers associated with time-restrictive trip schedules may be more averse to suffering additional units of schedule delay associated with later departure times compared to earlier flights. For those passengers who are beginning their trip and are only spending a short time at their destination, they are more likely, if given the choice, to select earlier flights, since this avoids a reduction in time spent at the destination activity, which selecting later flights would almost certainly involve.

In deriving an estimate of the value of schedule delay time, it is necessary to identify an appropriate analytical technique. Section 3.6 below, considers two methods: revealed and stated preference analysis which can be used to generate values of time.

3.6 Choice of analytical technique

3.6.1 Revealed preference analysis

Models of travel demand have traditionally been based on data obtained by direct observation of travel behaviour, or where data does not exist, through the use of passenger surveys. Applying appropriate statistical techniques, such as linear

regression and maximum likelihood methods, implicit utility functions associated with a group of travellers can be inferred. These functions can provide information on the relative importance of various factors influencing choice behaviour. This approach involves the generation of predictive models derived from historic data on passenger choice behaviour. One example has been the widespread use and application of the logit model to analysing choice behaviour within the field of air transportation demand analysis. This includes research by Kanafani and Ghobrial (1985), Alamdari (1989) and Hansen (1990), on modelling choices using existing origin-destination passenger flow data. Therefore, in seeking to estimate departure time choice probabilities within a specific city-pair market, the following data would be required. Firstly, time series data on passenger flows relating to each individual flight. Secondly, information on the daily distribution of ideal departure times, and thirdly, data on known supply-side characteristics such as frequency and fares. Having obtained this information, a model could be estimated which would incorporate additional variables to ascertain the extent to which schedule delay was an important factor in influencing passengers choice of flights. Whilst data can be readily sourced on aggregate passenger flows and supply side characteristics relevant to a specific city-pair market, commercially sensitive information on precise passenger loads for each individual flight is generally difficult to obtain. Analysis of passenger departure time choice behaviour, therefore, is handicapped, firstly by the unavailability of individual flight data, and secondly, by the absence of any measure of the distribution of ideal departure times for a given market. As a consequence, past research on passenger choice behaviour in the context of schedule delay time has had to make rather restrictive and narrow assumptions regarding both passenger loads on each flight and the preference distribution of departure times.

An alternative approach would be to construct what is called a revealed preference survey, where a sample of passengers on a given route are asked to identify both their ideal departure time, and how highly the convenience of a departure time supplied by an airline, influenced their choice of flight compared to other quality of service and cost variables. This is potentially a more fruitful approach to analysing revealed behaviour, and has for many years remained the most popular form of analytical

technique used to predict discrete choices. Therefore, by observing choices actually made between flights with known quality of service characteristics, one can generate value of time estimates and choice probabilities which can form the basis for forecasting or evaluating passenger choice behaviour. In deriving a value of schedule delay time, a revealed preference approach for example, could involve requiring the respondent to identify the extent to which the convenience of the departure time compared to fares, influenced choice. However, the problem with this approach is that the estimated fare coefficient is unlikely to exhibit degrees of statistical significance because, in the majority of airline markets fares tend not to be differentiated with respect to time of day. Therefore, there are limits regarding the extent to which revealed preference can be applied, since historic data and revealed behaviour may not provide the necessary product attribute trade-off information. Given the fact that values of schedule delay time may in fact be difficult to obtain from revealed preference analysis, an analytical technique such as stated preference methods based on the evaluation of hypothetical transport services may provide a solution to this problem.

3.6.2 Stated preference analysis

Originally developed as a market research tool in the United States, stated preference techniques have received increased attention in Europe over the last fifteen years. Research involving the derivation of demand elasticities amongst inter-city rail passengers (Sheldon and Steer 1982), and an examination of passenger investment priorities on Danish State Railways (Anderson et al 1986), are examples of the application of stated preference techniques to policy issues within a European context.

Stated preference experiments seek to obtain information on how passengers would respond to different hypothetical choice situations. Each travel situation typically describes the supply-side characteristics of a hypothetical transport service i.e. journey cost, service frequency and in-vehicle time. The individual is asked to evaluate each option in terms of the utility he or she is likely to derive from the presented travel alternatives. The perceived utility of each option is a function of both the value of each product attribute and the relative importance of each variable to the individual. Thus, a utility function measuring the relationship between behavioural

intention and product attributes is used to estimate the individual effects of each variable on choice, and vital trade-off information between product attributes, from which values of time can be estimated.

Each product attribute is usually presented within the context of the respondents present journey. For example, the hypothetical fare value can be expressed as an increase or decrease on the current level measured in either percentage or absolute terms. Thus, the respondent could face a choice between a series of paired comparisons between the current journey and a hypothetical alternative. Furthermore, each travel situation is designed in such a way as to ensure that the individual effect of each product attribute or variable can be quantitatively measured. The respondents state their preferences for each option by either ranking them in order of importance, rating them on a scale, indicating strength of preference or choosing the most preferred option from a pair or group of travel alternatives. The response represents the passenger's measure of utility and therefore operates as the dependent variable in the statistical estimation process. Thus, by expressing the product attributes as independent variables and the response as the dependent variable, either linear regression or maximum likelihood statistical estimation techniques can be used to derive appropriate parameter estimates.

3.6.3 Choice of Analytical Technique

Besides being able to evaluate products, services or situations which are qualitatively different to those that are commonly encountered, stated preference analysis enables the researcher to exert a significant degree of control over the experiment. Control can be exercised through isolating variables of interest and excluding additional factors that may or may not influence the choice process. By restricting the evaluation to either two or three variables, the respondent, therefore, is very much limited to evaluating those product attributes specified by the researcher. On the other hand, within a revealed preference context, the researcher is required to obtain information on what the respondent has identified as the factors that influenced a particular choice decision. The problem with this approach is that firstly, the respondent may identify factors that cannot be easily measured or quantified such as image and comfort, and secondly, if the researcher chose to pre-specify a set of variables, there is no

guarantee that all potential variables would have been included in the experiment. One weakness associated with revealed preference analysis, according to Ortuzar and Willumsen (1994), is the fact that observations of actual choices may not provide the necessary variability in behaviour required to generate accurate and efficient statistical estimates. Indeed one problem with revealed preference data highlighted by Kroes and Sheldon (1988), involves the issue of correlation between product attributes. Because the respondent is being asked to identify factors that influence a particular choice outcome, and given that a revealed preference survey is limited in the extent to which it can incorporate all variables of interest, strong correlation could exist between product attributes which will ultimately bias the statistical estimates and therefore substantially undermine the validity of using revealed preference methods. For example, passengers on a given airline market may identify both journey cost and travel time as the most important factors which influenced their choice of airline. However, both variables may be highly correlated since in most instances, journey cost increases with travel time. In addition, observed behaviour may in fact be dominated by one or two variables making it very difficult to identify the effect of other relevant product attributes on the choice process. Stated preference techniques, on the other hand, enables the analyst, both to exert a greater degree of control over the experiment in terms of defining the experimental conditions, and specification of the variables to be evaluated.

One advantage of stated preference analysis, is the ability to obtain efficient statistical models from relatively small sample sizes, since within each interview the respondent is asked to evaluate a range of hypothetical choice options, each offering different combinations of product attribute levels. On the other hand, within a revealed preference context, the respondent is asked to evaluate one travel choice. As a consequence a larger sample size is necessary in order to generate statistically significant results. Fowkes and Wardman (1988) point out, that in order to capture taste variation between respondents, across a particular sample of passengers, utility models can be calibrated for each user provided there are a sufficient number of choice sets per individual.

However, the main criticism levelled against stated preference analysis is the fact that given the purely hypothetical nature of the experimental design, a difference can emerge between what respondent say they would do and what they would do in practice (Ortuzar and Willumsen 1994). Research by Lin et al (1986) discovered, that when comparing stated preference choice outcomes with actual behaviour, individuals tended to exaggerate their responses. According to Bradley (1988), the complexity of the choice task can be expected to influence the level of error associated with each response. This implies, therefore, that error and randomness is generally greater than that experienced in revealed preference analysis For example, research by Wardman (1988), on a comparison of both revealed and stated preference methods within the context of an analysis of commuter mode choice decisions, revealed that whilst value of time estimates proved to be highly significant for both models, the revealed preference approach yielded a higher ρ^2 compared to the stated preference method. Indeed, it is generally the case, according to Bates (1984), that because of systematic bias associated with stated preference experiments, the explanatory power of such a model will be relatively lower compared to comparable revealed preference methods. Indeed, as Ortuzar and Willumsen (1994) also point out, whilst most respondents will understand the choice task, there is no guarantee that choice experiments can be completed with accuracy. Sources of error will therefore originate not from the omission of crucial variables as in revealed preference experiments, but in response bias and inconsistency. The degree of error in responses will depend firstly, on the extent to which the respondent has understood the task and secondly, the degree of realism in the experiment, and thirdly on the complexity of the task itself i.e. the number of variables and choice sets presented. Basically, if respondents are required to process a significant amount of information the ensuing respondent fatigue and greater likelihood of irrational responses, will adversely affect the significance and validity of the estimated parameters.

The objective in the design phase is to reduce sources of inconsistency and bias associated with the error component in order to improve the quality of responses and hence generate more efficient model estimates. Therefore, it is essential that the respondent understands the tasks and the complexity of the experiment itself is

minimised. In light of these inadequacies, Ortuzar and Willumsen (1994) propose that stated preference experiments should be validated by preliminary revealed preference research. The above mentioned authors derived a mixed estimation model, which integrates both methods. Results showed that sequential and simultaneous integration of both methods produced ρ^2 values of 0.175 and 0.165 respectively, compared to values of 0.17 and 0.12 for the separate stated preference and revealed preference models respectively. The ability to construct parallel revealed preference and stated preference experiments depends not only on time and cost but also on the extent to which a revealed preference model can validate stated preference outcomes.

Yoo (1995) in an analysis of Korean air passengers choice behaviour, similarly compares results generated by a stated preference model with that of a revealed preference model.

The author found that given higher margins of response error associated with the stated preference model, the revealed preference technique generated parameter estimates that were more statistically significant. The author estimates values of in-flight time of US$59 per hour for business passengers and US$48 per hour for non-business passengers using the stated preference model. The revealed preference approach yields values of US$43 and US$ 41 per hour for business and leisure passengers respectively. One particularly interesting observation of the results generated by the author is the significant difference in coefficient *t*-ratios between both methods. The revealed preference approach yields *t*-ratios that are significantly lower than those generated by the stated preference approach. For example, in-flight time coefficient *t*-ratios of -2.7 and -22.6 are generated by the revealed and stated preference (business passenger) models respectively. Although the high stated preference coefficient can be partially explained by the segmentation of the sample, the large difference is mainly due to the fact that passengers are restricted to evaluating four product attributes. Whereas, in the case of the revealed preference model, actual choice behaviour was influenced by factors other than those considered by the author. However, overall model statistical significance is lower for the stated preference model because of the greater magnitude of error that is inherent in responses to hypothetical choices.

Having examined the advantages and disadvantages of using revealed and stated preference methods, and given the nature of the research problem, stated preference analysis was found to be the most appropriate method to estimate the choice model parameters.

3.7 Summary and Conclusion

The main points covered in Chapter three are summarised below;

- Passenger choices whether it be choice of mode of transport or departure time tend to be more probabilistic than deterministic, in that passenger choice behaviour is subject to random influences.
- The logit model was selected in preference to the probit model as the most appropriate behavioural choice model for this study.
- There has been a notable absence of research into a more rigorous analysis of passenger choice of departure time particularly within an airline market context.
- In measuring or estimating the convenience or attractiveness of an airline schedule, research on passenger choice behaviour has tended to focus on the level of frequency as a significant factor. Whilst this is indeed valid, these studies do not provide relevant information regarding the convenience of individual departure times, which is probably more important for airlines aiming to optimise the attractiveness of their schedules.
- In terms of estimating model parameters, available techniques include revealed and stated preference analysis.
- Whilst there are advantages to using revealed preference techniques over stated preference, because of the hypothetical nature of the choice process, stated preference analysis was preferred to the revealed preference approach.

The following chapter focuses on the use of stated preference analysis to generate the required parameters necessary for passenger choice model calibration. The choice probabilities generated by this model, will then form the basis from which slot values will be estimated.

CHAPTER 4

Stated Preference Experimental Design And Simulation

4.1 Introduction

Having selected stated preference analysis as the most suitable parameter estimation technique, chapter four outlines the sequence of steps involved in stated preference experimental design. The first section focuses on the following experimental design-related issues: exposition of the theoretical framework, selecting appropriate product attributes (independent variables), defining the number of levels of each attribute, and finally, choosing an appropriate number and combination of choice sets. The second section defines a method of measuring passenger responses to the stated preference choice sets, since this will represent the dependent variable in the parameter estimation process. The third section considers the various steps involved in selecting the most appropriate combination of choice sets. This is followed by the final section of chapter four, which seeks to identify, through a process of response simulation, the experimental design which is expected to yield the most efficient and statistically significant parameter estimates.

4.2 Issues in experimental design

4.2.1 Choice of travel context

In seeking to estimate passengers' valuation of schedule delay time, the experiment involves the presentation of hypothetical travel alternatives to a sample of passengers on a given city-pair market. Each respondent is asked to choose between their current journey and a series of hypothetical alternatives. Before designing the experiment, the first step involves selection of an appropriate city-pair market from which to obtain the passenger sample.

An essential prerequisite to developing accurate and robust stated preference parameter estimates, is that the hypothetical values attached to each product attribute should appear realistic and plausible to each individual respondent within the sample. Implicit in this realism, is a recognition that, given the highly segmented nature of air transport demand, prior knowledge of existing city-pair demand characteristics is

required. These are; trip purpose (percentage split between, business, leisure, etc.), fares levied, proportion of non-UK passengers, proportion of transfer or interline passengers, and the number and timing of daily flights supplied by the operator.

Trip purpose could either be; visiting friends and relatives, returning from a business trip, or travelling on holiday etc. Given the nature of each trip purpose in terms of the extent of time constraint involved, values of schedule delay time will inevitably differ between passengers across the sample. For instance, corporate travel behaviour tends to be relatively more sensitive to increases in schedule delay time compared to leisure trips. Given the potential variation in passenger characteristics that is likely to exist within a sample, it is crucially important to identify features specific to the city-pair market selected, in order to ensure that the hypothetical travel options presented are both realistic and relevant to respondents. In achieving this objective, any stated preference design which is able to incorporate these features, can therefore accommodate wide variations in values of time across the passenger sample.

In setting hypothetical fare levels, it is necessary to identify how much passengers are currently paying on a given route. Substantial price discrimination implies that airlines levy a structure of fares set on the basis of maximising yield from different market segments. However, within highly competitive markets, the number of different fares will be of such a magnitude, that it would be almost impossible to customise a design to each individual passenger without the use of appropriate computer software. Consequently, one is therefore restricted to routes associated with a limited number of fare levels. Simplistic fare structures are usually levied on short-haul regional city-pair markets usually served by one carrier, where there is less product differentiation.

The units of measuring fare values will influence the suitability of a specific city-pair market particularly in cases where a significant proportion of passengers pay their fares in non-UK currency. Some of these passengers may have a fairly limited grasp of the English language, and would therefore find some difficulty in understanding the choice task. Furthermore, given their relative unfamiliarity with British currency units, a large number of these passengers could perhaps incorrectly perceive fare levels attached to each option. These two sources of error would introduce additional

bias and inconsistency in to each response, ultimately affecting the statistical significance and efficiency of the model estimates. In the absence of customised designs, analysis is restricted to domestic routes where the vast majority of passengers pay their fares in sterling. This ensures that sources of response bias are minimised and the time taken to complete each interview is effectively minimised.

Choice of route is further restricted to avoiding those city-pair markets associated with significant numbers of transferring passengers, i.e. those passengers who either started their journey on other flights and those who are transferring onto onward connecting services at the destination. Transferring passengers, given that their journeys involve more than one flight, will pay fares that are, in many cases, considerably greater than those levied on single flight segments. Without prior knowledge of the origin of each transfer passenger, hypothetical fare levels customised to origin destination travel would appear largely irrelevant, firstly because of the scale of fares, and secondly, the departure times offered may not be plausible given the arrival time of the inbound flight. Therefore, in order to avoid these problems, routes associated with significant levels of transfer traffic were not considered.

In order to comply with the aforementioned guidelines, the choice of passenger sample was restricted to analysis of short-haul domestic routes operating out of Manchester airport. It would have been, perhaps, more suitable to model passenger choices from either London Heathrow or London Gatwick, since both these airports are more slot constrained than Manchester. However, a high degree of design customisation would have been required to incorporate large numbers of both transfer and non-UK resident traffic at these alternative airports. Furthermore, in the case of non-UK resident passengers, language problems and unfamiliarity with British currency units would probably adversely affect the reliability of passenger responses.

The city-pair market that was chosen generally conforms to these specifications but cannot be identified for reasons of commercial confidentiality. Therefore, the selected city-pair market will be referred to as route *x*, the characteristics of which are outlined below.

- Similar percentage split between corporate and discretionary travel (CAA 1993b)
- Fares levied are within the range £130-£85 for return trips (ABC 1994b)
- Proportion of non-UK passengers travelling on route *x* is negligible
- Limited number of transfer passengers and onward connecting opportunities at the destination airport.(ABC 1994a)

Having identified the most suitable city-pair market in which to obtain the passenger sample, the next step involves the design of the experiment.

4.2.2 Choice of product attributes.

According to Bradley (1988), the choice of which product attributes to evaluate must include those that are considered to be the most important in relation to the context of the research. In addition, Swanson et al (1993) and Kroes and Sheldon (1988) suggest that, in order to keep the exercise within manageable proportions, and to optimise the reliability of each response, a maximum of three variables is generally advisable for stated preference experiments.

In estimating values of schedule delay time, a variable measuring the cost of the journey would have to be included in the experiment. Since, any departure time offered other than the current time will be associated with a degree of inconvenience and disutility, depending on the extent to which the actual flight corresponds to the respondent's ideal departure time. Therefore, in order to encourage a passenger to switch preferences from the current flight to the alternative hypothetical option, the respondent would have to be offered a compensating reduction on their current fare. In representing the fare variable, the researcher has a choice of either measuring it as a percentage reduction from the current fare, or as a decrease in absolute terms. By expressing the variable as a percentage reduction, the design will be more customised to passengers who pay different fares. However, given the mental arithmetic involved in calculating fare levels after taking into account a percentage reduction, it was thought more desirable to express fare reduction as an absolute value subtraction from the current fare.

The inconvenience associated with each alternative departure time represented by schedule delay time, measures the absolute difference between a passengers ideal departure time and the time where a flight is scheduled by the air transport operator. In order to obtain responses, passengers are expected to be sampled at the actual time of departure. Therefore, since a passenger's ideal departure preference is not known *a priori*, it has to be assumed that the actual departure time provided corresponds to the passenger's ideal time. This can, in some cases, be a misleading assumption to make, particularly in low service frequency markets where an airline is operating only two or three flights per day. Because, under these circumstances, it is almost impossible to tell whether passengers are travelling at their ideal times. On the other hand, on high frequency markets of say eight flights per day, passengers have a much greater choice of departure times and hence are able to select their optimum preference. Therefore, one can assume, with a greater degree of confidence, that the passenger is travelling at his or her preferred time. Routes associated with low frequency services were avoided and only those with high frequencies considered.

The selection of which product attributes to include in the experiment will depend on their relevance to the choice scenario. Both fare reduction and schedule delay time will enable monetary values of schedule delay time to be estimated. However traditionally, stated preference experiments do tend to involve more than two variables. The inclusion of an additional variable specifically time-related, will not only enable monetary values of this variable to be estimated, but will also enable one to evaluate the degree of interaction between schedule delay time and the additional time-specific variable. By including a variable representing journey or in-flight time, it would be possible to estimate trade-off information between schedule delay and in-flight time. For example, an individual respondent, for reasons of personal taste or time constraints, may not be tempted to reject the current flight in favour of a hypothetical alternative associated with a fare reduction of £10 and a schedule delay time of 1 hour. However, given say a reduced journey time of 20 minutes, the respondent may be willing to accept the alternative option. Therefore, in this instance the passenger places a high value on saving additional units of in-flight time compared to schedule delay time. The inclusion of journey time as an additional

product attribute would be represented as a change from current journey times and could provide potentially useful information on the relationship between schedule delay and in-flight time as well as adding value to the research. The product attributes selected for evaluation are; fare, schedule delay time and in-flight time.

Having identified the product attributes, the next step is to specify the theoretical framework which is assumed to govern passenger choice decision rules.

4.2.3 Theoretical framework

In seeking to establish a theoretical framework, the precise relationship between behavioural response and those product attributes considered requires specification. Respondents to the questionnaire are assumed to have a choice between the current journey which is fixed in terms of product attributes and a hypothetical option. Choice is determined by the perceived utility of each alternative. Utility is represented by a model which is linear and additive in the combination of product attribute levels as shown below.

$$U_i = \beta^f f_i + \beta^{sd} sd_i + \beta^t t_i \qquad (4.1)$$

$$U_j = \beta^f f_j + \beta^{sd} sd_j + \beta^t t_j \qquad (4.2)$$

Equations 4.1 and 4.2 represent the utility functions for both the current and hypothetical flight alternatives, where U_i and U_j measure the perceived utilities associated with the current flight i and alternative flight j respectively. Product attributes f, sd, and t represent fare, schedule delay time and in-flight time respectively. Whilst β^f, β^{sd} and β^t are parameters associated with each of the product attributes specified. These represent the weight or relative magnitude of each product attribute within the utility function.

In seeking to estimate the utilities of each alternative, it is established practice within the field of transportation choice modelling to measure utility in terms of common and recognisable units, such as money or time. This is achieved by calculating the generalised costs of travel for each choice alternative. Out of the three variables in the utility function, two are expressed in units of time and one in units of fare. In order to express the generalised cost of travelling in money terms, both time variables need to

converted to units of money. This is achieved through dividing the time parameters β^t and β^{sd} with the fare parameter β^f as shown below.

$$\alpha^{sd} = \frac{\beta^{sd}}{\beta^f} \qquad \alpha^t = \frac{\beta^t}{\beta^f} \tag{4.3}$$

The generalised cost of travel, measured in units of money, for both travel alternatives, *i* and *j*, is therefore:

$$GC_i = f_i + \alpha^{sd} sd_i + \alpha^t t_i \tag{4.4}$$

$$GC_j = f_j + \alpha^{sd} sd_j + \alpha^t t_j \tag{4.5}$$

Given that choice of flight is assumed to be based on the differences in the generalised costs of each option, for estimation purposes, generalised costs are expressed as differences between the current flight and hypothetical alternative as shown below.

$$GC_i - GC_j = f_i - f_j + \alpha^{sd}[sd_i - sd_j] + \alpha^t[t_i - t_j] \tag{4.6}$$

The basic decision rule governing passenger choice behaviour within the context of departure time choice is as follows:

If $GC_i > GC_j$ then choose alternative flight

If $GC_i < GC_j$ then choose current flight

If $GC_i = GC_j$ then indifference

These decision rules state that under purely deterministic behavioural assumptions, passengers are assumed to prefer the current flight, provided the generalised costs associated with the current flight are less than that associated with the alternative flight and vice versa. In addition, the passenger is said to be indifferent between options when the generalised costs are equal. The generalised costs associated with each choice will depend on the levels associated with each product attribute and on the money values of schedule delay and in-flight time.

4.2.4 Attribute levels

The choice sets presented to each respondent represent the different combinations of product attribute levels. The number of levels associated with each attribute will ultimately determine the number of choice sets in the experiment. According to Fowkes and Wardman (1988), in order to keep the experiment within manageable proportions, careful consideration must be given to the number of levels attached to each variable, given that respondents are only able to accurately evaluate a limited number of alternatives at any one time. Kroes and Sheldon (1988) suggest a maximum of sixteen choice sets.

The total number of choice sets is obtained by raising the number of levels to the power of the number of product attributes. For example, three attributes each represented by two value levels will generate a total of eight choice options (2^3). A different design associated with two three level attributes and two two level attributes would generate 36 choice options ($3^2 \times 2^2 = 36$). As mentioned earlier, a maximum of sixteen choice sets is considered desirable for stated preference experiments.

Implicit in optimal experimental design is the specification of realistic attribute levels, achieved, according to Anderson et al (1986) and Hensher et al (1988), through representing the hypothetical options as a change from present circumstances. In this case, the passenger is assumed to have a choice between their current journey characterised by a known fare level, departure time and in-flight time versus an alternative choice, with hypothetical values attached to each of the three product attributes. According to Bradley (1988), specification of attribute levels is based on obtaining values at which respondents are willing to trade preferences between the current flight and a hypothetical alternative, since it from trade-off information that values of time are estimated. In order to obtain values of both schedule delay and in-flight time, the fare variable would have to be entered at several levels. However, it is necessary to exercise caution in choosing attribute levels which are well outside the range of both current experience and realism. Indeed, given a high degree of market segmentation in air travel and a wide range of possible values of time, sufficient variation in the attribute levels would be necessary in order to produce meaningful behavioural responses, and therefore quality trade-off information. The values

attached to these levels depends on the likely point at which the passenger is willing to trade between options. The passenger essentially has a choice between the current journey and an alternative flight which is cheaper, operates at a different departure time and is associated with a different flying time. For example, a range of £2, £5, £8 and £11 fare reductions would probably encourage trade-off behaviour amongst low income discretionary travellers, whereas in the case of corporate passengers, generally associated with relatively time-constrained trip schedules, these fare reductions may not encourage sufficient trading between preferences. Therefore, while leisure passengers would be willing to trade additional schedule delay or in-flight time in return for low reductions in fare, the majority of corporate travellers would probably consistently choose the current flight in preference to the hypothetical alternative. Under these circumstances, since no substitution is effectively taking place, statistically biased value of time estimates will be generated. Clearly, the objective must be to derive values which can encourage trade-off behaviour between choices from a wide range of possible values of time.

On route *x*, the two full-flexible economy return fares fall within a range between £120 and £100. Without knowledge of the precise proportion of passengers selecting an individual fare type, fare reduction levels would have to be introduced which were capable of encouraging trade-off's from any value within the range. Although it would be possible to provide different questionnaires to both high and low fare paying passengers, in the interests of maintaining an acceptable sample size, fare levels generated would be applicable to all respondents.

The number of levels associated with the fare attribute will depend on the maximum number of choice sets permissible in the experiment. Entering the variable at four equally spaced intervals would ensure that both a sufficient range of values of time would be captured and the number of choice sets could be kept within the manageable number of eight. The essence of attribute level determination is realism in the range of levels and in the values themselves. For example offering reductions of say £20, £30 £40 and £50 would be unrealistic and implausible since these levels would correspond to economy return fares of say £65, £55, £45 and £35, which are significantly below minimum fare levels expected in terms of today's prices and in

terms of fare levels experienced on similar routes. Indeed, the danger associated with specifying cheap fares of such a magnitude is that little trading will effectively take place since the majority of passengers may select the hypothetical alternative when evaluating each paired comparison, regardless of schedule delay and in-flight time levels.

Having specified four intervals of fare reduction, the number of levels associated with both schedule delay and in-flight time is very much restricted to two levels. Firstly, because of the need to reduce the number of choice sets so as to keep the experiment within manageable proportions, and secondly, to ensure that the hypothetical values are realistic, plausible and capable of encouraging trade-off behaviour. Units of schedule delay time can be expressed in either minutes or hours. The hypothetical levels that were selected involved schedule delay times of 30 minutes and 1 hour from the current flight. Any degree of schedule delay time lower than 30 minutes, was deemed to make little difference in inconvenience terms, compared to the actual departure time. Furthermore, by specifying a low level of schedule delay time, passengers may be too willing to accept the alternative cheaper option, therefore adding substantial bias to the responses. The upper limit was set at 1 hour. Any level beyond that, it was felt that only a limited degree of trading would take place given the high degree of disutility involved. Given the characteristics of the route under analysis, in particular, the nature of passenger trips particularly within the business travel market, it was decided that alternative departure times beyond one hour would not generate the sufficient trade-off behaviour that is required. Similarly, specification of hypothetical journey times was restricted to two levels, primarily because of the need to recognise what is achievable in terms of potential flight time savings and additions. Alternative journey times basically represent flying times associated with alternative aircraft types. The two levels represent a time saving of 20 minutes on a 1 hour flight, through the introduction of one of the new generation of fast regional jets and a 20 minute addition to existing travel time through the introduction of a smaller turboprop aircraft, with reduced speed and travel time capabilities. The levels themselves are achievable and were set at a magnitude in order to encourage trade-off behaviour. Alternative journey times involving an

increase and decrease of 10 minutes was felt to be two low and insufficient to generate trade-off behaviour. Table 4.1, on the following page, summarises the variables and levels associated with the hypothetical travel alternatives.

Given the attribute levels specified in Table 4.1, the maximum number of combinations of each attribute or choice sets is 16 (4^1 x 2^2). Appendix A lists the total number of choice sets generated from the specified product attributes and the number of levels attached to each product attribute.

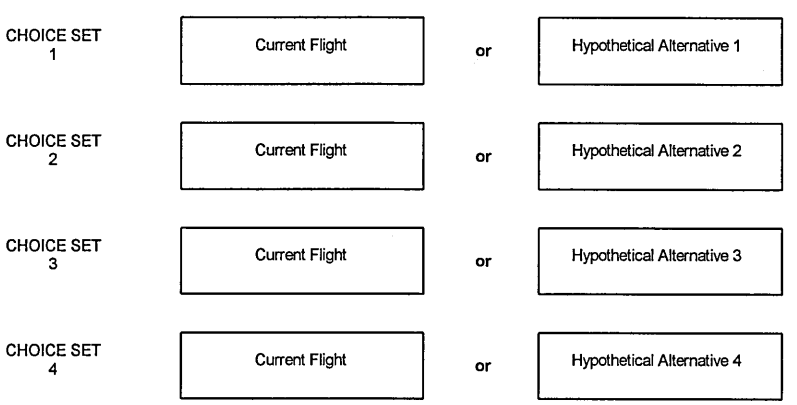
The format of the experiment involves the presentation of paired choice sets to each respondent. One alternative, which describes the product attributes of the current journey remains fixed.

Table 4.1: Product attribute levels

	fare (£)	schedule delay time (minutes)	in-flight time (minutes)
level 1	-10	30	20
level 2	-15	60	-20
level 3	-20		
level 4	-25		

The second alternative represents the characteristics of the hypothetical journey, which takes on a variety of product attribute combinations as shown below.

Figure 4.1: The choice process



In order to estimate the relative utilities associated with each alternative, it is necessary to establish a method of measuring passenger responses. Each response represents the dependent variable in the statistical estimation process. There are three

methods of measuring responses to stated preference experiments: discrete choice, ranking and rating.

4.3 Measuring responses

4.3.1 Discrete choice

The discrete choice method requires the respondent to either select one option from a pair of alternatives. The response, for example, could be a simple choice between Option A and Option B. For statistical estimation purposes, the response must take on a numeric value. Although there is no firm evidence which suggests that different numeric values generate more efficient model parameters, it is established practice within stated preference research to apply values of 1 and 0. Bradley (1988) and Hensher et al (1988) suggest that the discrete choice method offers the simplest and most effective means of analysing responses. Indeed, as Louviere (1988) points out, discrete choice designs, in which the individual simply selects the most preferred option from a pair or group of alternatives, is entirely consistent with the goal of achieving as much realism and simplicity as possible in the exercise. Through simplification of the task to a discrete choice response, experimental efficiency is increased through firstly, reducing the time respondents take in evaluating alternatives, and secondly, through enabling the researcher to introduce a greater number of choice sets to each respondent.

4.3.2 Ranking

Ranking involves the presentation of each individual alternative at once to the respondent who is then asked to rank them in order of preference. Besides being a relatively straightforward task, the advantage of the ranking method is that all options are considered simultaneously. Nevertheless, in ranking each alternative, the researcher is very much restricted in the number of choice options that can be offered without the respondent becoming fatigued. Therefore, it is generally considered that the respondents are asked to evaluate no more than eight choice alternatives.

4.3.3 Rating

Rating responses require the individual to express the strength of their preferences based on either a numeric or semantic scale. Within the context of a paired comparison, respondents are asked to indicate the strength of their preference, such as: definitely choose option A, probably choose option B etc. Alternatively, the passenger could be asked to score each alternative out 10. However, as this is not the exact process involved in choosing between real options, rating can be criticised for being too artificial and unrealistic. One advantage, nevertheless, is the ability to transform each response into plausible probabilities of choice. An example of which is the use of a five point semantic scale by Bates (1984) in estimating choice probabilities between rail and coach for commuting traffic between North Kent and Central London.

4.3.4 Choice of response measurement scale

In evaluating the effectiveness and applicability of each response measurement technique, a number of issues need to be taken into consideration. Firstly, which method can provide the most reliable responses ? and secondly, to what extent can existing statistical estimation techniques be used to analyse responses ? The discrete choice method can provide, according to Bradley (1988), the most reliable responses given the relative simplicity of the task respondents are asked to undertake, a simple choice between two alternatives. This is particularly appropriate in cases where passengers are asked to evaluate paired alternatives. However, in terms of statistical estimation, the researcher is constrained in the sense that least squares regression

cannot be used to estimate discrete choices. Software programmes such as the ALOGIT package, are specifically designed for stated preference parameter estimation and can estimate from discrete choice responses through maximum likelihood. Ranking response measurement techniques whilst adaptable, in the sense that responses can be analysed using least-squares regression, are generally not considered sufficiently response reliable. Firstly, the researcher is limited in the number of choice alternatives that can be presented, given a greater tendency for respondent fatigue, which is a feature of ranking choice options. Secondly, the time consumed to complete the task tends to be greater compared to both discrete choice and rating techniques. Indeed, given that passengers will be surveyed in an airport departure lounge, the number of passengers sampled at each flight may in fact be lower than if each passenger completed either a discrete choice or rating design. Given expected experimental conditions in the airport departure lounge, it was considered in the interests of both reducing the time taken to complete each questionnaire and in the interests of maximising sample size to reject the ranking technique.

Rating each alternative appears to be the most appropriate method in this particular case, for two reasons. Firstly, because of the fact that the dependent variable is expressed as five discrete intervals, as opposed to two in discrete choice, this is a more refined method of measuring the dependent variable and likely to generate a greater degree of statistical significance in the estimated parameters. Wardman (1988), who was involved in the North Kent commuter choice of mode study (Bates 1984), found that the rating method produced more satisfactory *t*-ratios than discrete choice. Indeed, the author also found that values of time obtained by the rating response scale were similar to those obtained using the discrete choice method. Secondly, the time taken to complete the task was judged acceptable in terms of experimental conditions likely to prevail at the survey location. However, it was important to acknowledge deficiencies associated with the rating method. Indicating strength of preference is a highly judgmental and subjective process. In reality, passenger choice decisions will tend to conform to discrete choice processes. However, it is indeed difficult to indicate strength of preference for a particular choice alternative. This potentially

could introduce additional sources of bias into each response, which may ultimately affect the statistical significance of the model estimates. Discrete choice on the other hand, effectively removes, this source of response bias by reducing the choice process to a simple decision of selecting one alternative over the other.

The issue of selecting an appropriate method of measuring responses will be further explored in the next chapter, where results obtained from the rating method will be compared to parameters obtained under discrete choice.

Selecting the precise form of response scale whether numeric or semantic will depend primarily on the analytical technique used to estimate the required parameters and on the need to eliminate or minimise potential sources of statistical bias in each response. The passenger, in evaluating each choice on the basis of a rating scale, will be asked to indicate their strength of preference for a particular option. Therefore, on the one hand the respondent could be asked to score each hypothetical alternative in terms of the current journey out of 10 or 100. Alternatively, the experiment can be treated as a paired comparison between the current journey and a hypothetical choice option whereby the respondent is asked to represent the strength of their preference on a semantic scale such as: definitely choose the current option, probably choose the current option etc. Within this context, the task of evaluating each response becomes highly judgmental, particularly in cases where respondents are asked to score each alternative. Past research tends to favour the five point semantic scale as described by Bates (1984), Black and Towriss (1993) and Bradley (1988). In these examples, respondents were asked to measure both alternatives in each choice set, on the basis of the following five-point scale:; definitely prefer A, probably prefer A, cannot decide, probably prefer B and definitely prefer B. Representing a dependent variable within the statistical estimation process, numeric values can be assigned to the semantic scale. However, established practice is to measure each response as a choice probability as described by Kroes and Sheldon (1988) and illustrated below.

Table 4.2: Response measurement scale

choice response	Scale
definitely choose current flight	0.1
probably choose current flight	0.3
indifferent / cannot decide	0.5

probably choose alternative flight	0.7
definitely choose alternative flight	0.9

One can assign a wide range of equally spaced numeric values to the semantic utility scale. For example using values 1 to 5 is unlikely to make an appreciable difference to the estimated values of time. However, since it is the probabilities that are being estimated, expressing the scaled utility values as choice probabilities, enables one to perform the necessary linear transformation in order to generate appropriate model parameters. This method of linearisation derived by Berkson (1953) will be described in the following chapter. Having identified the attributes in terms of numbers and levels, and having selected the most appropriate response measurement scale, the next step is to identify how many, and which of the sixteen possible choice sets to include in the experiment. The next section seeks to evaluate the effectiveness and suitability of two different choice set combinations within the context of simulating responses. The issue of response simulation is an essential prerequisite to ensuring that the design is able to generate the most accurate and statistically unbiased estimates of the values of both schedule delay and in-flight time.

4.4 Choice set design

4.4.1 Boundary values

According to Black and Towriss (1993), there are two basic and fundamental requirements regarding stated preference design. Firstly, they should aim to ensure that respondents are able to understand the choices presented and appraise their relative merits, and secondly, the choice sets should aim to avoid bias in the estimated parameters and seek to minimise the standard errors of those parameters. Furthermore, and crucial to obtaining statistically significant estimates, the design should be able to elicit trade-off behaviour from the majority of passengers from a sample that potentially may have large variations in values of schedule delay and in-flight time. The choices presented should be relevant to both passengers with high and comparatively low values of both schedule delay and in-flight time.

Since it is from trade-off information that parameter estimates are obtained, attention focuses on the conditions under which a passenger's choice of flight will change.

This trade-off occurs at those values of time, at which according to Fowkes (1991), passengers are indifferent between the current and alternative flight i.e. when the generalised costs of travel between the current flight *i* and the alternative flight *j* are equal.

$$GC_i - GC_j = 0 \tag{4.7}$$

This point of indifference is commonly referred to as a boundary value. For each paired comparison, a boundary line exists which represents those values of both schedule delay and in-flight time at which respondents are indifferent between both options. Therefore, individuals are indifferent between the current and alternative flight when;

$$f_i + \alpha^{sd} sd_i + \alpha^t t_i \quad = \quad f_j + \alpha^{sd} sd_j + \alpha^t t_j \tag{4.8}$$

For each paired choice set, values of schedule delay time consistent with generalised cost indifference can be obtained by inputting a range of values of in flight time into the following equation.

$$\alpha^{sd} = -\left[\frac{f_i - f_j}{sd_i - sd_j}\right] - \alpha^t \left[\frac{t_i - t_j}{sd_i - sd_j}\right] \tag{4.9}$$

The range of values of in-flight time to input will depend on the degree of *a priori* knowledge of established values of in-flight times empirically derived from past research. However, in the absence of this information, a range of between £0 and £50 can be substituted into the equation to obtain a set of values of schedule delay time consistent with choice indifference. Therefore, for the each paired choice option, combinations of both α^{sd} and α^t can be obtained, which represent the point of indifference between the current and hypothetical alternatives. These points of indifference or boundary lines are illustrated in the example shown on Figure 4.2 on the following page.

Each passenger is assumed to possess a value of schedule delay time and a value of in-flight time. However, these values are unknown. Therefore, as Fowkes and Wardman (1988) advise, an essential prerequisite to efficient statistical estimation is that the boundary lines associated with each paired comparison should cover all

possible combinations and ranges of both schedule delay and in-flight time. On the other hand, if the researcher can anticipate with a sufficient degree of confidence that values of time will fall within a particular range as in the case of research by Black and Towriss (1993), then the levels of each product attribute, and the choice sets and boundary lines can be readjusted accordingly. In order to illustrate the concept of boundary value maps, the reader is referred to Figure 4.2 on the following page, which describes a sample of three boundary lines associated with choice sets 1,6 and 8, obtained from Appendix A and shown on Table 4.3. The boundary values were derived from equation 4.9 and are based on an input range of α^t of between £0 and £50 per hour.

Assume that a passenger possesses a value of schedule delay time of £20 per hour and value of in-flight time of £30 per hour, illustrated as point A on Figure 4.2 below. In evaluating each of the three choice options, the passenger finds that with respect to choice 6 he/she is indifferent between the current and alternative flights. This can be verified by calculating the difference in generalised costs from equation 4.8.

Table 4.3: Sample choice sets

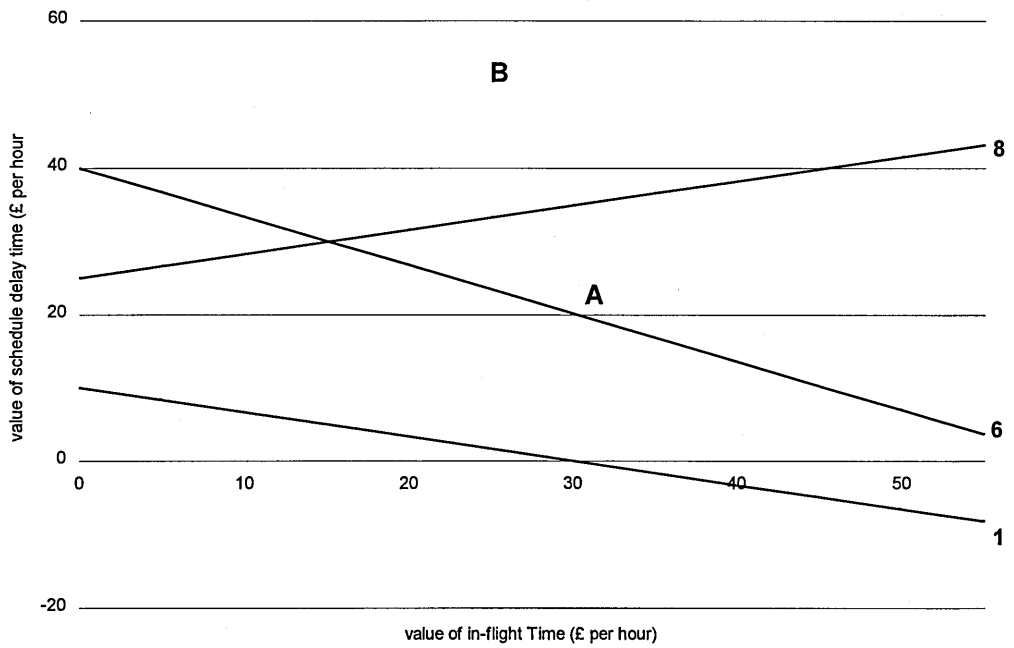
Choice set	f_i-f_j (£)	sd_i - sd_j (min)	t_i - t_j (min)
1	-10	-60	-20
6	-20	-30	-20
8	-25	-60	20

The boundary lines illustrated in Figure 4.2, correspond to those combinations of α^{sd} and α^t that are consistent with equal generalised cost between both the current and alternative flights.

In evaluating choice 1, the passenger elects to choose the current option. Firstly because, given a schedule delay time of 1 hour and increase in in-flight time of 20 minutes, the fare reduction offered is insufficient enough to tempt the passenger to select the alternative flight. The generalised costs associated with this flight are £20 higher than the current option. By contrast, in evaluating choice 8, the passenger selects the alternative flight. This is because, the inconvenience caused by the 1 hour in schedule delay time is sufficiently compensated by a £25 reduction in fare and 20

minute cut in journey time. Therefore, the generalised cost associated with the alternative option is lower than that associated with the current flight.

Figure 4.2: Sample choice set boundary values



Observation of Figure 4.2 and more specifically point B suggests that if a passenger's α^{sd} and α^{t} combination lies above the boundary line, then the respondent prefers the current flight, whereas if the point is below the line of indifference, the passenger selects the alternative option. In evaluating each of the three options, passenger preferences alternate between flight choices. Values of time are estimated through respondent trading between preferences as they are effectively crossing lines of indifference.

However, for some passengers, their respective combinations α^{sd} and α^{t} may lie outside the range of boundary lines as in the case of point B. In this instance, the passenger has not traded preferences between flights but has consistently selected the alternative flight. Therefore, since no trade-off information is recorded, statistical estimates will be biased since it could not be possible to ascertain which factors influenced the individuals choice decision. Therefore, the implications are that if the researcher has little knowledge of the likely range of values of time, then boundary lines should aim to cover as much of the map as possible. On the other hand, if the researcher can anticipate that passengers are likely to have combinations of α^{sd} and α^{t}

within a given range, then the product attribute levels should be changed so that the boundary lines intersect the relevant parameter space.

The maximum number of boundary lines in this experiment are the choice sets which embrace all possible combinations of fare reduction departure time and in-flight time. However, given then the need to minimise response fatigue, the number of choice sets and hence boundary lines must be restricted to less than 16. This poses a particular problem given the need to cover as much parameter space as possible. For example, referring to Appendix B, all possible boundary lines are included in the map. This illustrates the fact that with a full factorial design, most of the parameter space is covered. In light of the requirement to maintain the number of choice sets within manageable proportions, strategies need to be considered which are designed to reduce the number of choice sets. There are basically two types of strategies for reducing the number of choice sets and both have implications regarding the likely quality of responses and statistical significance of model parameter estimates. Constructing a fractional factorial design which ensures complete orthogonality (zero correlation between product attributes) and a random design which is selected to ensure that the boundary value lines intersect the relevant parameter space.

4.4.2 Boundary values versus orthogonality

Most commentators on stated preference analysis conclude that orthogonality is one of the most desirable properties associated with stated preference designs. One factor which will influence statistical significance of the parameter estimates is the degree of correlation between product attributes. Substantial correlation between attributes such as fare and schedule delay time would introduce additional bias in the standard errors of the correlated product attribute coefficients. An example of non-orthogonality would be if higher fare reduction levels were associated with higher levels of schedule delay time and conversely, low fare reduction levels were associated with lower levels of schedule delay time within specific choice sets. Such degrees of correlation would make it very difficult to identify the individual effects of each product attribute since both are strongly correlated. As a consequence, through introducing additional bias in the standard errors, the resultant parameter estimates may in fact be statistically insignificant at the 99% confidence level measured by their *t*-ratios or the signs of

each of the coefficients may deviate from *a priori* assumptions. On the other hand, an orthogonal design through eliminating or avoiding correlation between product attributes, will ensure that the individual effects of each variable can be identified.

However, by randomly selecting choice sets to ensure adequate boundary value coverage, this may introduce a degree of correlation into the design. Bradley (1988) suggests that there is a trade-off between efficient boundary lines and orthogonality. In that whilst a purely orthogonal design may reduce sources of estimation bias, the boundary values associated with such a design may not efficiently cover the relevant parameter space. Conversely a random design selected on the basis of adequate coverage of potential value of time combinations may in fact be highly correlated in terms of the product attributes. Whilst recognising that there appears to be an inherent conflict between orthogonality and efficient boundary lines, Fowkes and Wardman (1988), attempt to resolve this problem by suggesting that non-orthogonal designs based on efficient boundary vales may be an advantage. Furthermore, Bradley (1988) claims that a degree of orthogonality or low level of correlation between certain product attributes is a highly desirable property, in that the statistical significance associated with the estimated parameters may in fact, be greater in magnitude than that achieved through a purely orthogonal design.

The only means of testing these arguments is to select from the sixteen choice sets specified in Appendix A, a fractional factorial orthogonal design and a random design which focuses on efficient boundary value coverage. Once the designs have been selected, it is then possible to simulate the responses to each design and then assess the extent to which each design minimises bias in the parameter estimates. Design simulation is an important element in the process of developing stated preference experimental design and has sometimes been neglected in previous studies. One example of the use of design simulation was that applied by Holden (1991), in which the author measures the efficiency of three stated preference designs by simulating responses on the basis of assumed values of in-vehicle and crowding time and various assumptions regarding the scale of error in responses. In evaluating each design, the author measures efficiency in terms of the percentage variation between the inputted

and simulated values of time and in the magnitude of R^2. The method of simulating the designs is derived from Holden (1991), and is described in the following section.

4.5 Response simulation

4.5.1 Method

In order to examine the efficiency of each design, consider the generalised cost function that is of interest.

$$GC_{ij} = f_j - f_i + \alpha^{sd}\left[sd_i - sd_j\right] + \alpha^{t}\left[t_i - t_j\right] \qquad (4.9)$$

Where GC_{ij} represents the difference in generalised cost between the current flight i and the alternative flight j. As an initial starting point, each respondent is assumed to have the same values of schedule delay time and in-flight time α^{sd} and α^{t}.

The theory of random utility, assumes that there is an element of error within each response, whether it be response fatigue, failure to understand the task or perception errors regarding evaluation of each choice set and product attribute levels. Response error is typically represented by a random element ε attached to the utility function as shown below.

$$GC_{ij} = f_j - f_i + \alpha^{sd}\left[sd_i - sd_j\right] + \alpha^{t}\left[t_i - t_j\right] + \varepsilon \qquad (4.10)$$

The random component ε can be measured in identical units of generalised cost as a standard deviation from the deterministic element. However, specification of the random term requires that assumptions be made regarding its statistical distribution. In line with logit analysis, one would assume that the error term ε is logistically or gumbel distributed across the passenger sample. Since regression analysis is being used, it is assumed that the error term is normally distributed. Ben-Akiva and Lerman (1985) suggest that the normal distribution is a close approximation to the gumbel distribution.

The next step requires that the differences in generalised cost GC_{ij} be transformed to a numeric scale which corresponds to the semantic scale outlined in Table 4.2.

Consider the five point scale; 0.1, 0.3, 0.5, 0.7, 0.9. A response value of 0.5 indicates that the passenger is indifferent between both options. Logically one can assume that

if the differences in generalised costs are zero, the value of the dependent variable will be 0.5. However, the issue assumes more complexity when attempting to derive appropriate transformations when the differences in generalised cost are either greater than or less than zero. One is required, therefore, to specify a range of generalised cost differences consistent with each of the four remaining response scales. This process of establishing an appropriate transformation can become highly subjective in that one would have to ascertain, for example, at what level of GC_{ij} does a probably prefer response become a definitely prefer response. In order to confront this problem, the first step, is to specify what values of the response scale would be consistent with a straight choice decision between the current and alternative flights, based on the differences in generalised cost. If the current flight is selected, then this implies that the generalised cost of the current flight is lower than the alternative. The difference therefore, will be negative. Conversely, if the generalised costs of the alternative flight are lower than the current flight, then the difference will be positive and the respondent will either definitely prefer or probably prefer the alternative. Referring to the response measurement scale in Table 4.2, if the respondent prefers the current flight, the value of the dependent variable will either be 0.1 or 0.3 i.e. when the generalised costs of travel associated with the alternative flight exceed that of the current flight. However, when simulating the responses, the first objective is to calculate the difference in generalised costs associated with each choice set given an inputted combination of α^{sd} and α^{t}. The next step is to transform GC_{ij} into the appropriate values within the five point scale. It has already been established that if GC_{ij} is negative then the respondent will prefer the current flight (selecting either 0.1 or 0.3) and vice versa. However, at what magnitude of difference in generalised cost does a probably prefer selection change to a definitely prefer selection ? As mentioned earlier, this is a highly subjective process. In order to make both the scale and difference in generalised costs as consistent as possible, one approach would be to perform least squares regression on equation 4.9. using both the difference in generalised costs and varying specifications of the response scale i.e. ranges of GC_{ij} differences consistent with each of the five scale values as dependent variables. Inevitably, using generalised cost as the dependent variable the coefficient of determination R^2 will equal 1. Therefore, when using the five point scale as the

dependent variable the objective would be to achieve an R^2 equal to 1. Since any difference between the coefficients of determination would essentially represent bias associated with varying specifications of the response measurement scale.

Table 4.4: Response measurement scale and generalised cost values

choice response	Scale	$GC_i - GC_j$ (£)
definitely choose current flight	0.1	≤ -10
probably choose current flight	0.3	≤ -1
indifferent / cannot decide	0.5	0
probably choose alternative flight	0.7	≥ 1
definitely choose alternative flight	0.9	≥ 10

Table 4.4 above, outlines the differences in generalised cost consistent with the five point response measurement scale.

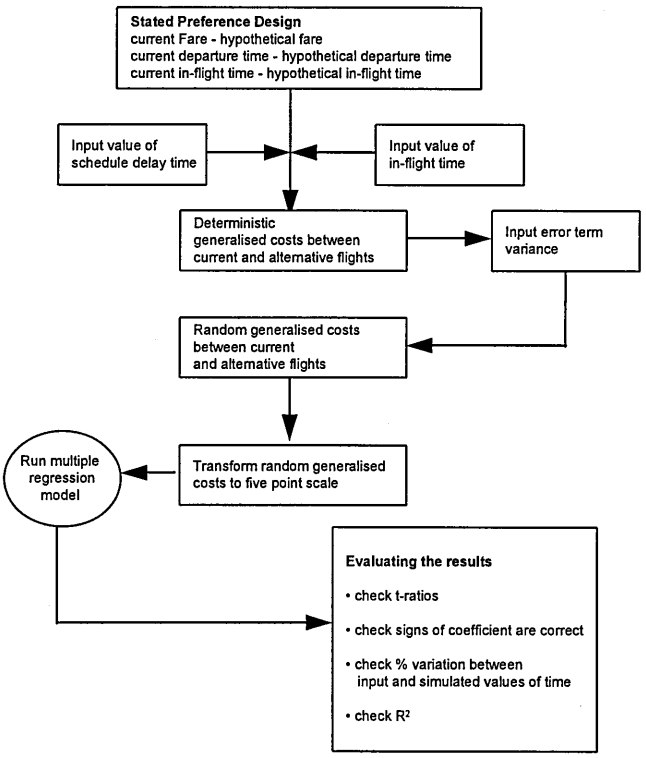
Having transformed generalised cost GC_{ij} to a choice probability scale dependent variable P_{ij}, the following linear regression equation is used to estimate both the simulated values of time α^{sd}_{sim} and α^{t}_{sim} respectively.

$$\begin{aligned}
&\text{if } GC_{ij} \leq -10 \quad \text{then} \quad P_{ij} = 0.1 \\
&\text{if } GC_{ij} \leq -1 \quad \text{then} \quad P_{ij} = 0.3 \\
&\text{if } GC_{ij} = 0 \quad \text{then} \quad P_{ij} = 0.5 \\
&\text{if } GC_{ij} \geq 1 \quad \text{then} \quad P_{ij} = 0.7 \\
&\text{if } GC_{ij} \geq 10 \quad \text{then} \quad P_{ij} = 0.9
\end{aligned}$$

$$P_{ij} = f_j - f_i + \alpha^{sd}_{sim}\left[sd_i - sd_j\right] + \alpha^{t}_{sim}\left[t_i - t_j\right] + \varepsilon \qquad (4.11)$$

Where P_{ij} acts as the dependent variable and takes on any one of five possible values (0.9, 0.7, 0.5, 0.3, 0.1) depending on the difference in generalised cost between the current flight i and any alternative flight j, GC_{ij}. Given inputted values of α^{sd} and α^{t}, the objective is to return simulated estimates α^{sd}_{sim} and α^{t}_{sim} using least squares regression under different assumptions regarding the magnitude of the error term. The closer the inputted coefficients are from the simulated coefficients, the more efficient the design. A flow-diagram is presented below designed to illustrate the processes involved in evaluating the efficiency of stated preference designs.

Figure 4.3: Design simulation flow-diagram



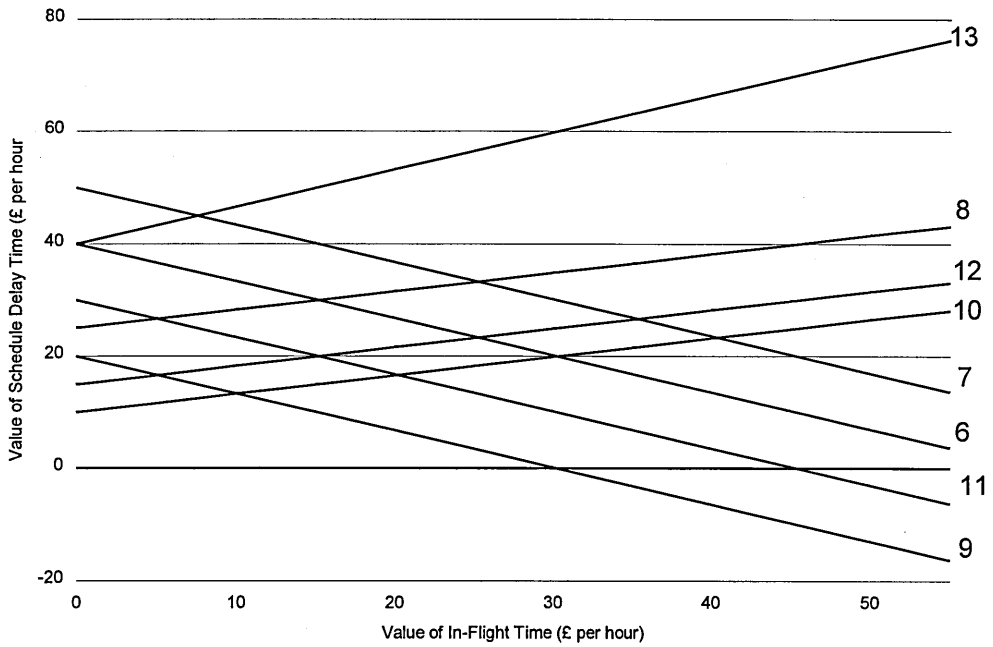
4.5.2 Orthogonal and non-orthogonal design features.

In simulating responses, stated preference allows two potential designs that can be evaluated; orthogonal and non-orthogonal. In examining the suitability of these designs, one immediately confronts the issue of whether orthogonal designs are more efficient compared to those designs that may be more successful at capturing wide variation in values of time, but are associated with a degree of correlation between alternatives i.e non-orthogonal designs. Given, the need to minimise respondent fatigue, but at the same time generate sufficient information from which statistically significant parameters can be estimated, each design is assumed to consist of eight choice sets each. The non-orthogonal design is constructed on the basis of achieving maximum coverage of the boundary value map as shown in Figure 4.4 below.

The choice sets included in the non-orthogonal design are selected from Appendix A and listed separately in Appendix B. They were selected on the basis that the

boundary values derived from these choice sets ensure maximum coverage of all possible combinations of α^{sd} and α^{t}.

Figure 4.4: Non-orthogonal design boundary value map



Therefore, the respective choice sets selected, are non-orthogonal, in the sense that correlation exists between product attributes, as shown in the matrix outlined in Table 4.5 below.

Table 4.5: Non-orthogonal design correlation matrix

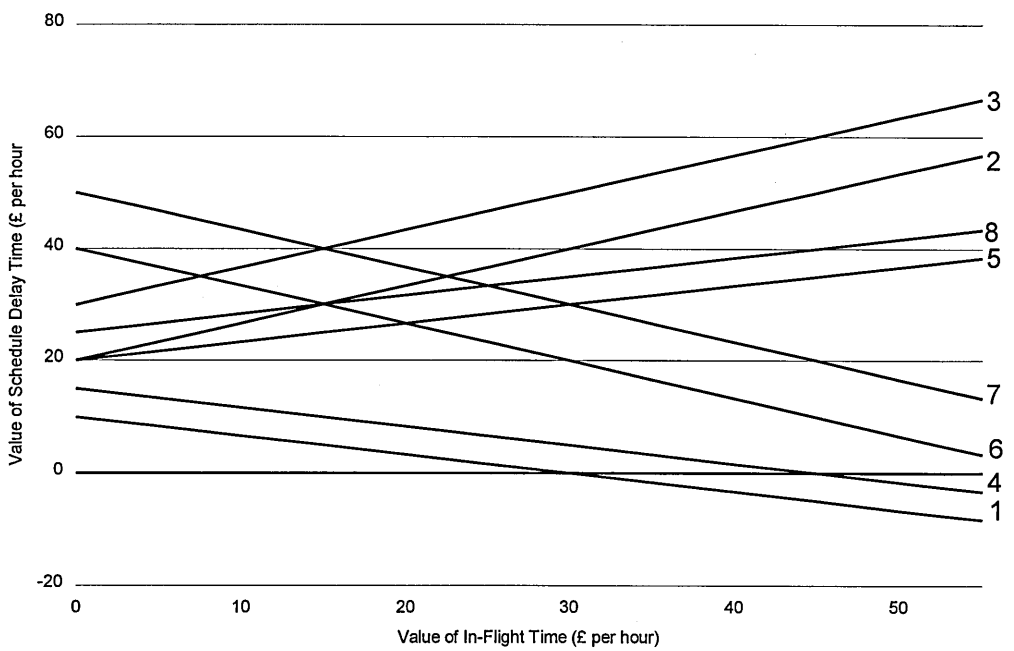
	fare	schedule delay time	in-flight time
Fare	1.00	0.26	0.22
Schedule Delay Time	0.26	1.00	0.55
In-Flight Time	-0.22	0.55	1.00

Ideally, one would expect more efficient coverage but because of the requirement to specify meaningful and realistic product attribute levels, one is restricted in the ability to achieve maximum coverage. However, bearing this limitation in mind, Figure 4.4 outlines the most efficient group of choice attributes that generates sufficient coverage of the map.

Consider the region of the boundary value map in Figure 4.4, where both the upward sloping and downward sloping lines intersect i.e. between £15 and £30 of α^{sd} and

between £5 and £30 of α^t. Within this parameter space, one would expect relatively accurate estimates of either α^{sd} and α^t can be generated given the substantial trading between current and alternative flight that is likely to take place. On the other hand, referring to the top left hand region, values of time within this space may not generate accurate or even statistically significant estimates. However, in order to test these presumptions, simulation of responses using various combinations of α^t and α^{sd} would need to be completed.

Figure 4.5: Orthogonal design boundary value map



As far as the orthogonal design is concerned (Figure 4.5), the choice sets were selected to ensure zero correlation between product attributes, hence eliminating any possible degree of colinearity between variables. The inherent trade-off between efficient boundary value coverage and orthogonality is clearly evident through comparison of both the orthogonal and non-orthogonal boundary value maps. In Figure 4.5 above, there is less coverage of those middle range combinations of α^t and α^{sd} that one would expect values of time to fall. The issue to consider, is the extent to which the orthogonal design with its associated zero collinearity can return efficient parameter estimates despite relatively poor boundary value coverage. On the other hand, despite degrees of collinearity in the non-orthogonal design, can it achieve a

higher degree of statistical significance in estimating the parameters through more efficient coverage of all possible values of both α^t and α^{sd} ?

4.5.3 Analysis of simulation results

In order to test the efficiency of both designs, six combinations of α^t and α^{sd} were selected. These combinations were then substituted into the generalised cost equation (equation 4.9) and then transformed to choice probabilities. Furthermore, all responses in the sample were assumed to have identical combinations of α^t and α^{sd}. For each combination, model calibration involves generating simulated values of schedule delay time and in-flight time estimates α^t_{sim} and α^{sd}_{sim}, given variation in the scale of error term variance at five intervals; £5, £10, £15 and £20. Simulation input assumptions are outlined in Table 4.6 below.

Table 4.6: Simulation input values of time

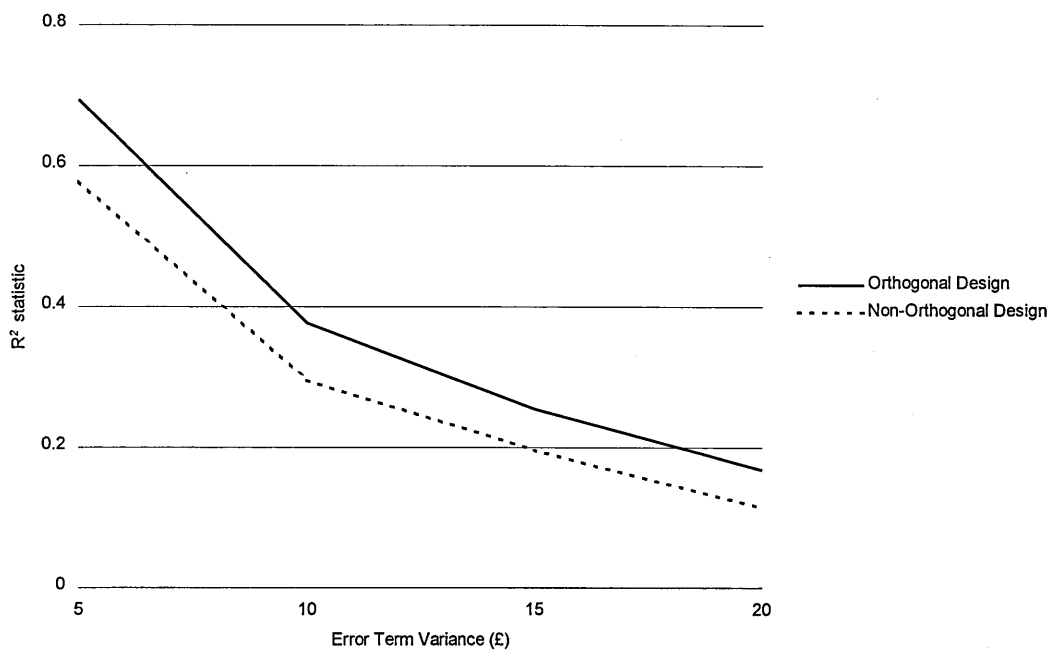
	values of schedule delay time	values of in-flight time
Combination 1	£15	£10
Combination 2	£35	£15
Combination 3	£20	£20
Combination 4	£25	£10
Combination 5	£30	£40
Combination 6	£10	£25

Simulation involves five iterations, each generating a distribution of estimated values of time from which a mean simulated value was obtained. At higher magnitudes of error term variance, given the wider dispersion of simulated values, ten iterations were completed for each combination of α^t and α^{sd}. The efficiency of each design was measured firstly, through the mean percentage variation between the inputted and simulated values, secondly through the mean R^2 and thirdly, through the mean simulated *t*-statistics produced by the simulation. Particular attention was paid to the performance of each design at error variance levels associated with an R^2 in the region of 0.15 to 0.20, as this represents the expected range of values likely to be produced from the real stated preference experiment.

Simulation results are graphically illustrated in Appendix D. Each chart represents for a combination of α^t and α^{sd} the difference between the inputted values and the mean

simulated values for both orthogonal and non-orthogonal designs. As far as simulated R^2 values are concerned the average estimate across combinations was plotted against error term variance. These results are illustrated in Figure 4.6 below.

Figure 4.6: Mean simulated R^2 performance by stated preference design



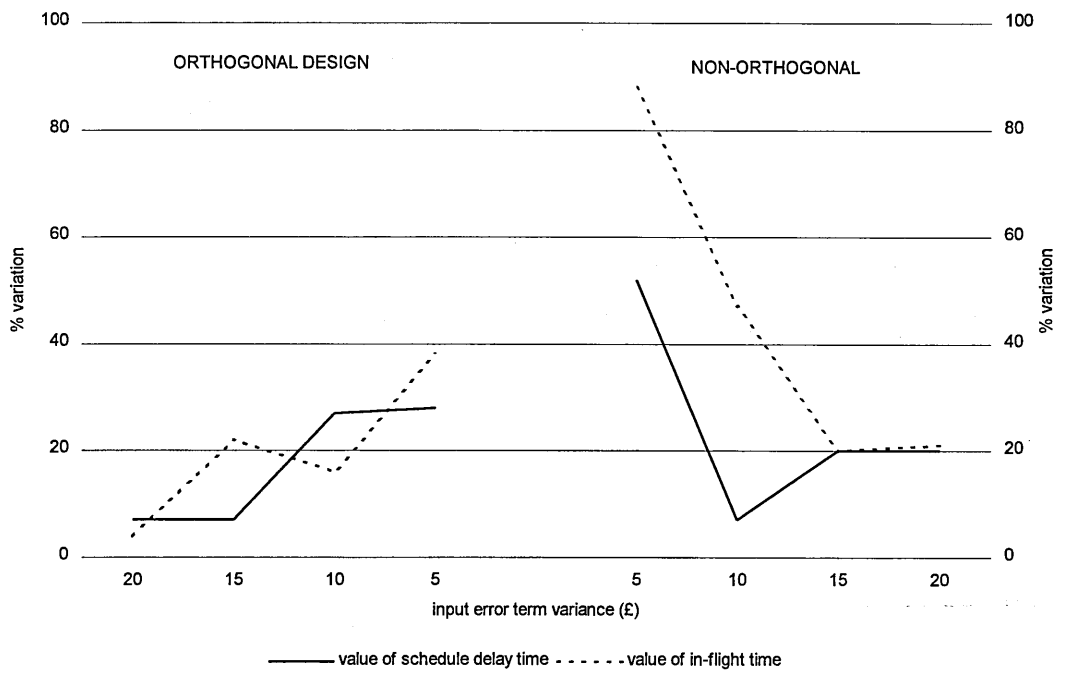
Observation of Figure 4.6 confirms that mean simulated R^2 declines as additional bias is introduced into response preferences. As the scale or error increases, passenger preferences become increasingly more random thereby reducing the explanatory power of the model.

Furthermore, the mean simulated R^2 generated by the non-orthogonal design is consistently lower at each level of error term variance despite more efficient coverage of the boundary value map. However, in addition to error variance, the R^2 statistic associated with the non-orthogonal design appears to be also affected by collinearity between variables. Indeed, the effect of collinearity, is to increase the standard errors associated with the parameter estimates, thereby reducing *t*-ratios and the statistical significance of the coefficient estimates themselves.

Appendix D outlines the relative performance of both designs with respect to each combination of values of schedule delay and in-flight time. Figures 4.7 to 4.11

contrasts the percentage variation between the input values of time and the simulated estimates generated by both methods for each combination of α^t and α^{sd} at four intervals of error term variance: £5, £10, £15 and £20.

Figure 4.7: Percentage variation between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £15 and α^t = £10

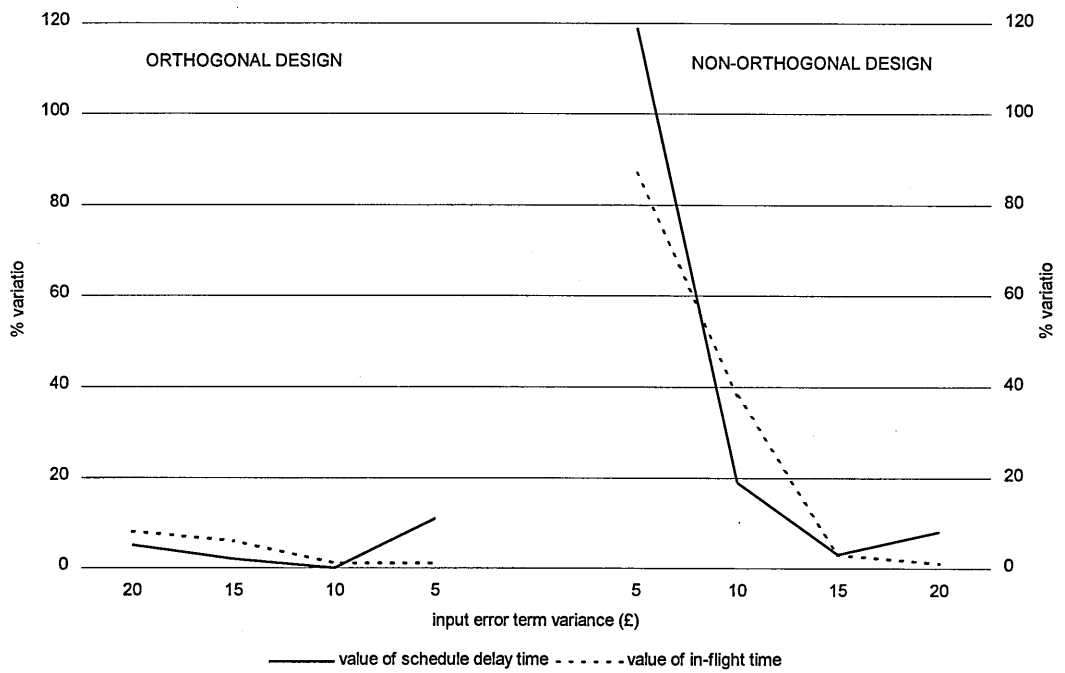


When α^{sd} is £15 and α^t is £10, the simulated estimates of both variables converge toward their input values of time as error term variance increases in magnitude. This is the case for both orthogonal and non-orthogonal methods However, the trend generated by the orthogonal model appears more consistent and more accurate at high levels of error term variance compared to the non-orthogonal design. This is borne out by observation of Figure 4.7 above, which shows that as the level of error term variance increases, the percentage variation between the input values of time and simulated estimates generated by the orthogonal method is lower compared to those produced by the non-orthogonal design.

For example, the percentage variation between the simulated value of schedule delay time and the input value declines from 28% when the magnitude of error term variance is £5, to 7% when the variance is £20. As far as the non-orthogonal design is

concerned, the percentage variation declines from 52% to 20% over the same range of error term variance.

Figure 4.8: Percentage variation between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £20 and α^{t} = £20



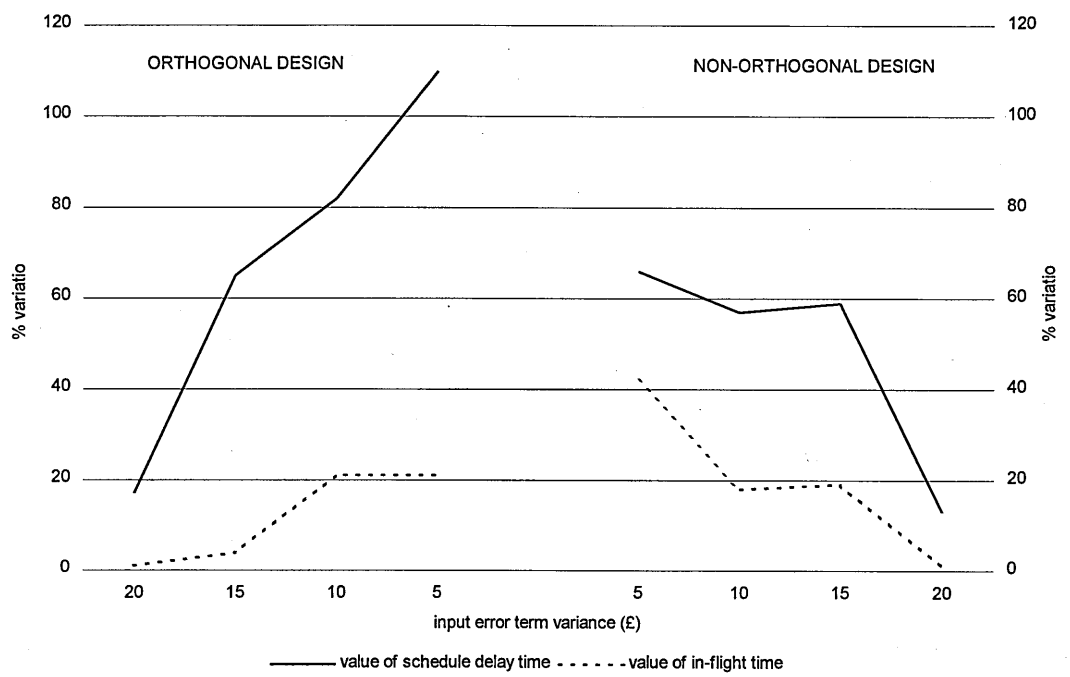
When both α^{sd} and α^{t} are £20, there is a clear difference in the relative performance of both models. The orthogonal design consistently generates accurate estimates of both variables at each interval of error term variance. As far as the non-orthogonal design is concerned, the simulated values of α^{sd} and α^{t} only intersect the inputted values of time when ε is £20. At lower intervals of error term variance, there is a significant difference between inputted and simulated variables.

In Figure 4.8 above, the percentage variation for both values of time is low with respect to the orthogonal design compared to the non-orthogonal method, although when the error term ε is £20, the percentage variation for both methods is relatively insignificant.

When α^{sd} is £10 and α^{t} is £25, both designs appear to generate accurate simulated estimates as the scale of error term variance increases. One important point to observe from chart six in Appendix D, is that the simulated estimate of α^{sd} generated by the

non-orthogonal design is wrongly signed when ε is £5, which is an indication of the presence of collinearity between product attributes. Figure 4.9 below outlines the percentage variation between input and simulated values of time for both methods at different intervals of error term variance.

Figure 4.9: Percentage variation in between input values of time and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £10 and α^{t} = £25

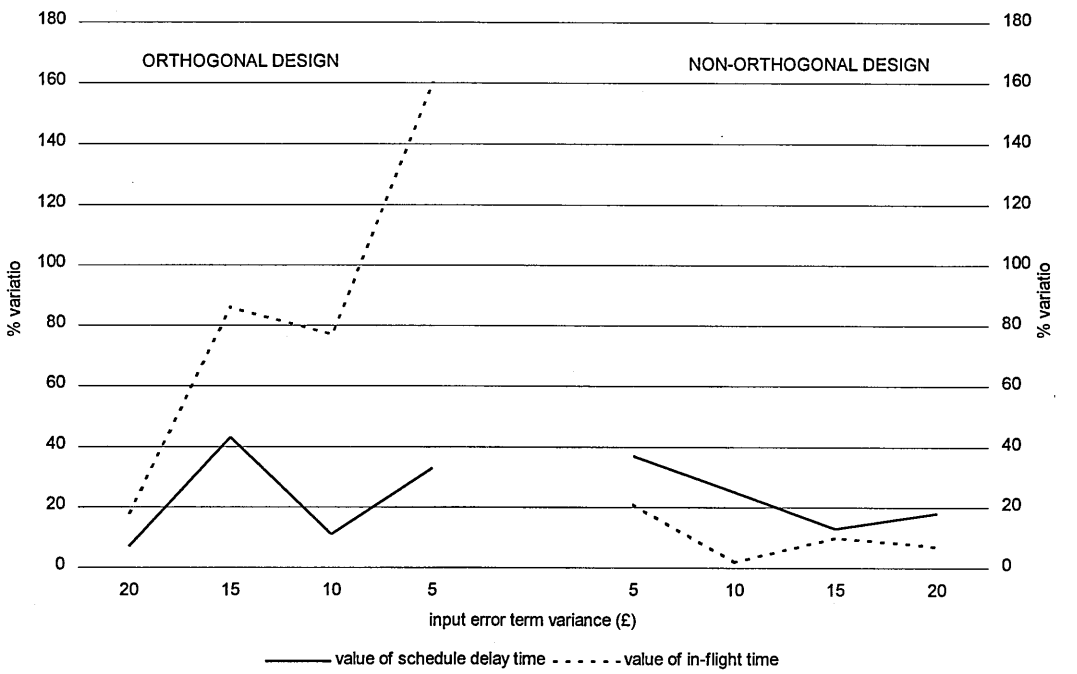


Although the non-orthogonal design generates slightly more accurate estimates of the input values of time, observation of the comparative coefficient statistical significance tests on Table 4.7 reveals that the *t*-ratios generated by the non-orthogonal design are lower compared to the orthogonal design. This is particularly so for the schedule delay coefficient which does not satisfy the required 99% confidence interval criteria for statistical significance.

The non-orthogonal model also out-performs the orthogonal design when α^{sd} is £30 and α^{t} is £40 and when α^{sd} is £35 and α^{t} is £15. This is shown in Figures 4.10 and 4.11. For the first combination, the difference appears to be quite significant. This suggests that the presence of collinearity within the orthogonal design appears to have had negligible impact on the accuracy of the simulated estimates. Indeed, observation

of both boundary value maps in Figures 4.4 and 4.5 shows that when α^{sd} is £30 and α^{t} is £40, the non-orthogonal design is more efficient in terms of its ability to capture values of time within this particular parameter space.

Figure 4.10: Percentage variation in between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £30 and α^{t} = £40



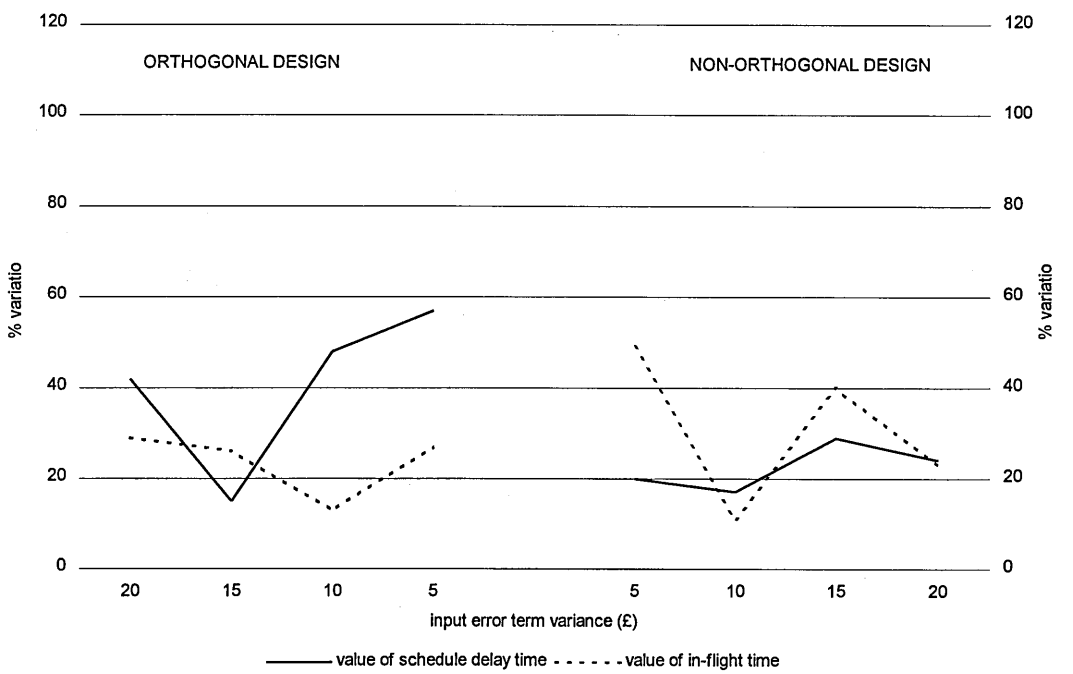
Despite these differences, however, both models generate relatively accurate simulated estimates, when ε is £20. Since it is expected, that the scale of error term variance will be high, greater weight should be attached to the performance of both models when error term variance is £20.

When α^{sd} is £35 and α^{t} is £15, there is little difference in the relative performance of both models. Although the orthogonal design does marginally out-perform the non-orthogonal design when ε is £20.

Whilst the orthogonal design out-performs the non-orthogonal design in two of the combinations of α^{sd} and α^{t}, both designs appear to generate parameters that are relatively accurate compared to the inputted values, at best at each interval of error term variance and at worst when ε is £20. In light of these trends, additional criteria

can be introduced which would enable one to determine the suitability of a given stated preference design.

Figure 4.11: Percentage variation in between input and simulated values of time generated by orthogonal and non-orthogonal designs when input values are α^{sd} = £35 and α^{t} = £15



Analysis of the mean simulated R^2 and the coefficient t-ratios, can provide a useful benchmark in evaluating both designs. Figure 4.6, which compares the mean simulated R^2 generated by both designs at each interval of error term variance, showed that model goodness of fit was consistently higher with respect to the orthogonal design. As far as coefficient *t*-ratio statistics are concerned, Table 4.7 below compares the mean *t*-ratios generated by both methods for each combination of α^{sd} and α^{t}. Results produced by the orthogonal design appear more satisfactory compared to the non-orthogonal design

For example, assuming an input combination of values of schedule delay and in-flight time of £15 and £10, the orthogonal design generates an average *t*-ratio for the schedule delay parameter β^{sd}_{sim} of -8.32 and for the simulated in-flight time parameter β^{t}_{sim} of -7.10. This compares favourably to *t*-ratios of -5.83 and -2.93 generated by the non-orthogonal design respectively. The difference is even more significant when the

input combination of values of schedule delay time and in-flight time is £10 and £25. This produces a large difference in *t*-ratios between both methods. Interestingly, the mean schedule delay early coefficient t-ratio is statistically insignificant at the 99% confidence interval. This confirms that the presence of correlation between product attributes has had a negative effect on statistical significance, and it is on this basis that one is inclined to reject the non-orthogonal design.

Table 4.7: Average coefficient t-ratio performance by stated preference design †

		Orthogonal design		Non-orthogonal design	
Inputted Combination		β^{sd}_{sim}	β^{t}_{sim}	β^{sd}_{sim}	β^{t}_{sim}
α^{sd}	α^{t}				
15	10	-8.32	-7.10	-5.83	-2.93
35	15	-11.83	-2.58	-8.04	-8.32
20	20	-10.95	-13.62	-7.17	-4.66
25	10	-10.51	-6.60	-8.32	-5.53
30	40	-7.03	-19.45	-8.09	-9.83
10	25	-8.44	-14.46	-0.73	-2.85

† average over each interval of error term variance

Although some authors such as Bradley (1988) have concluded that coefficient estimates derived from non-orthogonal designs can be more efficient that those produced by orthogonal methods, in this particular instance this is clearly not the case. At each interval of error term variance, and with each combination of input values of time, R^2 was consistently higher for the orthogonal design. Furthermore, analysis of simulated coefficient *t*-ratios produced by both methods, concluded that due to the absence of collinearity, the orthogonal design generates a greater degree of statistical significance compared to the non-orthogonal design.

Given the general conclusions drawn from the simulation exercise, the orthogonal design was selected for analysis.

4.6 Summary and Conclusion

The aim of chapter four was to outline the approach taken to constructing the stated preference experiment. The first section sought to identify the objectives and theoretical framework underlying estimation of the required parameters. This was followed by a discussion on optimising experimental design through identification of

a set of appropriate product attributes, defining the number of levels, and then selecting the number of choice sets and combinations of product attributes that can generate efficient and statistically significant parameter estimates. In selecting an optimal design, two separate designs with different statistical properties were evaluated. This was achieved through a process of simulating responses on the basis of varying levels of values of schedule delay and in-flight time. Key points from chapter four are outlined below.

- In designing stated preference experiments, it was important to define the objectives and in selecting and justifying an appropriate passenger sample.
- In the context of the thesis of objectives, fare, schedule delay time and in-flight time were selected for analysis.
- The most appropriate response measurement scale for this experiment was thought to be rating as opposed to discrete choice and ranking.
- Given the importance of both reducing the number of choice sets and maintaining a sufficient number in order to maximise efficiency, the maximum number of choice sets was limited to eight.
- Inherent in stated preference design is the trade-off between orthogonality and efficient boundary value coverage.
- Following a process of response simulation within which the efficiency of purely orthogonal and non orthogonal designs were evaluated, on different assumptions of α^{sd} and α^{t} and at various levels of error term variance, the orthogonal design was found to be the most efficient.

In the following chapter the selected design will be used to form the basis of the stated preference experiment from which passenger departure time choice model parameter estimates will be derived.

CHAPTER 5

Analysis of Stated Preference Results

5.1 Introduction

The purpose of this chapter is to present, interpret and validate results generated from the stated preference experiment. The first section focuses on issues related to interview technique, sampling strategy and questionnaire design. Before analysis and interpretation of the results, Section 5.3 considers the issue of determining whether alternative estimation methods and varying specifications of the response measurement scale generates large differences in the relative magnitudes of the parameters and in degrees of coefficient statistical significance.

Following on from this, the results are analysed and assessed to identify firstly, whether they are consistent with *a priori* expectations, secondly, whether degrees of parameter statistical significance are sufficient, thirdly, how the values of time generated relate to comparable estimates obtained from past research, and finally, the derivation of values of time from sub-samples of business and non-business respondents. Analysis then focuses on an examination of lexicographic responses to the stated preference questionnaire. This involves evaluating results when these responses are removed from the sample. The chapter concludes with estimation of the scale parameter β^0.

5.2 Experimental conditions

5.2.1 Interview techniques and sampling strategy

Experimental conditions likely to prevail at the time of the interview were expected to have a large bearing on both the quality of each response to the questionnaire and the statistical significance of the model estimates. Ensuring optimality of experimental conditions is all the more important given that error and bias is an inherent feature of responses to stated preference questionnaires. Therefore, establishing appropriate experimental conditions to obtain statistically significant parameters is an essential

ingredient in seeking to minimise potential sources of error that could invalidate the results.

In order to obtain the relevant information required for the stated preference experiment, and ensuring that only those passengers travelling on the selected city-pair market were included in the sample, interviews took place in a separate departure lounge. In seeking to minimise potential sources of bias in passenger responses and in optimising experimental conditions, the departure lounge was preferred to the check-in desk area or other parts of the passenger terminal. Firstly, because of the requirement to isolate those passengers targeted, secondly because of the reduced noise level, and thirdly, it was considered more appropriate from a response reliability perspective. One crucial factor also taken into consideration was the estimated time taken to complete each interview. The airport authority insisted that each passenger should spend no more than five minutes answering the questionnaire. Therefore in complying with this request, the design of the questionnaires, illustrated in Appendices E and F, involved a trade-off between, on the one hand, maximising the information obtained from each respondent and, on the other hand, minimising the time taken to complete the questionnaire. Sample size, a crucial determinant in generating statistical significance, largely depended on the time passengers spend in the departure lounge prior to boarding the aircraft. Since most flights are usually called thirty minutes prior to the scheduled departure time, most passengers on average usually spent ten to fifteen minutes in the departure lounge before boarding the aircraft. These circumstances imposed additional sampling constraints, since some travellers, particularly business passengers check-in late, with many spending at most five to ten minutes in the departure lounge prior to boarding. Sample size, therefore, largely depended on the arrival times of passengers in the departure lounge.

5.2.2 Questionnaire design

The questionnaire was designed to ensure an optimal trade-off between information content and timing. One potential source of response bias, is the failure of passengers to understand both the context of the research and more importantly, the choice task itself. Therefore, prior to evaluation of the eight choice sets, the objectives of the

study were fully explained to each respondent. With respect to the choice set evaluation element of the questionnaire, passengers were asked to make two assumptions. Firstly, to imagine that alternative flights to the destination were available and secondly that they were booking the flight. In order to maximise respondent appreciation of the exercise, several preliminary questions were asked in relation to the convenience or inconvenience of a set of alternative departure times. This was to ensure that passengers were gradually introduced to the concept of measuring schedule delay time. (see Q10 and Q11 late and early questionnaires in Appendices E and F). Respondents were also asked supplementary questions in order to obtain details of the respondent's journey such as, origin and final destination, journey purpose, whether the trip was an outbound or return journey, who paid the fare, and who booked the flight etc. Information regarding each passenger trip was collated in order to identify characteristics in response preferences between passengers belonging to specific behavioural categories i.e. business and leisure travel. For example, whether passengers who paid their own fare possessed a lower value of schedule delay time than passengers who did not pay their own fare. However, the extent to which this level of disaggregation could be achieved, depended on sample size. Although sample segmentation can improve the level of statistical significance, through isolating the influence of socio-economic factors, the inevitable reduction in sample size could have implications in regard to model and parameter statistical significance.

The stated preference element required each respondent to evaluate eight choice sets. In each choice set, respondents were asked to evaluate a hypothetical flight in relation to their current journey on the basis of an assumed reduction in fare, a new departure time, and a different flying time. Since the objective is to obtain parameter estimates representing schedule delay early and schedule delay late time, this would have required respondents to evaluate sixteen choice options, eight associated with hypothetical departure times scheduled earlier than their current flight, and eight associated with hypothetical departure times scheduled later than their current flight. However, given the problems that could emerge because of respondent fatigue, each passenger sampled was asked to evaluate only eight choice sets. Therefore, two

separate questionnaires were designed, one related to earlier and another related to later hypothetical departure times. Each consecutive passenger was presented with either a later or earlier departure time questionnaire. In order to reduce the potential for statistical bias, equal numbers of earlier and later questionnaires were issued. Those passengers interlining from earlier flights were excluded from the experiment, firstly, because of the fact that their arrival times at the airport may have been later than some of the hypothetical departure times specified in the earlier departure time questionnaire, and secondly, because they would have been paying significantly different fares compared to other respondents. Each passenger was interviewed in the departure lounge prior to boarding their flight.

Having obtained permission from the relevant airport authority to conduct the survey, 147 passengers (1176 choice set responses) were interviewed. All passengers were travelling to the same destination from Manchester Airport between the hours 0900-1900 during the week November 2-7 1994.

5.3 Sample characteristics

Analysis of journey purpose amongst the 147 respondents interviewed, revealed that 49% of journeys were business related, 34% leisure orientated and 17% of respondents were visiting friends and relatives. This is a relatively accurate representation of the actual split between journey purpose, as reported in the 1992/93 survey of passenger journey purpose on this route at Manchester Airport (CAA 1993b). When asked who had paid their fare, only a minority of passengers actually claimed to have paid there own fare (47%). Those passengers that did not pay for their own fare had their fare paid by either their company or a friend or relative. As far as the stated preference choice options were concerned, each respondent was asked to assume that he or she paid the fare for their particular trip.

Passengers were also asked, assuming they had flexibility of choice, to select their most preferred departure time for this trip prior to analysis of the choice sets (see Q11 in Appendices E and F). Whilst this generates a distribution of ideal departure times by time of day, it would not have been appropriate to use this statistic as a representation of passengers ideal departure time preferences, since there was

substantial variation in the number of passengers sampled at each flight. Nevertheless, through obtaining these preferences, one was then able to ascertain the correlation between passengers actual and ideal departure times. As mentioned in Chapter four, the validity of the stated preference experiment would have been seriously deficient, if there was a substantial divergence between passengers' actual and most preferred departure times. The correlation matrix illustrated below (Table 5.1) confirms that there was a strong relationship, measured by the correlation coefficient, between passengers ideal and actual departure times.

The correlation coefficient of 0.83 can be explained by the fact that the level of service frequency supplied by the operator was such, that this ensured that passengers had a sufficient choice of departure times within which an optimum preference could be selected.

Table 5.1: Correlation matrix: ideal and actual departure times

	ideal departure time	actual departure time
ideal departure time	1.00	0.83
actual departure time	0.83	1.00

On the other hand, had their only been two or three departures per day, then one would have expected a greater degree of dissatisfaction with the convenience of the operators schedule and therefore, a lower level of correlation between their actual and most preferred departure time. If this had been the case, parameter estimates generated under these circumstances, would either have been wrongly signed, or associated with statistical insignificance. This was one of the reasons why this particular route was chosen for analysis. Because the volume of frequency supplied by the operator was such that passengers had a sufficient choice of options from which to select their most preferred departure time.

5.4 Estimation method

5.4.1 Introduction

The aim of the stated preference experiment was to obtain parameter estimates associated with schedule delay time, in-flight time and fare which could then be substituted into the passenger departure time choice model developed in Chapter six.

An essential prerequisite to satisfactory stated preference parameter estimation, is the requirement to select an appropriate response measurement scale for the dependent variable, and a suitable statistical estimation technique to generate the model coefficients. This raises the important issue of determining whether different specifications of the response measurement scale, and the use of alternative estimation techniques such as linear regression and maximum likelihood, generates significant variation in the relative magnitude of the estimated parameters, standard errors and *t*-ratios.

From the stated preference experiments outlined in Appendices E and F, respondents were asked to choose between each paired comparison. In making a choice, they were asked to indicate the strength of their convictions along the following semantic scale: definitely choose current flight, probably choose current flight, cannot decide, probably choose alternative flight and definitely choose alternative flight. Model estimation requires that the semantic scale be transformed to a set of numeric values. Standard practice, particularly in the context of logit analysis, is to transform the semantic scale into assumed probabilities of choice, using the following numeric values: 0.1, 0.3, 0.5, 0.7, 0.9. Work by Bates (1984), Ortúzar and Garrido (1991) are two examples of the use of the five-point choice probability scale in stated preference experiments.

However, by using these values, one makes an assumption that a linear relationship exists between the dependent variable (choice) and the independent variables (product attributes). Since it is unlikely that such a relationship exists, the parameter estimates must be linearised in order to generate empirically valid choice probability estimates. A method of transformation which was initially derived by Berkson (1953) and

further extended by Theil (1969), forms the basis for parameter estimation within the context of a multinomial logit framework. The Berkson-Theil method, as it is more commonly known, transforms the dependent variable by taking the natural logarithm of the ratio of choice probabilities P_{ij} as shown in equation 5.1 below.

$$\ln\left[\frac{P_{ij}}{1-P_{ij}}\right] = \beta^{f} f_{ij} + \beta^{se} se_{ij} + \beta^{sl} sl_{ij} + \beta^{t} t_{ij} \qquad (5.1)$$

Where f_{ij}, se_{ij}, sl_{ij} and t_{ij} represent fare, schedule delay early time, schedule delay late time and in-flight time. Subscripts i and j are used to denote that the product attributes are represented as differences between the current flight i and the alternative flight j. While β^{f}, β^{se}, β^{sl}, β^{t} function as associated parameter estimates. Transformation of the ordered dependent variable P_{ij} yields the following response scale values: -2.20, -0.85, 0, 0.85, 2.20.

There are two issues to consider: firstly, whether the use of different statistical estimation techniques generates significant differences in the relative magnitudes and standard errors of the coefficients, and secondly, the need to ascertain whether stated preference model results are sensitive to varying specifications of the dependent variable numeric scale. In order to examine the first issue, the following three estimation methods were considered:

- First, a linear regression model applied to a five-point ordered dependant variable linearised using the Berkson-Theil transformation as shown in equation 5.1. The linear regression model that is applied was obtained from SPSS (Statistical Package for the Social Sciences) for windows version 6.1.

- Second, an ordered logit model applied to the non-linearised five point dependent variable scale (0.1, 0.3, 0.5, 0.7, 0.9) using STATA version 5.0.

- Third, an ordered probit model, as described in chapter three, applied to the same five-point dependant variable scale as ordered logit using STATA version 5.0.

As far as examining the sensitivity of model results to different specifications of the dependent variable is concerned, the following three intervals using the ordered logit model, were considered.

- First, a five-point dependant variable scale (definitely prefer current flight = 0.1, probably prefer current flight = 0.3, cannot decide = 0.5, probably prefer alternative flight = 0.7, definitely prefer alternative flight = 0.9).
- Second, a three point dependant variable scale (definitely and probably prefer current flight = -1, cannot decide = 0, and definitely and probably prefer alternative flight = 1)
- Third, discrete choice dependent variable scale, (definitely and probably prefer current flight = 0 and definitely and probably prefer alternative flight = 1). All cannot decide responses were excluded from the analysis.

5.4.2 Linear regression versus Logit and Probit

Results outlined in Table 5.2 below, shows that the coefficients are ranked in the same order of magnitude, in-flight time followed by schedule delay late time, schedule delay early time, and fare.

Table 5.2: Parameter results by estimation method based on five-point rating scale.

	Linear Regression [1]	Ordered Logit [2]	Ordered Probit [3]
β^f	0.026	0.032	0.018
t /z	2.95	3.23	3.17
β^{se}	-0.597	-0.532	-0.338
t /z	-2.20	-2.35	-2.47
β^{sl}	-1.469	-1.529	-0.930
t /z	-6.94	-6.42	-6.49
β^t	-1.844	-2.018	-1.212
t /z	-12.28	-11.79	-11.90

[1] Linear regression using *SPSS for windows version 6.1*

[2] Ordered logit estimation using *STATA version 6.0*

[3] Ordered probit estimation using *STATA version 6.0*

Variation in the values of the coefficients is expected, since there are differences in the magnitudes of the dependent variables between linear regression and both logit and probit methods. What is important, are the relative magnitudes of the coefficients between all four methods.

Comparing coefficient *t*-ratios between different estimation methods, shows that these results are broadly comparable. The standard errors generated by the linear regression method with regard to β^t and β^{sl} are lower compared to those obtained from the ordered logit and probit models. Whereas with regard to the two remaining coefficients: β^f and β^{se}, representing fare and schedule delay early time, the standard errors of the logit and probit coefficients are lower, resulting in slightly higher *t*-ratios. However the differences in scale between the t-ratios is relatively insignificant.

The most crucial inferences to be drawn from these results is to examine whether there are any substantial differences in the relative magnitudes of each coefficient between the models considered. Table 5.3 below, shows the ratio of each parameter to the in-flight time coefficient generated by the four estimation methods. The in-flight time coefficient is used as the base parameter, firstly, because of its robustness and high level of statistical significance, and secondly, because in the passenger departure time choice model, the generalised costs are converted to units of in-flight time.

Table 5.3: Ratio of parameter estimate to in-flight time coefficient by estimation method

	Linear Regression	Ordered Logit	Ordered Probit
β^t	1.000	1.000	1.000
β^{sl}	0.796	0.757	0.767
β^f	0.014	0.016	0.015
β^{se}	0.323	0.264	0.278

The ratios generated from coefficients derived by the three methods are broadly comparable. As far as the ratio between the schedule delay late parameter β^{sl} and β^t is concerned, the linear regression model yields a value of 0.80, compared to 0.76 and 0.77, generated by the logit and probit models respectively. The differences between the linear regression method and both maximum likelihood-based models is of the order of 5% and 4% respectively. As far as the ratio of β^f to β^t is concerned, the linear regression model yields a lower ratio of 0.014. compared to 0.016 and 0.015 obtained

from comparable logit and probit coefficients. The percentage differences are slightly greater in magnitude between linear regression and both maximum likelihood - based methods of estimation, 12% and 7% respectively.

Measuring the ratio between the schedule delay early and in-flight time parameters generates with regard to the linear regression, logit and probit models of 0.32, 0.26 and 0.28 respectively. The percentage difference between the ratio generated by the linear regression model and both logit and probit methods is 19% and 14% respectively.

Consistency in the relative magnitudes of the parameters between these methods was also found by Long (1997) when examining attitudes to working mothers in the United States. The author applies the following four-point rating scale: strongly agree, agree, disagree and strongly disagree, and compares results generated by linear regression, probit and logit models. The conclusions drawn from these results, showed that the relative magnitudes of the coefficient were very close, suggesting that there is little difference in results when applying these methods.

Although the results are broadly consistent between each method, it is necessary to examine, for validation purposes, the suitability of using linear regression on ordered data from a theoretical perspective.

Least-squares regression, because of its ease of use, and simple interpretation, is the most widely used statistical estimation technique in econometric research. When the dependant variable is continuous, it is almost universally applied. However, where the dependent variable is not continuous, i.e either ordered, or dichotomous, then the extent to which one can justify its use compared to other methods must be assessed. In those cases where the dependent variable is considered dichotomous (discrete), methods based on maximum likelihood techniques are applied, since use of linear regression will generate significant bias in the parameter estimates. When the dependent variable is ordered, as in the case of the stated preference results, then there appears to be a degree of debate as to the suitability of applying linear regression to cases where the dependant variable is measured in ordered terms. Some commentators, mentioned below, treat ordered dependent variables as continuous,

therefore, justifying the use of linear regression. By contrast others, do not consider linear regression as appropriate, and therefore suggest the use of maximum likelihood-based estimation methods.

The dependent variable, as applied to measure responses to the stated preference choice sets, is effectively an ordinal representation of an underlying latent continuous variable, which cannot be identified or measured. As such, assumptions need to be made regarding the mean and variance of the underlying latent variable and the distribution of error terms. Arguments against the use of least squares regression focus on two fundamental issues. Firstly, where the linear regression method is used, this involves an implicit assumption that the intervals between the ordered scale values are the same. For example, the distance between definitely prefer current flight and probably prefer current flight is the same as the distance between probably prefer current flight and cannot decide. In those cases where intervals are not equally spaced, Long (1997) does not consider linear regression to be an appropriate statistical estimation technique and that other methods should be considered. The second issue is that of the statistical properties of the error terms of sample observations. The linear regression model assumes that the error term is heteroscedastic, in other words, the error terms are not equal across observations and that the errors between observations are uncorrelated, so that for any two observations a and b, the covariance between ε_a and ε_b is zero.

The use of linear regression versus other statistical estimation techniques on ordered data is a recurring methodological issue. On the one hand, there are those who argue, such as Long (1997) and Winship and Mare (1984), that the biases in using continuous variable methods when applied to ordered data are large, and that alternative techniques specifically designed for ordered dependent variable parameter estimation should be applied. On the other hand, there are those such as, O'Brien (1979) and Labovitz (1967,1970), who argue that the use of linear regression on ordered dependent variables can be justified, because the power and flexibility gained from applying these methods outweigh the small biases that they may entail. Labovitz (1967,1970) demonstrates, in the earlier study, the validity of treating ordered dependent variables as continuous when measuring hypothetical responses to two

types of therapy on the basis of a four-point scale. Using two different response scales: highly skewed and equidistant intervals, the author found that both scoring systems produced largely similar results in terms of coefficients and *t*-ratios. In the later study, the author came to a similar conclusion when evaluating the relationship between occupation prestige, income and suicide rates in the United States. This time, comparing results generated by an equidistant response scale with nineteen different response scales with different intervals generated by a simulation model.

In assessing the relative advantages and disadvantages of different estimation methods, Green and Srinivasan (1978) conclude that when assuming a rating scale dependent variable, results generated from both linear regression and maximum likelihood methods do not differ significantly in their predictive validates. Indeed, Cattin and Wittink (1976) found that results generated by linear regression and maximum likelihood-based methods such as logit and LINMAP were virtually indistinguishable, with a difference of 0.03 units in terms of Pearson's rho.

As far as choice of estimation method is concerned, there is perhaps a greater degree of uncertainty regarding the relative efficiency of using linear regression methods compared to those models based on maximum likelihood techniques. As elaborated above, there are strong arguments when measuring a dependent variable on an ordered scale for using either logit or probit, as opposed to linear regression. Nevertheless, in some cases the use of linear regression can yield broadly comparable parameter estimates and associated *t*-ratios. Long (1997) concludes that in some instances, the use of these different methods can yield similar results, but cautions against the use of linear regression, because not all applications of this method to ordered dependent variables will yield consistent estimates, and that in some instances, misleading results may ensue.

5.4.3 Results sensitivity to variation in dependent variable scales

When the issue of using different methods of measuring responses to the stated preference questionnaire was examined in Chapter four, use of a five-point rating scale method was favoured to a discrete choice method of representing the dependent variable. According to Wardman (1988), the advantage of using a rating-scale

method, is that the more refined method of measuring the dependent variable yields parameter estimates associated with higher degrees of statistical significance compared to the discrete choice method.

Both Bates and Roberts (1983) and Ortúzar and Willumsen (1994) also raise the issue of whether assumptions made about the value and range of response scale values has an effect on the magnitude and statistical significance of the parameter estimates generated from a given sample of responses. Bates and Roberts (1983) conclude that in the case of stated preference estimation, varying specifications of the scale value dependent variable does not generate significant differences in the magnitude of the estimated parameters. The authors used three different scale transformations on the same data and found that while the results were not insensitive to the assumptions made through small differences in the standard errors of the coefficients and in goodness of fit, the order of magnitude remained broadly consistent in each case. Ortúzar and Willumsen (1994) similarly sought to investigate whether scale selection did make a difference to the results through a rating stated preference experiment. A sample of staff and students were asked to choose between bus and light rail on morning trips to work. Using a $3^2 \times 2^2$ factorial design and four different assumptions regarding the scale values, values of in-vehicle, waiting and walking time were derived. Results showed that for three out of the four scale values, values of in-vehicle time were £3.98, £4.01 and £4.11. For walking and waiting vales of time, variation was less pronounced with vales ranging from £24.91 to £21.63 and from £23.89 to £18.67 respectively. The goodness of fit measure: R^2 statistic ranged from 0.48 to 0.44.

Using three different methods of measuring the dependent variable, five-point rating scale, three-point rating scale and discrete choice, and applying the ordered logit model to the sample of responses, the following results are shown in Table 5.4.

There are differences in the magnitudes of the parameter estimates between each response scale measurement. This is expected, since the linear regression dependent variable scale is based on the Berkson-Theil transformation compared to probabilities of choice, as in the case of both logit and probit. The coefficient order of magnitude is

the same between each method, in-flight time followed by schedule delay late time, schedule delay early time and fare.

Table 5.4: Parameter results by dependent variable scale specification based on Ordered Logit Method.

	five-point scale [1]	three-point scale [2]	discrete choice [3]
β^f	0.032	0.024	0.025
t /z	3.23	2.12	2.19
β^{se}	-0.532	-0.792	-0.786
t /z	-2.35	-3.06	-3.01
β^{sl}	-1.529	-1.806	-1.730
t /z	-6.42	-6.63	-6.32
β^t	-2.018	-1.978	-1.959
t /z	-11.79	-10.26	-10.11

[1] 0.1, 0.3, 0.5, 0.7, 0.9

[2] -1, 0, 1

[3] 0, 1

However there are differences, though relatively insignificant between coefficient *t*-ratios across different dependent variables scales. These results do not necessarily conform with those conclusions drawn by Wardman (1988), who suggested that discrete choice methods generated consistently lower coefficient *t*-ratios. According to the above mentioned author's hypothesis, *t*-ratios should decrease in magnitude when reducing the number of interval scales.

The *t*-ratios generated are very similar, with only marginal differences recorded. The five-point scale yields *t*-ratios, but only for two coefficients, β^f and β^t. By contrast, estimating the parameters on the basis of a three three-point scale, the *t*-ratios are higher, with regard to the schedule delay late and schedule delay early parameters, β^{sl} and β^{se}. The differences are, nevertheless relatively insignificant. For example, with regard to β^{sl} the *t*-ratio generated by the five-point scale is -6.63 compared to -6.42, with respect to the three-point scale. Whilst as far as β^{se} is concerned, the *t*-ratio is slightly more significant when using a three-point scale. Comparing the discrete choice method with the five-point dependent variable scale, for the in-flight time and schedule delay late and fare parameters, the relative *t*-ratios conform with *a priori* expectations. However, with regard to the schedule delay early coefficient, the *t*-ratio is in fact higher.

Table 5.5 below shows the ratios of each coefficient to the in-flight time parameter, generated by each dependent variable scale.

Table 5.5: Ratio of parameter estimate to in-flight time coefficient by response scale

	five-point scale	three-point scale	discrete choice
β^{t}	1.000	1.000	1.000
β^{sl}	0.758	0.913	0.883
β^{f}	0.016	0.012	0.013
β^{se}	0.263	0.400	0.401

The ratios outlined above, do vary by response scale. Both the three-point and discrete choice scales are similar in magnitude. However they do differ from those ratios estimated using the five-point scale generated coefficients. These differences are not insignificant, especially, with regard to the schedule delay late and the schedule delay early parameters. For example, the difference between the five-point and discrete-choice methods is 15% with regard to β^{sl}, and 34% with regard to β^{se}.

Given the rather mixed picture generated by these results, it is not altogether clear whether based on these results, rating-scale has any significant advantages over discrete choice. As far as rating scale - linear regression is concerned, the estimated coefficients are slightly more significant, with the exception of one parameter, than the discrete choice method. It should be noted however, that this need not always be the case. More complex stated preference choice experiments, which require the respondent to evaluate a larger number of variables and choice sets, may in actual fact, favour the use of discrete choice because of the relatively more straightforward task of making a discrete choice between two alternatives.

The author acknowledges, that there are different methods for measuring responses to stated preference questionnaires. Although there are deficiencies associated with applying the rating scale, the relatively more refined method of measuring responses does tend to generate higher *t*-ratios. The advantages and disadvantages of using various response measurement scales are examined in greater detail in Chapter four.

5.5 Analysis of results

5.5.1 All respondents

By applying the rating-scale-linear regression method to the survey responses, without the constant term, the following results, summarised in Table 5.6 were obtained.

Table 5.6: Model results: all respondents

	Estimate	t-ratio
R^2	0.171	-
β^t	-1.842	-12.27
β^{sl}	-1.166	-7.10
β^{se}	-0.295	-1.93
β^f	0.040	6.38
α^t	£46.05	-
α^{sl}	£29.10	-
α^{se}	£7.35	-

These results are consistent with *a priori* expectations, regarding, firstly, the magnitude of R^2, secondly, the signs of the coefficient estimates, and thirdly, the relationship between β^{se} and β^{sl}.

One feature common to most stated preference experiments is the low magnitude of the goodness of fit statistic R^2, relative to comparable estimates generated by revealed preference methods. For example, Whelan (1995) in evaluating mode choice (air versus rail) for the UK inter-city corporate travel market using a stated preference method, generates an R^2 value of 0.15. Bates (1983), in comparing revealed and stated preference methods, generates an R^2 of 0.28 using stated preference, and 0.44 using revealed preference, when applied to a sample of commuters in North Kent.

Why should stated preference methods consistently generate low goodness of fit measures? Firstly, respondents are being asked to evaluate what are essentially hypothetical choice alternatives designed by the researcher. As a consequence, it is inevitable, that there will be an element of error in responses. This error can be manifested in different ways. Some individuals, for example, may incorrectly perceive attribute levels, thereby selecting one alternative over another alternative which logically dominates it in terms of the utility values of the product attributes. Secondly, respondents may fail to understand the objectives of the exercise or may

take little interest in the experiment itself. This has the effect of increasing the standard errors of the parameter estimates and reducing goodness of fit. Thirdly, those respondents whose values of time lie outside the range specified by the experiment, measured by the boundary values illustrated in chapter four, will not trade their response preferences between the current flight and the hypothetical alternative, specified by the experiment. This will also inflate coefficient standard errors and reduce R^2.

However, one additional explanation as to why stated preference methods generate consistently low goodness of fit, focuses on the wide dispersion in values of time across individuals that is sometimes implicit in samples of stated preference respondents. In air travel markets, where large variations exist in values of time, the set of paired choices will have been designed to ensure that a wide range of value of time combinations that exist within a sample can be identified. As a consequence, while the parameter estimates may in themselves exhibit high degrees of statistical significance, because of the ability of the design to capture or identify this variation, the overall goodness of fit may in fact be low. The issue of R^2 will be discussed later in this section when issues of trading and illogical responses will be considered in greater detail.

Observation of both the magnitude of each coefficient and its associated *t*-ratio, confirms that in-flight time was the most important product attribute influencing respondent preferences. The parameter magnitude of -1.84 and a t-ratio of -12.27 is explained by the fact that passenger preferences were strongly influenced by twenty minute variations in travel time on a one hour flight. If the sample had been obtained from a group of passengers travelling on a long-haul route, offering twenty minute increases or decreases of in-flight time may not have had a similar effect on passenger responses and consequently, the magnitude of the parameter and its associated *t*-ratio would have been perhaps lower.

In conforming with *a priori* expectations, the respective magnitude of β^{se} and β^{sl} suggests that passengers attached a greater degree of disutility to those hypothetical flights scheduled later than their most preferred departure time. However, the *t*-ratio

of -1.93 associated with β^{se} is insignificant at the 99% confidence level. This stems from the presence of additional error which appears to have adversely affected the statistical significance of the schedule delay early coefficient. Invariably, each response is associated with a degree of error, which are both response and stated preference design-related. Given, the significance of β^{se}, compared to other parameter estimates, the higher magnitude of error, probably stems from design-related deficiencies. Those passengers asked to evaluate later departure time questionnaires appeared to have been more willing to trade-preferences, whereas those passengers asked to evaluate early departure time alternatives possessed a greater tendency to select the definitely prefer alternative flight option.

Although one would have expected this pattern of preference behaviour *a priori*, additional error seems to have occurred because the hypothetical choices associated with the early departure time options may not have sufficiently covered those low combinations of α^{se} and α^{t} that exist in the sample. Therefore, the extent to which passengers failed to vary preferences between the current and alternative flights was greater for those early departure options compared to later. Since it is from trade-off information that values of time are derived, consistently selecting one specific preference over others is unlikely to provide the necessary degree of information that is required to estimate values of schedule delay and in-flight time.

Values of schedule delay late time, schedule delay early time and in-flight time obtained by taking the ratio of the time parameter with the fare parameter also confirms the relative importance of each of the time-related product attributes. A value of in-flight time of £46.05 and schedule delay late time of £29.10 per hour suggests that passengers were relatively more sensitive to variation in in-flight time compared to schedule delay time. Whereas a value of schedule delay early time of £7.35, suggests less respondent sensitivity relative to schedule delay early time, in that passengers appeared more willing to trade the inconvenience of earlier departure times in return of reductions in fare.

Asymmetry with respect to the relative disutilities associated with earlier and later departure times is represented in the Figure 5.1. This chart illustrates the differences

in relative rates of substitution between schedule delay early and late time and fare over a range of seven hours of early schedule delay time and seven hours of late schedule delay time. The chart illustrates the fact that respondents appeared more willing to trade the convenience of their most desired departure time for an earlier flight with a reduced fare, compared to flights scheduled later than their ideal time, where fare reductions of greater magnitude would have been necessary in order to induce the respondent to select alternative flights.

Whilst these results appear to confirm *a priori* expectations, to what extent do the values of time generated, relate to comparable estimates derived from past applications of stated and revealed preference methods to research problems in transportation?

Figure 5.1: Rate of substitution between schedule delay time and fare

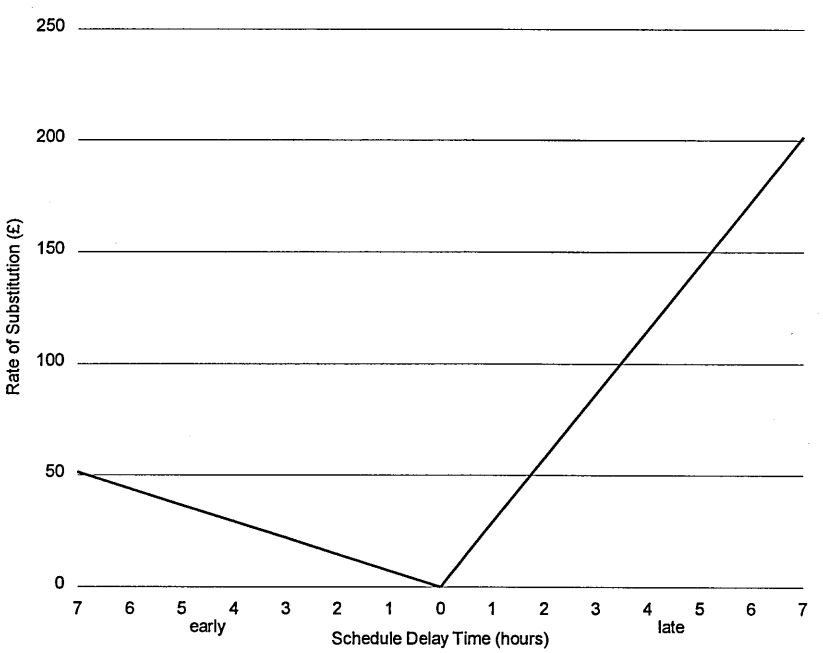


Table 5.7 below outlines a summary of values of in-flight and schedule delay time generated from past research. The most recent and, indeed one of the few applications of stated preference methods within an air transportation context, was an analysis of Korean passengers choice of flight by Yoo (1995).

Table 5.7: Values of in-flight and schedule delay time: past research

	method	in-flight time	schedule delay time
Yoo (1995)	SP	£34.97	
Yoo (1995)	RP	£26.53	
Gunn et al (1992)	SP	£16.50	
Morrison & Winston (1985)	RP[1]		£18.70
Dobson & Lederer (1993)	RP[1]		£15.79
Kanafani & Ghobrial (1985)	RP[1]	£27.14	

[1] Aggregate data

The author generated both stated and revealed preference values of in-flight time for long-haul passengers at Seoul International airport on flights to the United States and Europe. Using a self-administered discrete-choice stated preference questionnaire, the author, generates stated and revealed preference values of in-flight time of £34.97 and £26.53 respectively. This is lower than the value of in-flight time generated from this thesis, which was £46.05. This is a higher estimate, primarily because the values of time were estimated from a sample of short-haul air travellers, a market generally considered to be associated with higher values of in-flight time.

On the other hand given, longer sector distances involved in the study of Korean passengers choice of flight, values of in-flight time were found to be lower. Indeed the author also estimates values of in-flight time from samples of business and non-business passengers separately. As expected, these are only marginally different to the aggregate sample value of in-flight time. These are: £36.98 and £28.94 respectively. Gunn et al (1992) in using stated preference analysis to forecast the demand for high-speed inter-city rail in Australia, derives a value of in-flight time of AU$ 30.00 per hour, which converted to UK currency and adjusted for inflation, yields a value of in-flight time of £16.50, which is lower than the value of in-flight time estimated in this thesis. This is not surprising since values of time generated from air travellers is typically higher than those generated from inter-city rail travel. As far as values of time from revealed preference aggregate data is concerned, Kanafani and Ghobrial (1985) derived a value of in-flight time of US$ 30.00 per hour which, converted into UK currency and adjusted for inflation, yields a value of in-flight time of £27.14. The authors generated this estimate from an analysis of air passengers route choice behaviour in the south-eastern region of the United States.

Compared to this research, the value is lower. However, this is expected, since the nature of the research, sample characteristics and general context is totally different from that pertaining to this thesis. Nevertheless, it does provide a useful benchmark within which to compare or relate results generated from this thesis.

As mentioned previously, few authors have attempted to undertake a rigorous application of the concept of schedule delay time to air transportation research problems, especially within a stated preference context. Therefore, the author could not identify comparable values of schedule delay time. Dobson and Lederer (1994) in developing an airline scheduling algorithm for simulating traffic flows within a hub and spoke system, generate a value of schedule delay time of £15.79, which is somewhat lower than that generated in this study. In a much earlier paper, Morrison and Winston (1985), estimate a value of schedule delay time of £18.70 in an analysis of choice of mode within inter-city passenger markets in the United States. Unfortunately, it is difficult to directly compare results generated in this thesis, since neither of the authors mentioned above, generated separate estimates of both schedule delay early and schedule delay late time.

5.5.2 Business and non-business respondents

Through disaggregating the sample into separate groups of business and non-business passengers, values of time associated with corporate and leisure travel can be derived. Table 5.8 below, outlines linear regression parameter estimates and values of time obtained from business and non-business samples separately.

Table 5.8: Model Results : business and non-business passengers

	business		non-business	
	estimate	t-ratio	estimate	t-ratio
R^2	0.163	-	0.241	-
β^t	-1.841	-8.57	-1.844	-9.14
β^{sl}	-1.343	-5.75	-0.980	-4.42
β^{se}	-0.529	-2.37	-0.101	-0.49
β^f	0.028	3.25	0.050	6.01
α^t	£65.75	-	£36.80	
α^{sl}	£47.96	-	£19.56	
α^{se}	£18.89	-	£2.01	

During each interview, respondents were asked to specify their journey purpose. They were given the choice of selecting which, out of the following four options, was the most relevant to their journey: business, visiting friends and relatives, holiday or other. Business passengers represented 49% of the sample and non-business 51%. Table 5.8, shows that there is a marked variation in R^2 between business and non-business passengers. Furthermore, there are also differences in the values of time, magnitudes of the parameter estimates and *t*-ratios between both samples.

Results generated with respect to business passengers confirms *a priori* assumptions regarding values of time one would expect from corporate travel markets. Values of α^{se}, α^{sl}, and α^{t} of £18.89, £47.96 and £65.75 per hour respectively, are higher than those obtained from the entire sample in Table 5.6. All parameter *t*-ratio's appear to have marginally decreased, with the exception of β^{se}. This is expected, given the reduction in sample size. For the non-business passenger sample, lower values of time were obtained, £2.01, £19.56, £36.80 for α^{se}, α^{sl}, and α^{t} respectively. However, the one interesting feature of the results in Table 5.8, is the difference in the β^{se} coefficient *t*-ratio between both samples. When estimating this parameter from the business sample, its statistical significance increases through a higher *t*-ratio compared to its *t*-ratio shown in Table 5.6 (all respondents). Furthermore, when estimating from the non-business segment of the sample, there is a significant deterioration in statistical significance. This difference in performance can be attributed to the fact that a greater number of passengers in the non-business sample, were not trading between choice options when asked to evaluate earlier hypothetical departure times. This suggests that their values of schedule delay time were outside the limits set by the stated preference design and could therefore not be identified. Most early departure time non-trading respondents selected the definitely prefer alternative option, when evaluating each choice set, therefore since no information can be gained from a set of non-traded responses, values of time estimates cannot be inferred.

5.6 Lexicographic Analysis

5.6.1 Non-trading respondents

In light of this apparent tendency amongst some passengers to resist trading preferences between alternatives, how then should one handle or accommodate non-trading responses? Should they be eliminated from the sample, since their omission would improve goodness of fit and parameter statistical significance ? On the other hand, through eliminating the choice preferences of non-trading trading respondents, one is losing important information regarding values of time in the sample. Indeed, although it is impossible to estimate values of time from non-trading individuals, nonetheless, their selections are considered rational and should therefore should be included in the sample. Non-trading respondents made up a significant proportion of the total sample. Of the 147 respondents interviewed, 90 traded between alternatives and 57 did not. Table 5.9 below, compares parameter estimates generated from trading respondents only and those generated from the entire sample.

Comparing results with those obtained from the entire sample, by excluding non-trading respondents, there is a significant improvement in both R^2 and in the *t*-ratio statistics. Values of in-flight and schedule delay time also increase, from £49.82 to £59.30 and from £7.35 to £21.13 respectively. The value of schedule delay early time increased by a factor of 187%.

Table 5.9: Model Results : trading respondents only

	all respondents		trading respondents only	
n	147		90	
	estimate	t-ratio	estimate	t-ratio
R^2	0.171	-	0.321	
β^t	-1.843	-12.27	-2.787	-17.05
β^{sl}	-1.166	-7.10	-1.249	-7.07
β^{se}	-0.295	-1.93	-0.993	-5.83
β^f	0.040	6.38	0.047	6.97
α^t	£46.05	-	£59.30	-
α^{sl}	£29.10	-	£26.57	-
α^{se}	£7.35	-	£21.13	-

This confirms that a large proportion of responses to early schedule delay time alternatives were non-trading, and therefore their elimination has the effect of

increasing the magnitude of β^{se}. Similarly, elimination of non-trading responses has the effect of improving R^2, from 0.17 to 0.32, while the *t*-ratios associated with β^{se}, β^{t} and β^{f} also improve.

However, the magnitude of the schedule delay late parameter β^{sl} and the value of schedule delay late time, α^{sl}, change only slightly. Indeed, there is even a marginal reduction in the *t*-ratio and a reduction in the value of schedule delay time from £29.10 to £26.57. This is because, β^{sl} remained largely unaffected by the elimination of non-trading respondents. In light of the apparent improvement in model goodness-of-fit and in the parameter *t*-ratios, to what extent is it justifiable to use these results as the basis for passenger departure time choice model calibration and to reject those parameter estimates and values of time generated from the entire sample ?

While there is a case for incorporating trading respondent preferences only, there are two weaknesses associated with accepting this approach. Firstly, eliminating non-trading respondents involves a loss of information. Irrespective of whether there is trading behaviour or not, this information is useful, since it represents those combinations of values of in-flight time and schedule delay time that lie outside the range specified by the stated preference designs. Therefore, by retaining this information, those values of time that undoubtedly exist but lie outside the range specified by the stated preference design are incorporated in the results. Secondly, since most non-trading responses were associated with early departure times, the loss of these statistical observations creates an imbalance in the number of respondents who evaluated early and later departure times. This is reflected in the close proximity of the schedule delay early coefficient β^{se} to the schedule delay late coefficient β^{sl}, -0.99 and -1.24 respectively.

5.6.2 Illogical respondents

Another use of lexicographic techniques to improve model and parameter statistical significance, is to identify and eliminate those responses to the stated preference choice sets that are considered to be 'illogical' or 'inconsistent'. Firstly, one needs to define the term 'inconsistent responses'. This is achieved by identifying those instances where an individual selects one alternative over another which logically

dominates it i.e. is equal to or better for every attribute. For example, consider the choice alternatives presented in Figure 5.2 below. Two of the eight choice sets used in the late departure time questionnaire are considered, the full version of which is outlined in Appendix E.

Figure 5.2: Irrational choice example

CHOICE A

CURRENT FLIGHT	ALTERNATIVE FLIGHT
current fare	current fare **minus £10**
current departure time	departure time **1 hour later**
current in-flight time	in-fight time **20 minutes longer**

def current	prob current	indifferent	prob alt'ive	def alt'ive
			✓	

CHOICE B

CURRENT FLIGHT	ALTERNATIVE FLIGHT
current fare	current fare **minus £25**
current departure time	departure time **½ hour later**
current in-flight time	in-fight time **20 minutes longer**

def current	prob current	indifferent	prob alt'ive	def alt'ive
	✓			

The choice preferences of this hypothetical respondent is an example of an illogical response. In choice A, faced with an alternative flight which is £10 cheaper, departs one hour later, and is associated with an in-flight time which is twenty minutes longer, the respondent selects the probably prefer alternative option. When the same individual is faced with choice B, which is £25 cheaper, departs half an hour later and is associated with twenty minutes greater in-flight time, he/she selects the probably prefer current flight option. This is clearly inconsistent since the alternative flight in choice B is superior in utility terms to the alternative flight in choice A, in two product attributes, fare and schedule delay time, whilst they are the same for in-flight time.

A rational or consistent response would be for the individual to opt for the definitely prefer alternative option in choice B. In most stated preference studies, a proportion of respondents will exhibit irrational behaviour when selecting preferences. This could be due to several factors, such as, failure to understand the task, lack of interest in the experiment, and incorrect perception of product attribute levels. For example, in some instances, individuals may select inconsistent choice preferences in two out of the eight paired comparisons, these inconsistent preferences could either be associated with the first two paired comparisons, a juncture in the experiment where the respondent has not appreciated the choice task, or alternatively at the end of the experiment, where the respondent is fatigued and indifferent.

The researcher has three options when faced with the presence of illogical responses in a given sample: accepting these responses, eliminating these responses, and thirdly, eliminating the entire set of preferences of those respondents who exhibit inconsistent behaviour when evaluating some paired comparisons. Since inconsistent responses, inflate the standard errors of the parameters, their removal should improve goodness-of-fit and parameter statistical significance. However, there is a major weakness associated with this approach. The removal of inconsistent responses only, would violate, design orthogonality which guarantees zero-collinearity between product attributes. Thus, while the elimination of these responses may improve model statistical significance, the standard errors of the parameter estimates may in fact increase as a direct consequence of the presence of collinearity between product attribute levels. Under these circumstances, the only option available, is to eliminate the entire set of preferences of an individual who responded irrationally to two or three paired comparisons. Unfortunately, whilst this approach avoids the problem of collinearity, the loss of the entire set of an individuals responses would also imply that his or her 'rational responses' would also have to be eliminated. The effect of eliminating 'rational ' responses from the obvious reduction in sample size would probably lead to higher standard errors of the estimated parameters. Table 5.10 below compares estimates generated by the model from the entire sample and from a sample of rational respondents only.

5.10: Model Results : rational respondents only

	all respondents		rational respondents only †	
n	147		41	
	estimate	t-ratio	estimate	t-ratio
R^2	0.171	-	0.458	
β^t	-1.843	-12.27	-3.623	-15.59
β^{sl}	-1.166	-7.10	-1.474	-5.91
β^{se}	-0.295	-1.93	-1.312	-5.38
β^f	0.040	6.38	0.057	5.89
α^t	£46.05		£63.22	
α^{sl}	£29.10		£25.72	
α^{se}	£7.35		£22.89	

n = sample size

† = excludes non-trading responses

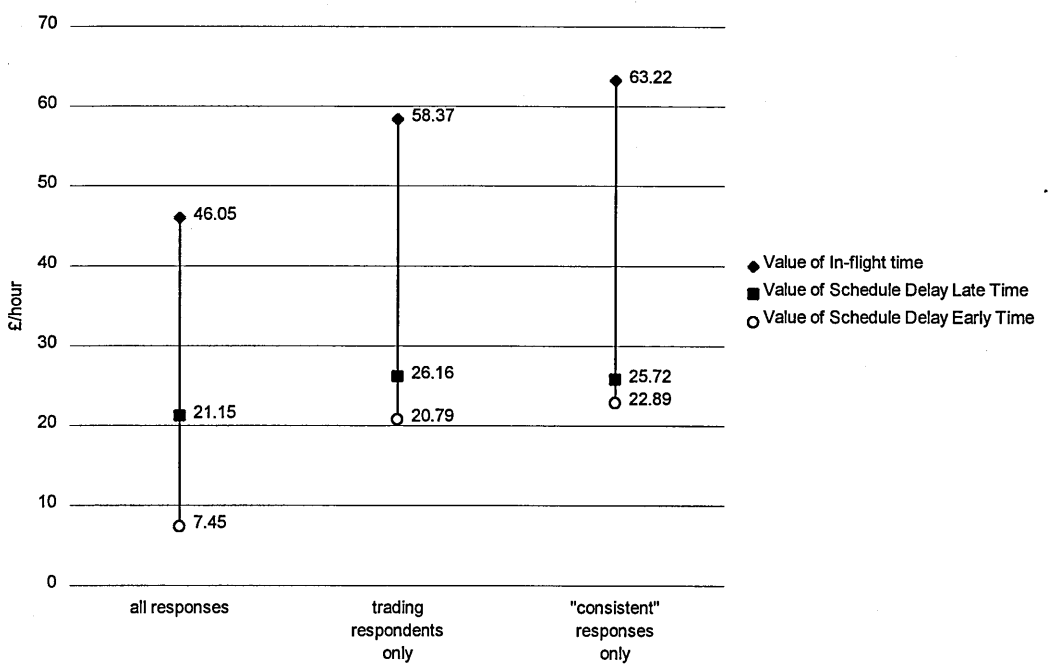
The proportion of purely rational respondents is small. Only 41 out of the 147 individuals in the sample, responded logically to each eight paired comparison. As expected, the removal of inconsistent respondents, improves R^2, from 0.17 to a respectable 0.46. The magnitude of the parameter estimates also change. However, two parameter estimates, β^{se} and β^t, have higher *t*-ratios, whereas for β^{sl} and β^f there is a marginal reduction in their respective *t*-ratios. Although it is difficult to explain or identify any specific reason for the increase in the statistical significance of β^t, for the schedule delay early parameter β^{se}, the removal of those respondents who made 'inconsistent' choices appears to have had a marked effect on its statistical significance. This confirms that a significant proportion of response errors were associated with the early departure time questionnaire, where individuals were asked to evaluate departures times scheduled earlier than their actual/ideal departure time.

For β^{sl} and β^f, there is a slight decrease in statistical significance. This is probably due to the reduction in sample size. The values of time derived from obtaining the ratio of time to cost coefficients also shows a marked change following elimination of inconsistent responses. The value of in-flight time increases from £46.05 to £63.22 per hour and the value of schedule delay early time α^{se} changes from £7.35 to £22.89. The value of schedule delay late time however, falls marginally to £25.72 from £29.10 per hour.

5.6.3 Results summary

Figure 5.3, below, provides a summary of the values of time obtained from samples containing: all respondents, trading respondents only and consistent respondents only.

Figure 5.3 Summary values of time: all respondents, trading respondents only, consistent respondents only



Applying lexicographic techniques has the effect of increasing the magnitude of both the value of schedule delay early time α^{se} and the value of in-flight time α^{t}. The scale of the increases is quite significant especially with respect to the value of schedule delay early time, increasing from £7.35 to £20.79 when removing all non-trading responses, and increasing further to £22.89 per hour when eliminating inconsistent responses. This confirms earlier findings, which suggests that the stated preference early departure time questionnaire did not capture very low values of scheduled delay early time that existed in the sample. As a consequence, a large proportion of respondents when choosing between their current flight and the hypothetical alternative offered, repeatedly chose the alternative flight, because it was cheaper.

For schedule delay late time, its magnitude remains more or less stable, with only marginal changes under lexicographic adjustments to the sample. The value of in-

flight time nonetheless increases from £46.05 to £58.37, assuming trading only respondents are included in the sample, and to £63.22 under the assumption that consistent respondents only are included sample. Table 5.11 below summarises the R^2 and parameter estimate *t*-ratio statistics obtained from the three samples.

Table 5.11: Model Results: summary R^2 and *t*-ratios (three samples)

			t-ratios			
	n	R^2	β^t	β^{se}	β^{sl}	β^f
all respondents	147	0.17	-12.27	-1.93	-7.10	6.38
trading respondents	90	0.32	-17.05	-5.83	-7.07	6.97
consistent respondents	41	0.46	-15.59	-5.38	-5.91	5.89

Applying both lexicographic methods, inevitably produces a higher R^2 statistic. Two sources of response error have been eliminated from the sample; non-trading and irrational respondents. When including only those individuals trading between alternatives, the model generates an R^2 of 0.32. The removal of inconsistent trading respondents from this sample increases the R^2 statistic to a respectable 0.46. Nonetheless, a significant degree of unexplained variation remains.

This is accounted for by the wide dispersion in values of time across individual respondents. Indeed, low goodness of fit statistics is a characteristic feature of estimating parameters from disaggregate choice data. Had individual's combination of in-flight time and schedule delay time converged within a specific range, then the R^2 would have been much higher. If values of schedule delay and in-flight time could have been anticipated *a priori* from past research, then the stated preference choice sets could have been designed to capture these values of time. However, in air transport, substantial variation in values of time can be expected within and between a city-pair market. Given the lack of *a priori* information on likely values of time, under these circumstances, it was necessary to establish a design which captured a sufficient range of value of time combinations.

Table 5.11 also confirms the significant improvement in coefficient *t*-ratios when removing non-trading respondents from the sample. Especially with regard to the in-flight time and schedule delay early coefficients, but less so for fare. The schedule

delay late coefficient experiences a marginal reduction in statistical significance. The concentration of non-trading responses amongst those individuals who were asked to evaluate earlier departure time choice set pairs, appears to have significantly affected the statistical significance of the schedule delay early parameter. Removal of these statistical observations, significantly improves its *t*-ratio. When inconsistent respondents are eliminated, the sample size falls to forty-one individuals. As a result of this loss of information, there is a reduction in the *t*-ratios with respect to each parameter estimate. Indeed, through eliminating the entire set of responses of an individual, because of one or two irrational or inconsistent preferences, the net effect is to reduce the statistical significance of the estimated parameters. This raises the important issue of having to decide to what extent is one justified in removing what are in some cases, perfectly rational and appropriate responses to the questionnaire ? On the one hand, the results do improve, but on the other hand there is a significant loss in information. Non-trading responses are perfectly rational in that the value of time combinations of the individual lie outside the range specified by the stated preference choice sets. Furthermore, the removal of irrational respondents also requires that their 'rational' responses be removed leading to a further loss in important information from the stated preference survey. In adjusting the sample by removing those responses that inflate standard errors of the parameters, this creates an imbalance within the sample. In seeking to derive estimates of schedule delay early and schedule delay late time, equal numbers of questionnaires with hypothetical early departure times and hypothetical late departure times were delivered. By removing respondents from the sample because they are non-trading, creates an imbalance in the sample because the majority of non-trading respondents were those individuals who were asked to evaluate early departure time questionnaires. As a consequence, both β^{se} and α^{se} are over-estimated to such an extent that the value of schedule delay late time α^{sl} is only marginally greater than the value of schedule delay early time, £26.16 and £20.79 respectively.

Whilst analysis of model results under different lexicographic assumptions has been a useful contribution to the analysis, the original parameter estimates generated from the whole sample (Table 5.6) were selected in order to calibrate the departure time choice

model. While a significant proportion of respondents did not trade between alternatives in their choice preference, there is little justification in eliminating them from the sample, since their choices do appear consistent, in so far as their values of both schedule delay time and in-flight time lie outside the range specified by the stated preference design. Secondly, individuals will respond inconsistently or irrationally to the choice options. Removal of those individuals that do so, has the effect of improving the goodness of fit of the model. Nevertheless, their removal also eliminates some consistent responses, since within each individuals set of responses, some are consistent whilst others are inconsistent. This has the effect of inflating the standard errors and reducing the *t*-ratios of the parameter estimates. However, it is difficult to expect individuals to respond rationally to all paired comparisons within each choice set, since there will inevitably be perception errors and bias caused by fatigue and lack of interest.

5.7 Estimation of β^0

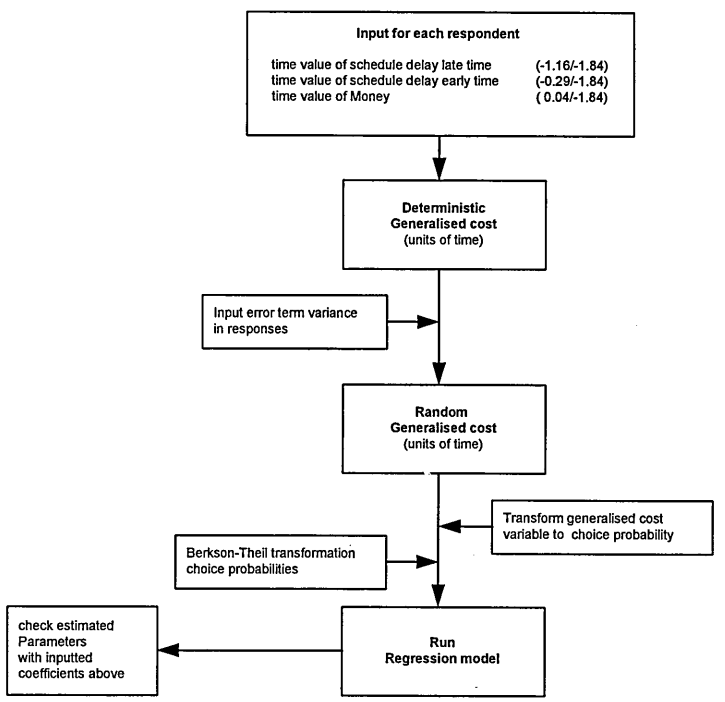
5.7.1 Method

In addition to the stated preference derived parameter estimates β^f, β^{se}, β^{sl}, β^t, an essential prerequisite to logit model calibration, is the need to obtain an estimate of the scale parameter β^0. The scale parameter functions as a constant in the logit model and represents the effect of error in respondent choice behaviour. Error is manifested in the following terms: firstly, those respondents who did not trade between their current flight and any of the hypothetical alternatives offered, and secondly, those inconsistent or irrational behavioural responses which were described in the previous section. Non-trading responses, strictly speaking, cannot be considered as "irrational" since the presence of these responses is directly attributable to the fact that the stated preference boundary values did not capture a sufficient range of value of time combinations that existed within the sample. However, from a stated preference perspective, any variation in value of time combinations across individuals within a given sample, must also be captured in the variance of error terms. The lower the dispersion in values of time the greater the goodness of fit of the model. However, with so much variation in individual values of both schedule delay and in-flight time,

a low R^2 statistic is inevitable, despite the fact that the parameter estimates may be statistically significant. Therefore, the scale parameter not only accounts for the effect of irrational and non-trading choices, it also represents the dispersion of values of schedule delay and in-flight time across the sample.

In generating the scale parameter, it is necessary to estimate the variance of error across the sample of individuals. The method derived, follows the flow diagram in Figure 5.4 below.

Figure 5.4 Simulation method flow-diagram



This is achieved by running a simulation exercise similar to that in chapter four which was specifically designed to test the efficiency of two stated preference designs. In the simulation, each individual is initially assumed to have the same value of schedule delay late, scheduled delay early and in-flight time, α^{sl} , α^{se} , α^{t}. These values are: £29.10, £7.35 and £46.05 respectively. Each individual is also assumed to have an error term ε, which is a standard deviation from the deterministic component of the generalised cost function. The error term is initially set at zero which assumes that there is no error in responses and that each individual has exactly the same values of

time (α^{sl}, α^{se}, α^{t}). The objective of the simulation is to identify a level of error term variance σ^2_{ε} which returns an R^2, β^{f}, β^{se}, β^{sl}, β^{t}, comparable to those obtained in Table 5.6.

Since the generalised cost component within passenger departure time choice model, described in the following chapter, is expressed in units of time, it is necessary to transform all the variables into a common unit of time. Each variable is transformed into units of in-flight time as shown in equation 5.2 below.

$$GC_{ij} = \frac{\beta^{t}}{\beta^{t}} t_{ij} + \frac{\beta^{f}}{\beta^{t}} f_{ij} + \frac{\beta^{se}}{\beta^{t}} se_{ij} + \frac{\beta^{sl}}{\beta^{t}} sl_{ij} + \varepsilon \qquad (5.2)$$

In equation 5.2 above, the difference in generalised cost between current flight *i* and alternative flight *j*, (GC_{ij}) can be represented in units of in-flight time by dividing fare schedule delay early and schedule delay late parameter estimates β^{f}, β^{se}, β^{sl} by the in-flight time parameter estimate β^{t}. The error term is represented by ε. Making an appropriate transformation of the differences in generalised cost GC_{ij} into five-point scale of assumed probabilities of choice P_{ij} (0.1, 0.3, 0.5, 0.7, 0.9), equation 5.3 below estimates the simulated parameters, β^{se}_{sim}, β^{sl}_{sim}, β^{f}_{sim}, β^{t}_{sim},

$$\ln\left[\frac{P_{ij}}{1-P_{ij}}\right] = \beta^{f}_{sim} f_{ij} + \beta^{se}_{sim} se_{ij} + \beta^{sl}_{sim} sl_{ij} + \beta^{t}_{sim} t_{ij} \qquad (5.3)$$

Generating *k* runs of the model at each interval of error term variance will produce a vector of simulated coefficients β^{x}_{sim1}, β^{x}_{sim2} ..... β^{x}_{simn}, shown below.

$$\begin{bmatrix} \beta^{se\ k=1}_{sim} & \beta^{se\ k=2}_{sim} & \beta^{se\ k=3}_{sim} & \ldots\ldots & \beta^{se\ k=n}_{sim} \\ \beta^{sl\ k=1}_{sim} & \beta^{sl\ k=2}_{sim} & \beta^{sl\ k=3}_{sim} & \ldots\ldots & \beta^{sl\ k=n}_{sim} \\ \beta^{t\ k=1}_{sim} & \beta^{t\ k=2}_{sim} & \beta^{t\ k=3}_{sim} & \ldots\ldots & \beta^{t\ k=n}_{sim} \\ \beta^{f\ k=1}_{sim} & \beta^{f\ k=2}_{sim} & \beta^{f\ k=3}_{sim} & \ldots\ldots & \beta^{f\ k=n}_{sim} \end{bmatrix} \qquad (5.4)$$

The mean simulated estimate of attribute *x* from the number of runs *k* is derived in equation 5.5.

$$\hat{\beta}^{x}_{sim} = \frac{\sum_{k=1}^{k} \beta^{x}_{sim}}{k} \tag{5.5}$$

In seeking to obtain an estimate of the scale parameter β^0, the model simulation identifies a range of error term variance which generates mean simulated model parameter estimates β^{se}_{sim}, β^{sl}_{sim}, β^{f}_{sim}, β^{t}_{sim} and a simulated measure of goodness of fit, R^2_{sim} which closely correspond to the original inputted stated preference parameter estimates outlined in Table 5.6. In doing so, both inferences can be made regarding the scale of error in units of hours, and an approximate estimate of the scale parameter β^0 can be derived.

The error term variance is then substituted into equation 5.6 derived by Ortuzar and Williamson (1994) to yield an estimate of β^0.

$$\beta^{o} = \frac{\pi^2}{\sqrt{6\sigma^2}} \tag{5.6}$$

Simulation results with respect to each parameter are summarised in Table 5.12 below, and outlined in detail in Appendix G.

5.7.2 Results

At each interval of error term variance, the model is estimated on the basis of fifteen runs, in which at each run, a distribution of random terms is generated across each simulated sample of individuals. Having generated the error components, linear regression is performed on the sample to yield simulated estimates of the stated preference parameters. Table 5.12 compares the inputted stated preference coefficients with the mean simulated parameter estimates generated at each interval of error term variance.

The performance of the mean simulated estimates derived from fifteen runs of the model vis a vis their input coefficients are graphically illustrated in Figures 5.6 to 5.9. Figure 5.5, outlines the mean simulated estimates generated at each level of error term variance.

Table 5.12: Model simulation results

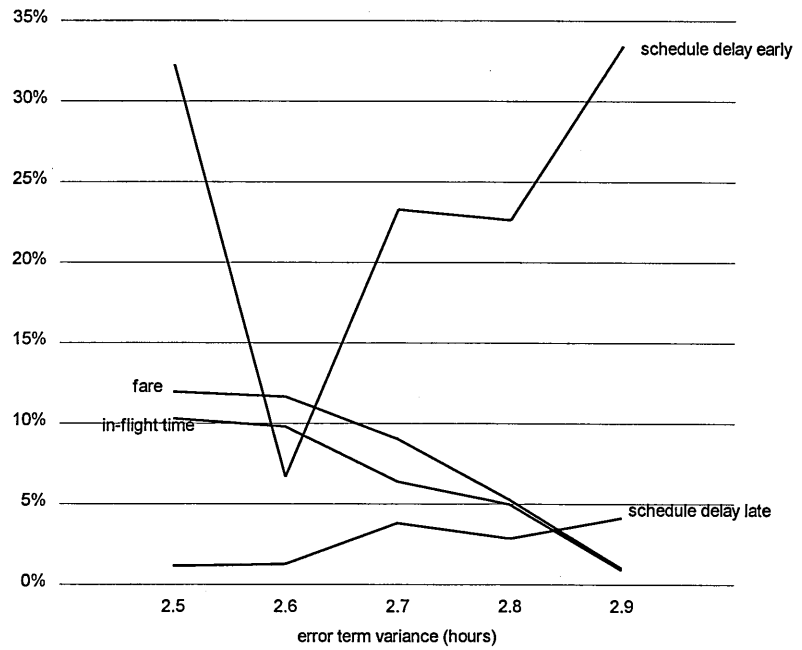
mean estimate†	error term variance (hours)				
	2.5	2.6	2.7	2.8	2.9
β^{f}_{sim}	0.0457	0.0455	0.0442	0.0425	0.0398
β^{se}_{sim}	-0.2231	-0.3161	-0.2393	-0.2406	-0.2211
β^{sl}_{sim}	-1.1797	-1.1514	-1.1231	-1.1336	-1.1196
β^{t}_{sim}	-2.0543	-2.0427	-1.9685	-1.9387	-1.8593
R^2_{sim}	0.1815	0.1763	0.1635	0.1574	0.1493

Calibrating the model on assumed levels of error term variance, revealed that simulated estimates comparable to those obtained from the actual sample in Table 5.6 were estimated within a range of 2.5 to 2.9 hours of error term variance.

The simulation exercise generated values of R^2 comparable with the 0.171 obtained from the initial stated preference estimation. The decline in the mean simulated R^2 from 0.18 at 2.5 hours of error term variance to 0.15 at 2.9 hours of error term variance, conforms with the expectation, that inflating the variance of error terms reduces model fit. Ideally, when the simulated R^2 intersects the stated preference R^2, one would also anticipate that at this interval of error term variance (2.6 hours to 2.7 hours), the mean simulated parameter estimates would likewise intersect their respective stated preference coefficient. However, when evaluating the actual performance of each simulated parameter vis a vis its stated preference value, this does not take place.

As the scale error term variance increases from 2.5 to 2.9 hours, the magnitude of the mean simulated fare coefficient declines from 0.4567 to 0.0398. The mean simulated parameter intersects the actual stated preference coefficient between 2.8 and 2.9 hours of error term variance. Ideally, one would expect the point of intersection to fall within the range 2.7 to 2.8 hours error term variance, as this is the interval within which the mean simulated R^2 intersects the stated preference R^2 (0.171). Despite, this inconsistency, the percentage variation between the mean simulated and the actual coefficient remains below 15%. Indeed the percentage variation narrows from 15% when the error term variance is 2.5 hours to 1%, when the variance is 2.9 hours as shown in Figure 5.7.

Figure 5.5 % variation between input and simulated parameter



The mean schedule delay late simulated estimate β^{sl}_{sim}, on the other hand intersects its stated preference coefficient (-1.166) between 2.5 and 2.6 hours of error term variance. This is both inconsistent with the R^2 point of interaction, and with the fare coefficient. where both simulated and actual stated preference estimates intersect between 2.6 and 2.9 hours of error term variance. Nevertheless, the percentage variation between the mean simulated estimate β^{sl}_{sim} and the stated preference coefficient β^{sl} , illustrated on Figure 5.8, is very low, ranging from a maximum of 4.1% at 2.9 hours of error term variance to 1.16% at 2.5 hours.

Evaluating the performance of the mean simulated in-flight time coefficient in Figures 5.5 and 5.8, *vis a vis* its inputted stated preference equivalent, reveals a similar degree of robustness. As the scale of error term increases in magnitude from 2.5 hours to 2.9 hours, the percentage variation between the mean simulated estimate and the actual stated preference coefficient β^{t} declines from 10% to 1%. The mean simulated estimate does not intersect the inputted coefficient within the range of error term variance specified.

Figure 5.6: Simulated fare parameter

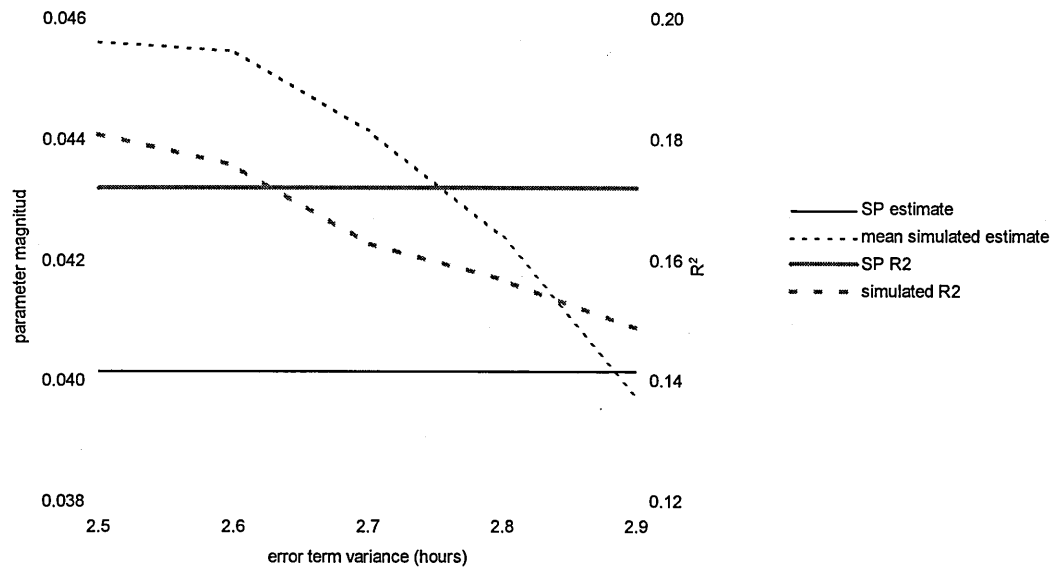


Figure 5.7: Simulated schedule delay late time parameter

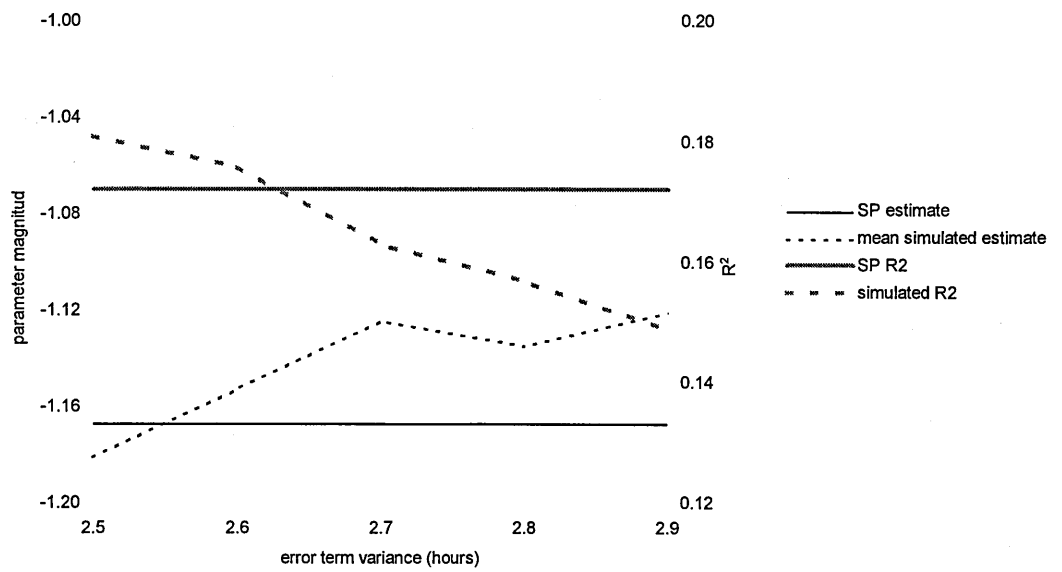


Figure 5.8: Simulated in-flight time parameter

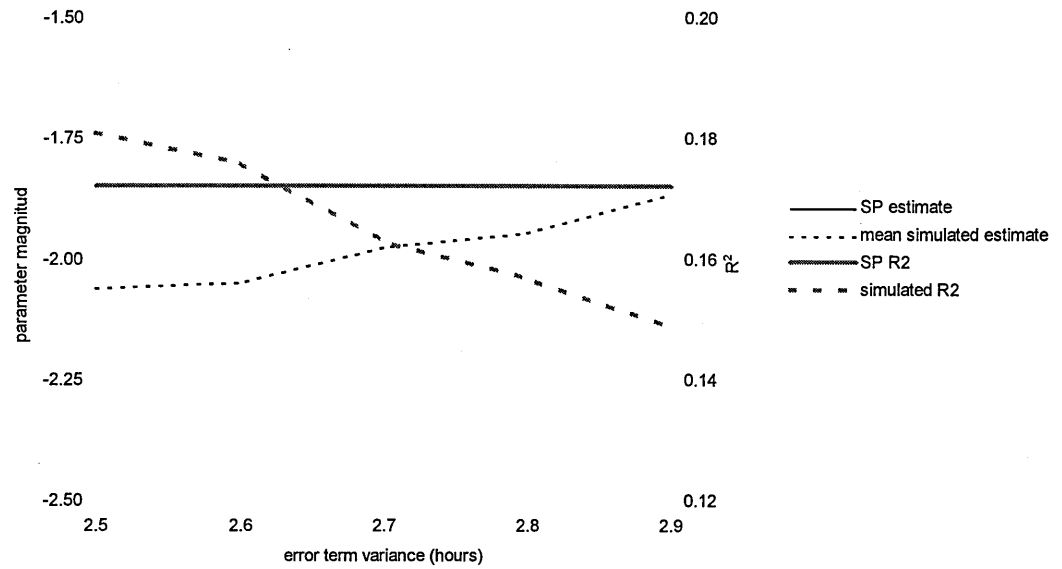
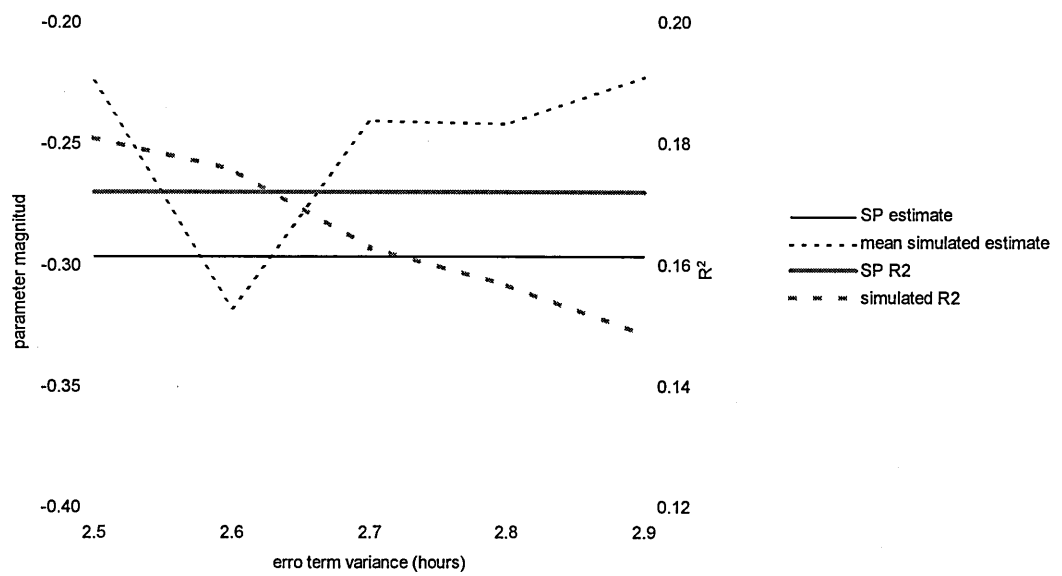


Figure 5.9: Simulated schedule delay time early parameter



Whilst fare, in-flight time and schedule delay late time parameters can be regarded as statistically robust coefficients in terms of simulation performance, analysis of the schedule delay early coefficient results appears to confirm earlier findings regarding its statistical significance. In Figure 5.9, as the magnitude of error increases, the simulated coefficient initially declines from -0.22 to -0.31, and then increases to -0.22 when the variance of error terms is 2.9 hours. Other parameter estimates appear consistent in that as the magnitude of error term variance increases, the mean simulated parameters appear to exhibit a consistent downward or upward trend. Inconsistencies associated with the schedule delay early coefficient stem primarily from design-related deficiencies where a large number of individuals, because of their low valuation of schedule delay early time, did not trade between their current flight and the hypothetical alternatives when evaluating the eight paired choices.

Figure 5.5 illustrates the percentage variation between the mean simulated parameters and the actual stated preference parameters. As the magnitude of error term variance increases from 2.5 hours to 2.9 hours, the percentage variation between simulated and actual stated preference parameters declines to less than 5% for three our of the four parameters, schedule delay late time, in-flight time and fare. The only inconsistency is the significant percentage variation associated with the schedule delay early parameter. In order to generate β^0, an estimate of the scale of error term variance is required. Ideally, one would obtain an estimate of the error term variance by identifying the interval of error term variance at which all simulated estimates intersect their stated preference estimates. For example, at the interval of error term variance where the mean simulated R^2 is close to the stated preference R^2 (0.171), β^t_{sim} should equal β^t, β^{sl}_{sim} should equal β^{sl} and so on. However, from Table 5.12, it clear that the mean simulated parameters do not intersect their stated preference parameters at the same interval of error term variance.

In the absence of any consistency in the relative performance of the mean simulated parameter estimates, one can deduce that the variance of error must lie between 2.5 and 2.9 hours of error term variance, since each simulated parameter intersect their respective stated preference coefficient within this range.

Table 5.13: Interval of σ_ε^2 point of intersection

β^{f}_{sim}	2.8-2.9
β^{se}_{sim}	2.5-2.7
β^{sl}_{sim}	2.5-2.6
β^{t}_{sim}	2.9
R^2_{sim}	2.6-2.7

If one takes the mid-point of this range, 2.7 hours, as an approximation to the true level of error term variance, then substituting this term into equation 5.6, yields an estimate of the scale parameter β^0 of 1.49. This value is a re-scaling factor which readjusts the deterministic component of the logit model, to take into account the magnitude of error term variance. The magnitude of error term variance consists of the following elements:

- non-trading responses. i.e. those respondents who consistently chose one alternative over the other
- inconsistent responses. i.e. those respondents who incorrectly selected one alternative over another, which is logically superior or equal in every attribute,
- variation in the value of time between respondents in the sample.

Unfortunately, no method exists which can separate the elements of error in response behaviour and the variation in values of time between individuals. Nonetheless, this value will effectively determine the distribution of choice probabilities when passengers select departure times. It should be remembered, however, that the β^0 parameter, being a measure of the extent of randomness in choice decision-making and variation in values of time between individuals, cannot be accepted as a precise estimate primarily because of the varying performance of the simulated parameters, but nevertheless can be accepted as a reasonable approximation to the true value of β^0.

Indeed, it is unlikely that selecting any of the possible ranges of β^0 would have made a significant difference to the distribution of choice probabilities. Clearly the importance of β_0 cannot be underestimated, since it will ultimately have a large bearing on choice probabilities generated by the logit model. The issue of β^0 will be discussed within the context of the model sensitivity analysis in Chapter seven.

5.8 Summary and Conclusions

The aims of this chapter were to present, interpret and validate the results obtained from the stated preference experiment. Furthermore, in advance of developing a passenger choice of departure time model, one key objective of this chapter was to use these results to generate appropriate parameters for logit model calibration. The final section of chapter five focused on estimating the logit model scale parameter β^0. The main points from Chapter five can be summarised as follows:

- In designing the questionnaire, the objective was to achieve an optimal trade-off between information required and the time taken to complete each interview. This process was constrained firstly, by the airport authority, which restricted questioning to a five minute period, and secondly, by the late arrival of passengers in the departure lounge from where respondents were interviewed.

- A total of 140 passengers were sampled for the stated preference experiment. The breakdown of journey purpose in the sample conforms to the actual distribution of passengers by journey purpose obtained from a UK Civil Aviation Authority survey.

- In order to validate the choice of the rating scale least squares regression method, these results were compared to those obtained using ordered logit and ordered probit methods. Whilst recognising that there are deficiencies associated with applying linear regression on ordered dependent variables, these results were broadly comparable to those generated by ordered logit and probit techniques. In light of these results and conclusions reached in past research, on the sensitivity of model parameter estimates to estimation technique, it was decided to accept the linear regression method. However it is recognised that not all applications of linear regression to ordered dependent variables will yield consistent estimates vis a vis those generated by maximum likelihood-based estimation methods.

- Results from the regression analyses confirm *a priori* expectations of the magnitude and signs of the parameter estimates. As expected, passengers attached a greater degree of disutility to later departure times compared to earlier flights.

In-flight time was found to be the most important variable that influenced choice and fare was found to be the least important given the magnitude of their respective parameters. However, this chapter also recognised the presence of stated preference design related weaknesses, manifested in the low *t*-ratio associated with the schedule delay early parameter.

- The application of lexicographic techniques by removing both non-trading and inconsistent responses generated some interesting results. As expected, model goodness-of-fit improves with the elimination of these responses. Removing those respondents that did not trade between choices had the effect of also improving parameter statistical significance, this was particularly relevant for the schedule delay early parameter. Although removal of inconsistent respondents, does improve goodness of fit, this also has the effect of reducing the *t*-ratios of each parameter, with the exception of β^{se}. Although the application of lexicographic techniques improved parameter statistical significance and model fit, those results generated from the unadjusted sample of responses were selected. This was due to the imbalance in the sample, caused by the elimination of non-trading responses which led to β^{se} and α^{se} being over-estimated. Furthermore, the removal of those respondents who answered irrationally to the stated preference choice options also eliminates their rational choices, thereby reducing parameter statistical significance.

- In seeking to generate an estimate of the scale parameter β^{0}, a process of simulation using the linearised parameters was undertaken. Results showed that while there appeared to be a degree of uncertainty over the precise value of β^{0}, because of inconstancies between the simulated parameter estimates and the actual inputted stated preference coefficients, a valid approximation estimate was generated.

Having focused on issues related to passenger choice, the following chapter considers those decision-rules which governs both passenger's choice of departure times and how flights are scheduled at each departure slot.

CHAPTER 6

Slot Value Simulation Model

6.1 Introduction

Having discussed the issue of model estimation and empirically derived the passenger choice model parameters in Chapter five, this chapter examines the methodology used to estimate slot values. Within this context, decision-rules governing passengers' choice of departure time and operator slot scheduling are formulated. These rules are then combined within the context of a simulation model in order to generate the necessary information from which slot values will be derived.

Section 6.2 focuses on developing a model of passenger's choice of departure time. This is followed, in Section 6.3, by a description of the relevant operator departure slot scheduling decision rules. Both sets of decision-rules are combined to construct a simulation model in Section 6.4. Further to describing the basic structure of the model, assumptions underlying its operation and any limitations will also be examined in sub-sections 6.4.1 and 6.4.3 respectively.

6.2 Passenger departure time choice model

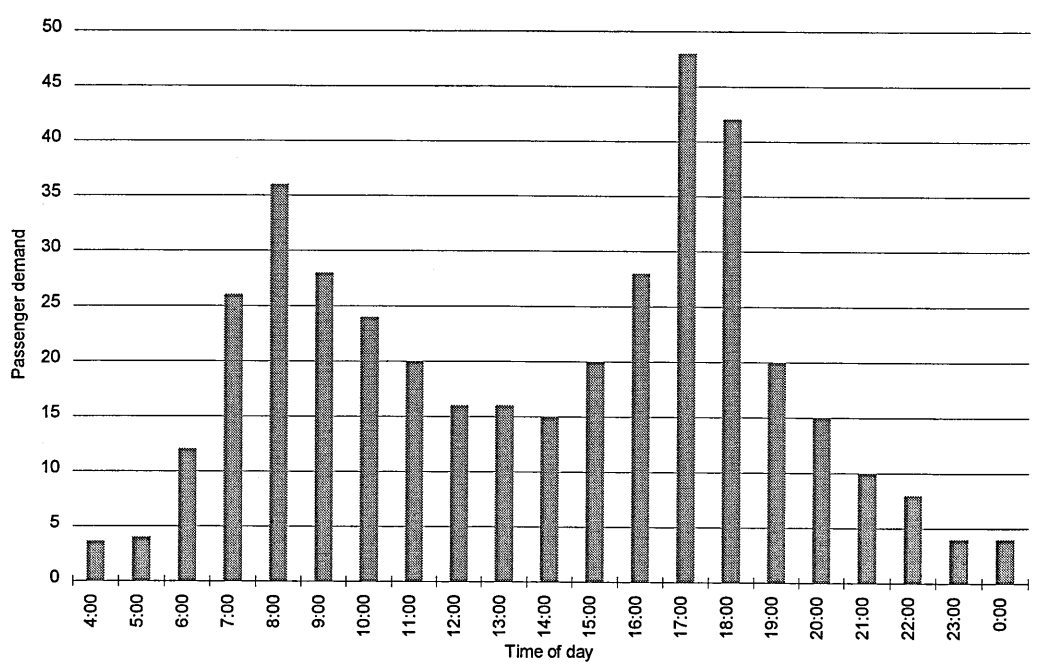
Passenger's choice of departure time is evaluated within the context of an origin-destination city-pair market, where it is assumed that passengers, who desire to travel in this market, possess an ideal or most preferred time of departure at the origin. The demand to travel at a specific departure time on any day, is dependant on the hourly distribution of ideal departure time preferences. For example, assuming that the level demand on any weekday is four hundred one-way trips, passenger demand to travel at each hour is based on the same hourly density distribution, as outlined in Figure 3.1, at each ideal departure time *i*. This is shown in Figure 6.1 below. Demand in the morning period peaks at 08:00, where thirty-six passengers have selected this slot as their most ideal departure time. During the late afternoon - early evening period, demand is highest at 17:00 and 18:00, where forty-seven and forty passengers prefer to depart respectively. Because of the inconvenience of travelling before 06:00 and after 21:00, only a small number of passengers elect to travel at these times.

Let there be n departure time intervals with d_i representing the number of passengers with ideal departure time i, where i = ($1,2,3,.....n$). The probability that these passengers, who possess an ideal departure time i, choose any departure time j, where j = ($1,2,3,.....n$), P_{ij}, can be estimated using the passenger departure time choice logit model illustrated below.

$$P_{ij} = \frac{\lambda_j \, exp^{-\beta^0 GC_{ij}}}{(\forall \lambda_j = 1)\sum_{j=1}^{n} exp^{-\beta^0 GC_{ij}}} \qquad (6.1)$$

There are two elements to the passenger departure time choice model; a dummy variable λ_j which indicates whether there is a flight scheduled at j and the logit model function which estimates passenger choice probabilities. The dummy variable λ_j can take on one of only two possible values; 1 if there is a flight, and 0 if there is no flight at departure time j.

Figure 6.1: Passenger demand by time of day: 400 passenger trips



Passengers select those departure times where a flight is offered. Given the requirement to generate profits, it is unlikely that flights will be scheduled at each ideal departure time interval. Depending on the pattern of flight departure time

scheduling, some passengers will inevitably experience a degree of inconvenience, since they are unable to depart at their preferred time. The logit function, which is the second element, estimates the probability of a passenger who prefers to depart at ideal time i, choosing any departure time j. This is based on each passenger's generalised cost, GC_{ij}, which is a function of the fare levied by the operator and the magnitude of schedule delay time experienced by passengers. Schedule delay time measures the absolute difference between a passenger's ideal time of departure i and the actual departure time j scheduled by the operator. Since departures scheduled earlier than a passenger's ideal time and departures scheduled later than a passenger's ideal time are valued differently, schedule delay time is represented by two separate variables: schedule delay early time and schedule delay late time. These are denoted as se_{ij} and sl_{ij}, and are derived as follows.

$$se_{ij} = |i - j|_{i>j} \tag{6.2}$$

$$sl_{ij} = |i - j|_{i<j} \tag{6.3}$$

Equation 6.4 below describes the model used to estimate an individual passengers' generalised cost at any departure time j.

$$GC_{ij} = \frac{\beta^{se}}{\beta^{t}} se_{ij} + \frac{\beta^{sl}}{\beta^{t}} sl_{ij} + \frac{\beta^{f}}{\beta^{t}} f_j + \frac{\beta^{t}}{\beta^{t}} t_j \tag{6.4}$$

Fare is represented by f_j and in-flight time is denoted by t_j. Since generalised cost (GC_{ij}) is measured in units of time, the product attributes: se, sl and f are transformed into units of in-flight time by dividing their associated parameter estimates: β^{se}, β^{sl}, β^{f}, generated from the regression analysis in the previous chapter, by the in-flight time parameter estimate, β^{t}.

One important component of the logit model is the scale parameter β^{0}, which was empirically derived in Chapter five. This represents, firstly, the aggregate scale of error associated with passenger choice decisions, and secondly, the degree of variability in values of schedule delay early time, schedule delay late time, and in-flight time between respondents in the stated preference sample. The value of β^{0} has a

significant effect on the distribution of choice probabilities and therefore, the pattern of flight scheduling, and ultimately the value of departure slots.

Having described the model which governs passengers' choice of departure time, the following section focuses on those decision-rules relevant to operators' choice of slots.

6.3 Operator choice of slot decision-rules

In formulating a set of departure time scheduling decision-rules, one is required to make assumptions regarding the environment within which competition for departure slots is to be modelled. Individual operators are required to make three decisions:

- whether to enter the market or whether to leave.
- at what departure slot times to operate a service.
- what level of fares to charge.

The total revenue generated from operating a flight at any departure time j, R_j, is given as follows:

$$R_j = f_j \sum_{i}^{n} P_{ij} d_i \qquad (6.5)$$

Where d_i represents the number of passengers who choose to fly at ideal time i, where $i = (1,2,3.....n)$. Fare f_j is levied on the basis of pricing decision rules outlined in the following section.

There are costs incurred associated with the scheduling of an individual flight, depending on the type of aircraft. These costs are assumed not to vary by time of day, but only by type of aircraft. The total costs of operating a flight at any departure slot j using aircraft type a, C_{aj} is shown below.

$$C_{aj} = DC_a + IC_a \qquad (6.6)$$

Where DC_a and IC_a represent the direct and indirect operating costs associated with aircraft type a. A more detailed examination of how these costs were derived is outlined in appendix H. The profit π generated by a flight at any departure time j is therefore:

$$\pi_j = R_j - C_{aj} \tag{6.7}$$

One frequently used indicator of profitability in the aviation industry is known as the load factor ratio which measures the proportion of aircraft seats occupied by revenue passengers. The operator will consider the minimum load factor required to cover operating costs. The cost per aircraft seat η_a is defined as follows;

$$\eta_a = \frac{C_a}{S_a} \tag{6.8}$$

Where C_a and S_a are defined as the total costs and seating capacity associated with aircraft type a respectively. The break-even load factor ratio λ_a which measures the minimum passenger load factor required to generate a profit is defined as follows.

$$\pi_j = 0 \quad if \quad f_j \lambda_{aj} S_a = C_a \tag{6.9}$$

Therefore:

$$\lambda_{aj} = \frac{C_a}{S_a f_j} = \frac{\eta_a}{f_j} \tag{6.10}$$

Let the decision to schedule a flight at any departure time j be represented by dummy variable λ_j. This variable can take on one of only two possible values: 1 or 0. These values indicate whether there is a flight scheduled at departure slot j. Each unoccupied departure slot is examined. The scheduling of a flight is based on satisfying the following conditions.

$$\lambda_j = \begin{cases} 1 & if \quad \pi_j > 0 \\ 0 & if \quad \pi_j \leq 0 \end{cases} \tag{6.11}$$

Departure slot scheduling is basically a two-stage process. Firstly, each individual departure slot is evaluated, based on the conditions specified above. Passengers, who are positioned at their ideal departure time, decide whether they prefer to depart on this flight. This evaluation is based on the passenger departure time choice model. From the operator's perspective, a decision is made on whether to schedule a flight or not to schedule a flight at a slot. If profit at j is greater than zero, then a flight is

supplied. If, on the other hand, profit is less than or equal to zero then departure slot j is rejected and the next slot is evaluated.

Equations 6.1 to 6.11 describe a set of decision-rules which govern passenger's choice of departure time and operator's choice of departure slot. These behavioural rules are static, since they only apply at a specific point in time. However, an equilibrium solution to these decisions can only be achieved after a sequence of iterations. Therefore, any model that seeks to simulate these processes has to be iterative as opposed to static. Through combining both passenger and operator flight scheduling decision-rules outlined above, a simulation model can be developed which is able to generate the information that is needed to estimate the value of departure slots.

6.4 Simulation model

6.4.1 Basic assumptions

In simulating the supply of flights, there are two issues that need to be considered: firstly, at what time will flights be scheduled ? and secondly, at what price ? These decisions are based on the profit generated at a specific departure time. This in turn is a function of the choice probabilities or market share of this service determined by the passenger departure time choice model. Market share is a function of the positioning and pricing of other services in the market. The previous section described the basis of these decisions.

In order to translate these two models (passenger choice and operator choice) into a model of market behaviour with interacting players, it is necessary to develop a computer programme capable of simulating the timing and sequence of both passenger departure time choices, operator slot scheduling, and pricing behaviour. The outcome of this model is a distribution of flights throughout the day, with levels of demand, fare, and profit associated with these flights.

The model consists of two elements; a passenger choice model, which predicts passenger's choice of flight and a structure of decision-rules which govern operator departure slot scheduling and pricing behaviour. There are two types of decision-maker: operator and individual passenger. Decisions are tentative rather than final in that decision-making takes place within the context of a sequence of iterations of the

simulation model. Within each iteration or time period, players in the market continually adjust their behaviour in response to the previous period's information. Therefore, decisions taken in period or iteration t are based on information from period t-1. For example, having scheduled a flight and set a fare based on the decision-rules outlined in equations 6.5 to 6.11 in one iteration, the operator may alter it's decision in the following iteration as other flights are scheduled.

This process is continuously repeated until equilibrium is achieved. Model equilibrium is defined as the point at which:

- all passengers are satisfied with their choice of flight and have no incentive to select an alternative.
- operators of existing services are content to leave their scheduling and pricing decisions unchanged, and profits are positive on all services and cannot be increased by changing fare.
- there are no longer any further opportunities for the supply of additional services in the market and all existing slots with no service do not offer a profit at any fare.

Each run of the simulation model consists of a number of iterations t, where t = (1,2,3.....n). The number of iterations in any run depends on the time taken to achieve equilibrium. In the first iteration of any run, it is assumed that all departure slots are evaluated with the same fare. This fare is a basic one-way fully-flexible economy-class fare denoted as f^B. Therefore:

$$\text{If} \quad t = 1 \quad \text{then} \quad f_j = f^B \tag{6.12}$$

In the following iterations, new operators evaluate each available or unoccupied departure slot. In doing so, the fare set at this slot in the previous iteration is reduced by a fixed amount ∂f. This could be, the fare set by the last operator to schedule a slot at this time. Therefore, the new fare f_j, is defined as follows:

$$\text{If} \quad t > 1 \quad \text{and} \quad \lambda_j = 0 \quad \text{then} \quad f_j = f^{t-1} - \partial f \tag{6.13}$$

If, by setting a fare f_j a flight is scheduled, in the following iteration the flight at this departure slot j, leaves fare unchanged, if passenger demand is above break-even and below seating capacity.

Therefore:

$$\text{If} \quad t > 1 \qquad \lambda_j = 1 \qquad \text{and} \qquad \lambda_{aj} S_a \leq \sum_i^n P_{ij}\, d_i \leq S_a$$

then

$$f_j^t = f_j^{t-1} \tag{6.14}$$

The fare at departure slot j in iteration t is the same as the fare set in the previous iteration.

If, as a result of the scheduling and pricing decisions at other departure slots, demand exceeds seating capacity at j, then the fare set in the previous iteration t-1 is increased by a margin of ∂f. Therefore:

$$\text{If} \quad t > 1 \qquad \lambda_j = 1 \qquad \text{and} \qquad \sum_i^n P_{ij}\, d_i > S_{aj}$$

then

$$f_j^t = f_j^{t-1} + \partial f \tag{6.15}$$

By altering the magnitude of ∂f for each run of the simulation model, a set of equilibrium scheduling and pricing decisions can be observed. When equilibrium is achieved, the simulation model generates a distribution of flights at various departure slots. These flights are associated with a level of passenger demand and equilibrium fare. The value of a departure slot is therefore, the maximum profit that is generated at that specific departure slot, which is derived from various runs of the simulation model, each based on different values of ∂f.

In advance of formulating the structure of the model, some basic assumptions need to be clarified regarding the context within which the simulation model is operationalised:

- The model is applied to a route on a specific city-pair market, where there exists a number of passengers who desire to depart from this airport to the destination in one day.
- On this route, there are a total of twenty-one hourly departure slots from the originating airport that are available to operators in order to schedule flights. These hourly slots range from 04:00 to 00:00.
- Passengers who wish to travel on this route, have a desired or ideal departure time. The distribution of ideal departure times is represented in Figure 3.1.
- Passengers within this market are assumed to be homogenous, in the sense that there is no differentiation between passengers with respect to income and journey purpose. Although it would have been interesting to model both business and non-business departure time choices separately, the magnitude of the stated preference sample size was not considered sufficient enough to generate statistically significant parameter estimates.
- Passenger choice decision-making is based on the departure time choice model (equation 6.1), which is calibrated on parameter estimates empirically derived from the stated preference experiment in chapter five.
- Each individual flight that is scheduled, is supplied by an individual operator.
- In any run of the model, aircraft type is the same for all operators
- The supply of flights is assumed to be elastic, in the sense that network-wide scheduling and other supply-side considerations are not incorporated in the model. These restrictions could either be aircraft maintenance or crew rostering arrangements. Entry and exit is therefore costless. The issue of supply inelasticity is discussed in greater detail in sub-section 6.4.3.

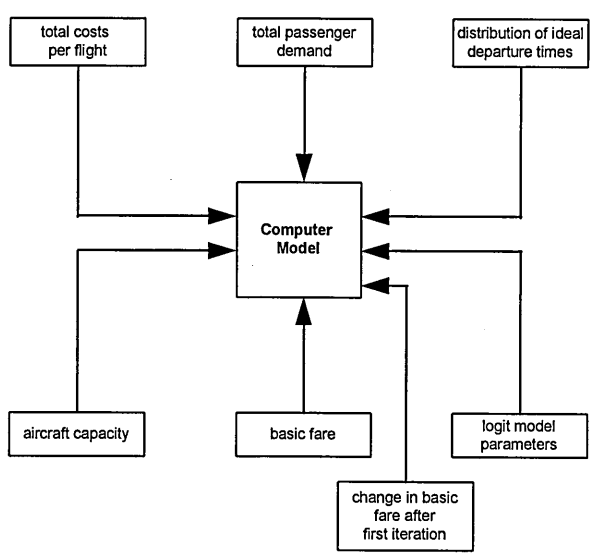
- In terms of operator departure time scheduling, it is assumed that there are no artificial entry or exit barriers such as fixed or sunk costs. The only restriction to scheduling, is if a departure slot is already occupied by another flight.
- Operators, in making decisions, are assumed to have complete knowledge of passenger's generalised costs.

6.4.2 Model structure

The flow-diagram (Figure 6.3), on the following page, illustrates the sequences, processes and decision-rules applicable to the first iteration of the simulation model.

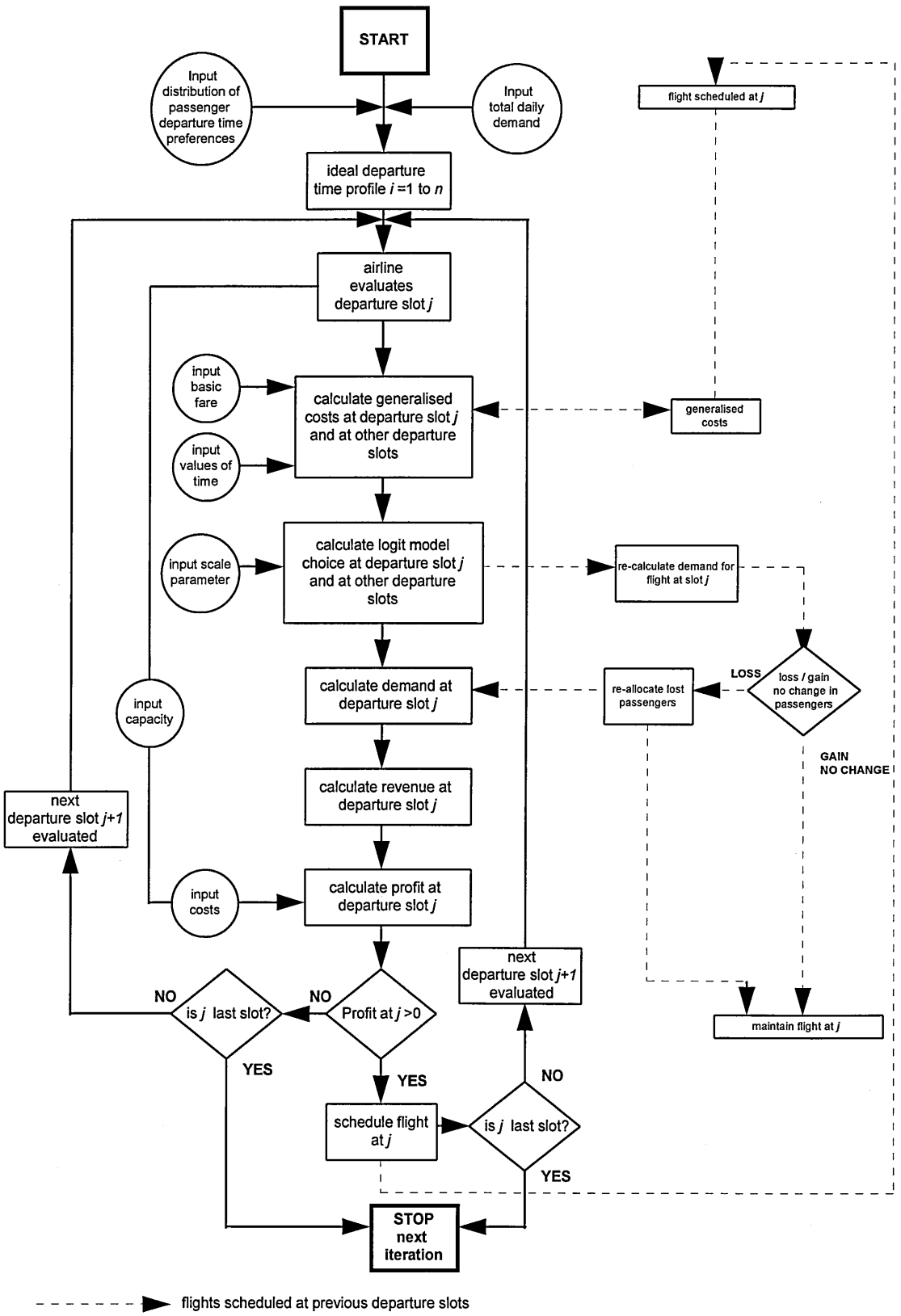
In order to operationalise the model, there are six items of information that are required: total daily passenger demand, the distribution of ideal departure times, basic one-way economy fare, aircraft type and their total costs, passenger choice model parameters, and in the second and subsequent iterations, the variation in basic fare ∂f, as shown in Figure 6.2 below.

Figure 6.2: Required simulation input parameters



The demand to travel at each departure time (d_i) is generated from total daily demand and the distribution of ideal departure time preferences. The first departure slot at 04:00 is evaluated in order to ascertain whether, in terms of profitability, it is worth scheduling a flight at that time. Evaluation of this departure slot, is based on setting a basic one-way fare and selecting an aircraft type with associated costs and seating

Figure 6.3: Computer model flow-diagram: first iteration



capacity. In the first iteration, the fares set are the same for all flights. Scheduling a flight at j (04:00) and a basic fare f_j, the generalised costs to all passengers of departing at this particular departure slot j can then be calculated. The generalised costs associated with all other departure times are also derived.

These generalised costs are then substituted into the logit model which estimates the choice probability or market share associated with a flight scheduled at 04:00. Therefore, the demand to travel and the profit generated from supplying a flight at this time can be evaluated.

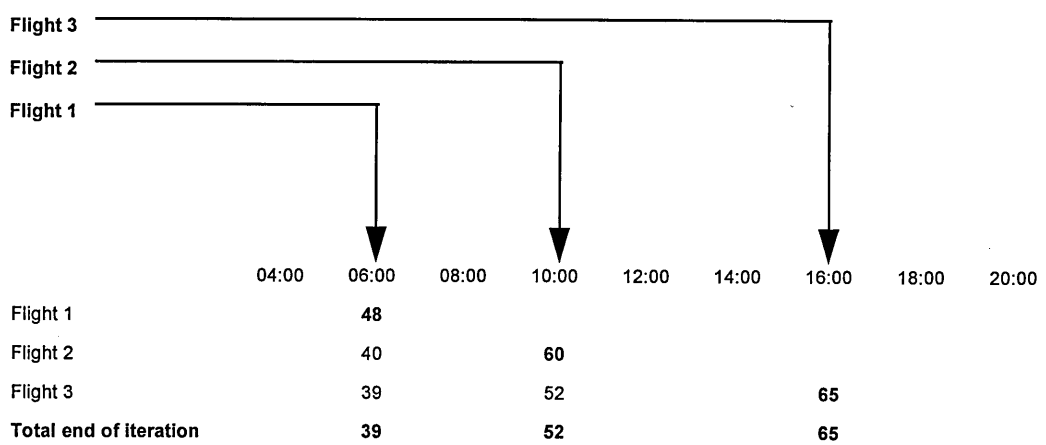
If profit is not greater than zero i.e. if this slot cannot generate any profit, then departure slot 04:00 is rejected and the following departure slot is evaluated at (05:00). If profits can be generated from operating at 04:00, a flight is scheduled. For the first iteration, once a flight has been scheduled, the next departure slot is evaluated. For example, a flight may be scheduled at 10:00. In scheduling at this time, this flight may have attracted passengers from the previous flight at 04:00. The extent to which demand on the first flight departure (04:00) is reduced depends on the difference in schedule delay between both flights and how highly passengers value schedule delay early and schedule delay late time. As there is no difference in fare between individual flights in the first iteration, passengers are selecting their preferences only on the basis of the relative schedule delay time between departures. This process is repeated until all twenty-one slots have been evaluated.

At the end of the first iteration of the programme, a set of flights scheduled at various departure times has been generated. However, the model has not corrected for any excess demand (where demand for a flight at j is greater than aircraft seating capacity) that may have arisen, nor has it corrected for any reduction in demand, below break-even, on previous flights after flights have been scheduled.

For example, before completion of the first iteration, as flights are generated at subsequent slots, demand for the first airline which scheduled at 04:00 may fall below break-even, even as other flights are scheduled later in the day. Figure 6.4 below is an illustrative example of how the model functions within each iteration.

Firstly, assume that aircraft capacity is 65 seats and total demand is 156 passenger trips on one day. After evaluating slot 04:00, a flight is scheduled at 06:00. Demand for this flight is forty-eight passengers, which is above break-even. The second airline schedules a profitable flight at 10:00, attracting 60 passengers, this flight is also above break-even. In the same process, it has managed to attract eight passengers from the flight at 06:00, which was scheduled by the first airline. As a consequence, demand for the first airline falls below break-even. The third airline schedules a flight at 16:00, generating 65 passengers, and at the same time attracting passengers from those flights scheduled at 06:00 and 10:00, one and eight passengers respectively. At the end of the this iteration, two flights are in profit and one flight is operating at a loss. The process of examining each flight opportunity is repeated in the next iteration and so on until equilibrium is achieved. That is until all flights generated are profitable and no additional profit can be achieved by reducing fare, and all remaining (unoccupied) slots are unprofitable.

Figure 6.4: Example of flight scheduling and demand per flight in one iteration



In the second and subsequent iterations, departure slots are re-evaluated in light of the distribution of flights and the characteristics of these flights in terms of fare and demand in the first iteration. The reader is referred to Figure 6.5 on the following page which provides a model flow-diagram describing the processes involved in the second and subsequent iterations.

If the slot was unoccupied from the previous iteration, then it is re-evaluated to ascertain whether it is profitable to schedule a flight at this time. In doing so, fare set

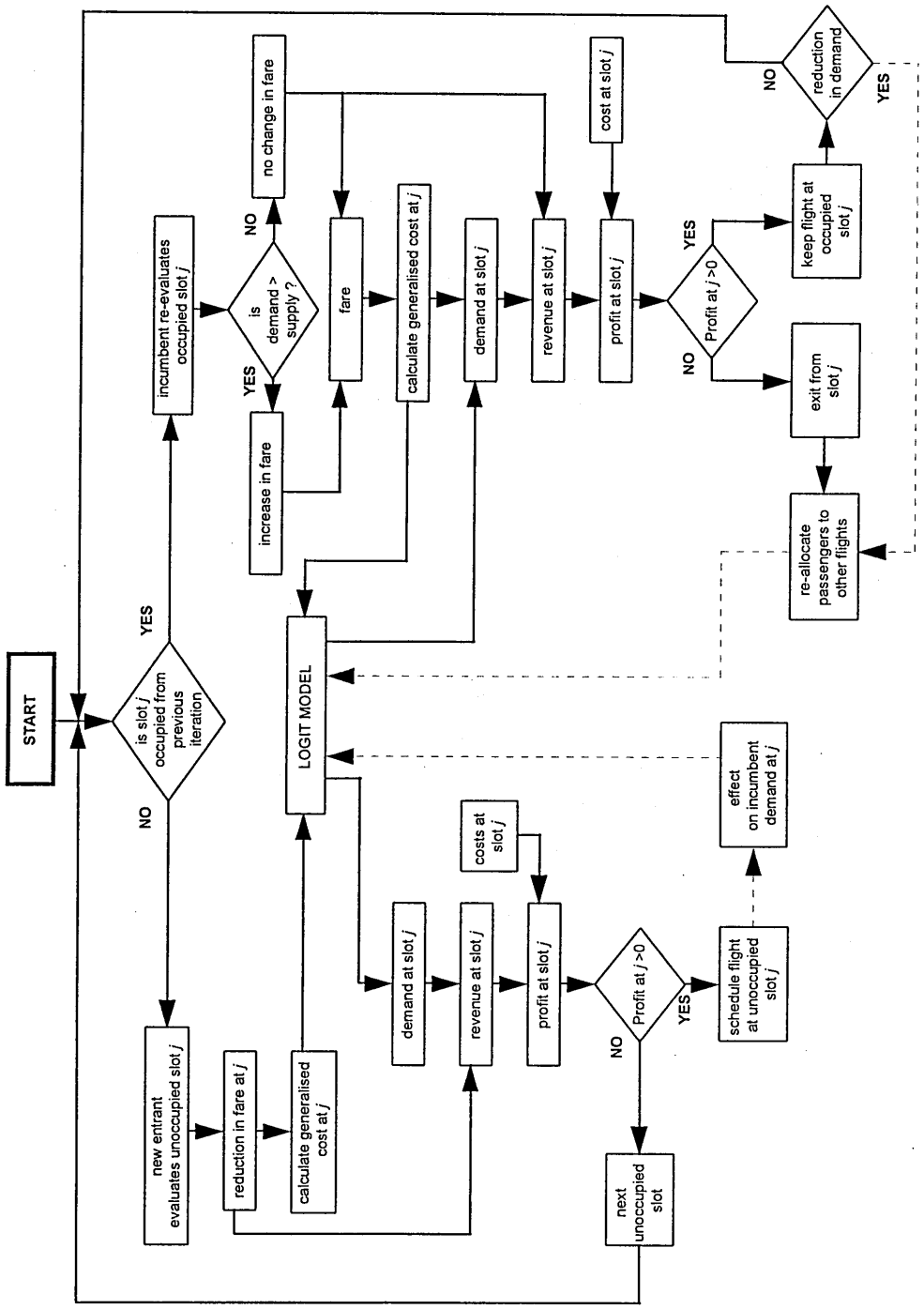


Figure 6.5: Computer model flow-diagram: second and subsequent iterations

in the previous iteration, is lowered by a fixed amount, ∂f. This command is designed to introduce an element of fare discounting in simulating competition. Having reduced fare by the fixed amount, the generalised costs associated with scheduling a flight at this time and the generalised costs associated with other times are calculated from which the market share is derived via the logit model. Having generated a level of demand, the profit derived from scheduling a flight at this time is estimated given the new reduced fare and the total flight costs. If profit is generated, then a flight is scheduled and the next unoccupied slot is evaluated. If no profit is generated then the following slot is also evaluated.

If a slot is occupied from the previous iteration, it is re-evaluated in light of the scheduling or withdrawal of other flights. Fare does not change from the previous iteration unless demand for the flight exceeds seating capacity. If there is excess demand, fare is increased by the same margin as it was reduced in the case of new flights. If demand is not greater than supply, then fare remains unchanged.

The implications of these decisions and the scheduling of additional services on the generalised costs are then substituted into the logit model which generates the market share associated with this flight. If this flight is still able to still generate a profit, then the flight remains at occupied slot j. If there is a loss of demand, these passengers are then re-allocated to other flights. If demand falls below break-even, this flight exits the market and all passengers are then re-allocated to other flights. This process is repeated with additional slots being re-evaluated, until the last slot at midnight (00:00), where the iteration is complete. In the following iterations, these processes are repeated until equilibrium is achieved i.e. the point at which passengers and operators are satisfied with their decisions, have no incentive to change, and there are no longer any scheduling opportunities for additional flights.

Therefore, for each run of the programme, which consists of several iterations, different assumptions can be made regarding the extent to which airlines can vary fares. Each run, which is based on different assumptions on the change in fare ∂f, generates an equilibrium pattern of flights, associated with a specific fare and level of

passenger demand. From this information, it is possible to calculate the maximum profit generated at each slot, which is the measure of the value of each departure slot.

The following equations describe, in mathematical terms, the processes and sequences of the simulation model. Assume that any flight n possesses a strategy ϕ which involves setting a fare f and supplying a flight λ at a departure time slot j.

$$\phi_n = f_j \lambda_j \tag{6.16}$$

The amount of profits π generated by flight n is assumed to be a function of its strategy employed.

$$\pi_n = f(\phi_n) \tag{6.17}$$

One restriction that is applied is that the total number of flights F cannot at any time exceed the total number of departure slots.

$$F \leq \sum_{j=1}^{n} j \tag{6.18}$$

Decision-making within this competitive environment is assumed to be sequential. Therefore, within each iteration of the model, slots are re-evaluated, those that are unoccupied and occupied from the previous iteration. Equilibrium is achieved when all operators are content to leave their decisions unchanged. These decisions are based on a reaction function. The reaction function represents those responses by individual flights to the decisions of others operating in the market. The supply of flights is assumed to be perfectly elastic, in the sense that the market is fully contestable with no artificial barriers to entry or exit.

In entering the market, operator n will schedule a flight and set a fare in the first iteration. The choice of departure slot is determined by the decision-rules outlined in equations 6.3 to 6.15. The precise time of departure that it selects, depends on the positioning and pricing of other flights k already scheduled in the market, as shown in equation 6.19 below. In the first iteration, the strategy of operator n involves scheduling a flight and setting a basic fare f^{B} and scheduling a flight at j, which depends on the departure time position of other carriers k in the market.

$$\phi_n = \left[f_{nj}^{B} \; \ell_{nj}^{k} \right]^{t=1} \tag{6.19}$$

Thus, f^{k}_{nj} represents the fare set by flight n at departure slot j, which is a function of the fare set by other flights k in the market. Similarly, ℓ^{k}_{nj} represents a departure scheduled by flight n at slot j, which is based on the departure times of other flights k in the market. When the iteration is complete, other flights have been scheduled. In the following iteration, flight n must react to the policies of other flights k. The reaction function θ^{k}_{n} represents the pricing and departure time scheduling strategy supplied by flight n, which is a function of the pricing and departure time scheduling decisions of other flights k, who also scheduled new services in the previous iteration. (t-1). The reaction function θ^{k}_{n} consists of three options. Firstly, to decide whether to leave fare unchanged and to maintain a flight at departure slot j in response to the actions of others k. One restriction that applies is that any departure time j selected by a flight n during any one iteration cannot be already occupied by another flight k. This rule applies to all flights and to all subsequent iterations. Therefore, the first option is outlined in equation 6.20 below.

$$\left[\partial f_{nj}^{k} = 0 \quad \ell_{nj}^{k} = 1 \right]^{t+1} \tag{6.20}$$

The second option is to increase fare in response to excess demand, caused by the actions of other flights k in the market. This could arise if some flights have exited the market.

$$\left[\partial f_{nj}^{k} > 0 \right]^{t+1} \tag{6.21}$$

The final option is to exit the market, where

$$\left[\ell_{nj}^{k} = 0 \right]^{t+1} \tag{6.22}$$

A flight exits the market, if profits are less than or equal to zero. This can be due to the scheduling of other flights k. These flights are either cheaper in terms of fare, more convenient in terms of departure time, or a combination of both. Combining all the options available to flight n, its strategy ϕ_n is outlined in equation 6.23 below.

$$\phi_n = \left[f_{nj}^{B} \, \ell_{nj}^{k} \right]^{t=1} \theta_n^k \begin{bmatrix} \partial f_{nj}^k = 0 \, , \ell_{nj}^k = 1 \\ \partial f_{nj}^k > 0 \, , \ell_{nj}^k = 1 \\ \ell_{nj}^k = 0 \end{bmatrix}_{j_k \neq j_n}^{t+1} \tag{6.23}$$

A run of the model consists of a number of iterations t, where t = (1,2,3, ...n). For each run and after the first iteration, fare can change by a fixed amount, ∂f where ∂f = (1,2,3,.....n). Thus, a vector of profit levels can be generated for all departure slots j with respect to each iteration t and assuming fare changes by a fixed amount ∂f.

$$\begin{bmatrix} \pi_1^{t=1} & \pi_1^{t=2} & \pi_1^{t=3} & \ldots\ldots\ldots\ldots\ldots\ldots & \pi_1^{t=n} \\ \pi_2^{t=1} & \pi_2^{t=2} & \pi_2^{t=3} & \ldots\ldots\ldots\ldots\ldots\ldots & \pi_2^{t=n} \\ \pi_3^{t=1} & \pi_3^{t=2} & \pi_3^{t=3} & \ldots\ldots\ldots\ldots\ldots\ldots & \pi_3^{t=n} \\ \vdots & & & & \\ \vdots & & & & \\ \pi_{21}^{t=1} & \pi_{21}^{t=2} & \pi_{21}^{t=3} & \ldots\ldots\ldots\ldots\ldots\ldots & \pi_{21}^{t=n} \end{bmatrix}^{\partial f = n} \tag{6.24}$$

Equilibrium, in each run of the model, is achieved, when there are no longer any additional incentives to alter fare and departure times, and passengers are satisfied with their choice of flight. In the next run of the model, the amount by which operators are permitted to vary fares can be changed. This generates a different set of equilibrium results. Therefore, a vector of equilibrium profit levels for each departure slot j can be derived at different intervals of ∂f, as shown below, with equilibrium profit levels at each departure time denoted as, $E\pi_j$.

$$\begin{bmatrix} E\pi_1^{\partial f=1} & E\pi_1^{\partial f=2} & E\pi_1^{\partial f=3} & \ldots\ldots\ldots\ldots\ldots\ldots & E\pi_1^{\partial f=n} \\ E\pi_2^{\partial f=1} & E\pi_2^{\partial f=2} & E\pi_2^{\partial f=3} & \ldots\ldots\ldots\ldots\ldots\ldots & E\pi_2^{\partial f=n} \\ E\pi_3^{\partial f=1} & E\pi_3^{\partial f=2} & E\pi_3^{\partial f=3} & \ldots\ldots\ldots\ldots\ldots\ldots & E\pi_3^{\partial f=n} \\ \vdots & & & & \\ \vdots & & & & \\ E\pi_{21}^{\partial f=1} & E\pi_{21}^{\partial f=2} & E\pi_{21}^{\partial f=3} & \ldots\ldots\ldots\ldots\ldots\ldots & E\pi_{21}^{\partial f=n} \end{bmatrix} \tag{6.25}$$

The value of any given slot j is assumed to be a function of the maximum equilibrium profit generated from operating a service at that particular departure time. The maximum profit generated at each slot is derived by calibrating the simulation model

on different intervals of fare variation ∂f. For each run of the model, which consists of a number of iterations, fares do not change, increase, or decrease by the same amount, depending on the decision-rules already specified.

The maximum profit obtained from this process is achieved under conditions of equilibrium, where operators and passengers have no longer any incentive to alter their preferences. In estimating the monetary vale of a slot, the time period with respect to tenure would also have to be defined, since equilibrium profits refer to the profit generated on a specific weekday. The value of the slot is a function of the expected maximum profit generated over the period of tenure i.e. scheduling season. Let there be a total of n weekdays where $p = (1,2,3.....n)$. The estimated monetary value of a given slot at departure time j for a set period of time n is derived from equation 6.27 below

$$S_j = \sum_{p=1}^{n} max\left(E\pi_j\right) \tag{6.27}$$

Where S_j represents the monetary value of departure slot j, which is derived from the maximum equilibrium profit generated at j. This is obtained from a vector of profit levels (equation 6.25), on the basis of assumed variation in fare (∂f) from 1 to n units of currency.

6.4.3 Model limitations

Before calibration of the model and analysis of the results, it is necessary to acknowledge weaknesses and limitations in the assumptions used to develop the simulation model.

Each passenger is assumed to possess an ideal time of departure. What is not considered is the issue of time of arrival. In reality, passengers when making a journey, also consider time of arrival at the destination. This is particularly important for long-haul trips. Furthermore, the vast majority of journeys made, involve a return flight combination, as opposed to a one-way trip. The model considers only one-way trips (departures) but does not incorporate the issue of when passengers return.

One assumption used in the simulation model is the absence of any form or degree of market segmentation. The issue of journey purpose is not considered. In reality, passenger responses to differences in fare and departure time and the trade-off between both variables, will be different between the business and discretionary market. The model, on the other hand assumed that the market is homogenous. Although stated preference parameters were estimated from samples of business and non-business respondents, in the case of the non-business responses, the schedule delay early parameter β^{se} was considered to be too insignificant to have any confidence in it's ability to estimate the value of schedule delay early time.

Whilst demand for a different flight will vary by departure slot, total demand is not linked to overall fare levels and is therefore held constant. The market is essentially captive, in that transfers to other competing modes is not incorporated in the model. Neither are decisions by discretionary travellers to cancel their travel plans because of high fares. In reality, fares in airline markets are also influenced by fares on competing modes of transportation. Therefore, equilibrium fares generated by the simulation model, may in some instances, given the assumption of demand captivity, be excessive. This issue will be considered in the following chapter.

As mentioned in sub-section 6.4.1, the model is applied to an individual route, and flights are supplied by individual operators. The supply of these flights is assumed to be perfectly elastic, in the sense that, where opportunities to schedule profitable services exist, operators can schedule flights. One weakness in this assumption, is that supply inelasticities are not considered or incorporated in the model. Choice of slots and the ability to schedule profitable services can be constrained by operational limits in the extent to which aircraft can be readily available, such as the need to satisfy network-wide scheduling requirements. Therefore, how highly slots are valued, will not only depend on the maximum profit generated, but on the whether it is feasible to supply flights at that time. For example, a carrier may consider scheduling a flight at 17:00. However, the ability to schedule could be limited by the lack of arrival slots before 17:00, or the unavailability of suitable aircraft. The model, on the other hand assumes that there is perfect elasticity in the supply of departures in

that there are no restrictions in the availability of both arrival slots and aircraft. In this sense, an element of realism is effectively removed.

The model assumes that entry and exit is both free and costless. This is a rather simplistic assumption to make since, in reality, entry and exit in most markets is neither free nor costless. For example, in entering markets, airlines have to make necessary sunk investments such as marketing, promotion, recruitment of ground base staff, purchase of ground facilities etc. One weakness of the simulation model is that it does not take these considerations into account.

The fare associated with each flight, is assumed to be fully-flexible and since the value of departure slots is being estimated, fare is also assumed to be one-way. All passengers pay this fare. This assumption is difficult to defend in marketing terms since, airlines given substantial product differentiation, usually set different fares with varying terms and conditions according to different segments of the passenger market. Setting only a fully-flexible economy fare is more appropriate in domestic short-haul business-dominated routes and less so on high-density international city-pairs.

The simulation is completed after a sequence of iterations, after which, the model achieves equilibrium. At this point, passengers are satisfied with their choice of flight and have no incentive to select an alternative, operators are content to leave their pricing and scheduling decisions unchanged, and there is no scope or incentive for the provision of additional services. To what extent does this process of iterative decision-making and final equilibrium mirror real-life airline market behaviour? Or more importantly can equilibrium be achieved in reality ?

The difficulties associated with designing models, which attempt to simulate interactive decision-making and market behaviour, focuses on the extent to which they are able to replicate both real-life decision-making and the competitive outcomes that emerge from these decisions. The simulation model in this instance is iterative in nature, with both passenger choice decisions and flights being scheduled tentatively before final equilibrium is achieved. In this respect, the model can be considered as a reasonable approximation to reality, where the impact of deregulation or new entrant behaviour on airline markets has in the past, led to initial periods of instability where

incumbent airlines react both in scheduling and pricing terms. One example was the initial impact of airline deregulation in the United States in 1978, where a number of new airlines were launched in order to take advantage of new opportunities offered by liberalisation. By the mid-nineteen eighties many of these airlines had disappeared due in a large part to the actions of established carriers. Although it is difficult to compare each iteration with a period of time, the processes involved do, to a large extent, mirror those in reality where flights are scheduled and later withdrawn and prices are lowered and later increased. However, there are limits to the extent to which a simulation model can replicate real-life decision-making.

Real airline markets do not function according to clearly defined parameters and decision-rules, but are subject to a range of factors which makes the attainment of equilibrium highly unlikely. For example, operators will set fares and schedule flights on the basis of imperfect knowledge of the distribution of ideal departure times and values of time in any market. As such, their pricing and departure time scheduling decisions are, to a large extent conjectural, based on what they perceive to be the most attractive departure time or most appropriate fare, rather than on any pre-defined passenger demand function. These decisions are also influenced by a variety of factors such as network-wide scheduling considerations and the availability of suitable departure slots. But even if these constraints did not exist, it is unlikely that these decisions can be considered as optimal, since operators do not possess perfect knowledge.

The conditions necessary for equilibrium will also be different between a simulation model and reality. Model equilibrium is defined as the point at which there is no longer any advantage for both passengers and operators to alter their decisions. Actual equilibrium, based on these conditions, may be difficult to attain. In some cases a form of equilibrium may exist, where an airline market has evolved into an oligopolistic or monopolistic structure, with a settled pattern of departure times and fares, and little incentive for new entry. Many small low-density regional markets probably conform to this model, but in larger more heavily trafficked routes, opportunities exist for carriers to realign departure times and to change fares.

6.5 Summary and Conclusions

The aim of chapter six was to specify the methodology used to estimate slot values. Key points are summarised below.

- The value of a slot is determined by calculating the maximum profits generated at each departure slot. This is influenced by how highly passengers value travelling at different times of the day. Therefore, decision-rules on both passenger and operator choice of slots, were formulated.

- The model used to define passenger choice decision-rules is based on the multinomial logit model which generates choice probabilities on the basis of levels of schedule delay time, fare, and passenger choice model parameter estimates generated in Chapter five.

- Operators' decision-rules specify the conditions necessary for the provision of profitable flights and the setting of fares on these services.

- Passenger and operator decision-rules are combined to develop a simulation model of market behaviour. This generates an equilibrium pattern of services, with associated levels of demand, costs and fare from which slot values can be derived.

- The value of a slot is a function of the maximum profit generated from operating a flight at any departure time j.

In seeking to estimate slot values in the following chapter, the model derived in chapter six , is calibrated on the basis of parameter estimates generated in Chapter five and assumed levels of daily passenger demand and aircraft operating cost data. These input assumptions will be fully specified in the following chapter.

CHAPTER 7

Slot Value Simulation Model Results

7.1 Introduction

Having calibrated and validated the model parameters with regard to the passenger departure time scheduling function in Chapter five and having developed the simulation model in Chapter six, the purpose of this chapter of the thesis, is to estimate the monetary value of departure slots.

This chapter is divided into seven sections, and is structured accordingly. Section 7.2 focuses on the data used to calibrate the model and any analytical assumptions that are required to be specified. This is followed by Section 7.3, which uses the simulation model to generate patterns of flight scheduling using three different aircraft types, at different intervals of demand, and assuming fares are fixed across departure times. Section 7.3 concludes with an analysis of the impact of these scheduling patterns on passenger generalised costs and average profits per flight. Section 7.4 outlines the basic assumptions applied to estimate slot values. Section 7.5 focuses on the slot value estimates derived by the simulation model on a fixed level of passenger demand and under three different aircraft types. In evaluating the value of departure slots for each aircraft type, fare is permitted to vary by time of day. Within this context, patterns of flight scheduling and pricing behaviour will be evaluated in addition to the levels of profit generated and the maximum slot values obtained. Section 7.6 discusses the validity of the model results and attempts to interpret any inconsistencies. Section 7.7 examines the transferability of the model through re-calibrating the simulation on the basis of different model input assumptions. Chapter seven concludes with a discussion of any policy implications arising from these results.

7.2 Data and analytical assumptions

The simulation model is demonstrated within the context of a city-pair route, which is 177 miles in distance. This corresponds to the city-pair market from which the stated preference questionnaire was applied.

The slot values generated by the model refer to twenty-one hourly departure time intervals from 04:00 to 00:00 on this city-pair route.

The passenger departure time choice parameters used to demonstrate the simulation model are based on the findings in Chapter five.

Slot value estimates are generated for three different aircraft types: a 100-seat jet, 65-seat turboprop and 36-seat turboprop. These correspond to a British Aerospace 146-200, British Aerospace ATP, and Shorts 360 respectively. The total flight departure costs for the four aircraft types are shown in Table 7.1 below. A detailed breakdown of these costs is shown in Appendix I.

Table 7.1: Total costs per departure by aircraft type

100-seat jet	£3,672
65-seat turboprop	£2,305
37-seat turboprop	£1,264

Source: Appendix I

The basic one-way fare applied to all flights irrespective of aircraft type is assumed to be £55. This represents half the average return fare paid by respondents who were interviewed in stated preference experiment, which was £110.

7.3 Patterns of flight scheduling with demand = 100, 200, 300, 400, and fares fixed at £55 by aircraft type

7.3.1 65-seat turboprop

In seeking to forecast patterns of departure time scheduling using 65-seat turboprop aircraft, the simulation model is calibrated on four levels of total passenger demand: 100, 200, 300, and 400 one-way passenger trips per day. Analysis consists of evaluating equilibrium solutions from four runs of the model, each corresponding to an interval of total daily demand. Within each iteration of the model, departure slots are evaluated by individual operators using 65-seat turboprop aircraft. In evaluating each slot, individual operators set a basic one-way fare of £55. This level of fare does not change at any time, and remains fixed throughout each iteration of the model (i.e $\partial f = 0$). As such there is no difference in the fare set by individual flights. When evaluating each slot, the individual operator is assumed to estimate the passenger

demand to depart and the profits generated if a flight is scheduled at that time. Flight scheduling decision-rules are then applied in order to ascertain whether it is profitable to operate a flight at a specific departure slot.

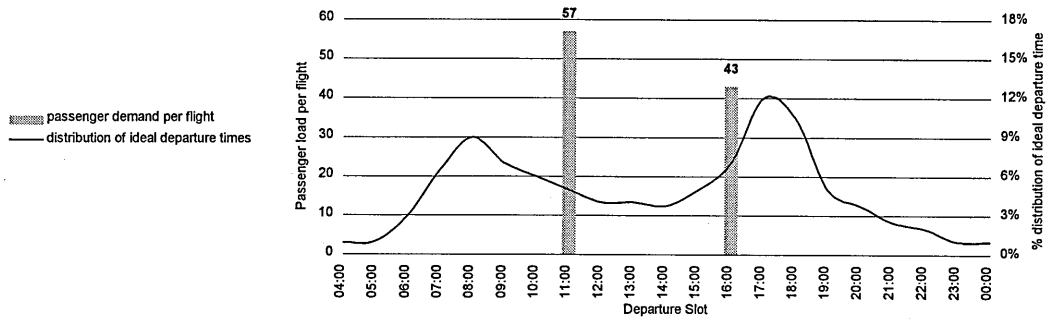
Figure 7.1 on the following page, consists of four charts. Each chart illustrates patterns of flight scheduling across departure slots, at four levels of total daily one-way passenger demand. The grey bars refer to individual flights, with the data labels indicating passenger load on each flight. The pattern of scheduling is measured against the distribution of ideal departure time preferences.

The first chart of Figure 7.1 illustrates a pattern flights generated by the simulation model assuming there are 100 daily passenger trips from the origin to the destination. The simulation model generates two equilibrium flights, one at 11:00 and the other at 16:00. As total demand is 100 passengers, 57 choose to depart at 11:00, and the remaining 43 at 16:00. One would expect, *a priori*, that given the distribution of ideal departure times, flights should be scheduled in close proximity to the peaks in ideal preferences, i.e. between 07:00 and 09:00, and between 17:00 and 18:00. In this particular example, one flight is scheduled at 16:00, which is during the late afternoon - early evening period, whilst the other flight is scheduled at 11:00, which is considered as an off-peak departure time.

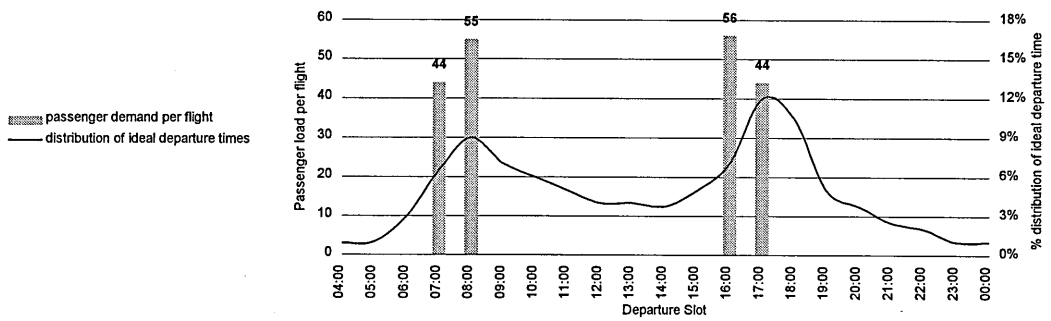
As total demand increases to 200 passenger trips, the model generates four flights: at departure slots: 07:00, 08:00, 16:00, and 17:00. All flights are scheduled in peak period slots. With increased demand, the market is able to accommodate additional flights. As there is more competition in scheduling, flights cluster within both peak periods. Outside these times there is little incentive or opportunity to operate profitable flights e.g. 20:00. When demand increases to three and four hundred passenger trips per day, the market accommodates additional flights, each one scheduled in close proximity to the other. The bracketing of flights mirrors competitive scheduling in high density markets, where competing airlines schedule flights in close proximity to their competitors. With fares fixed between departure times, flights are scheduled on the basis of schedule delay time only, hence the cluster of flights scheduled during the most popular periods of the day. When total demand is

Figure 7.1: Flight time scheduling and passenger load per flight when demand = 100, 200, 300, 400, and ∂f =0: 65-seat turboprop

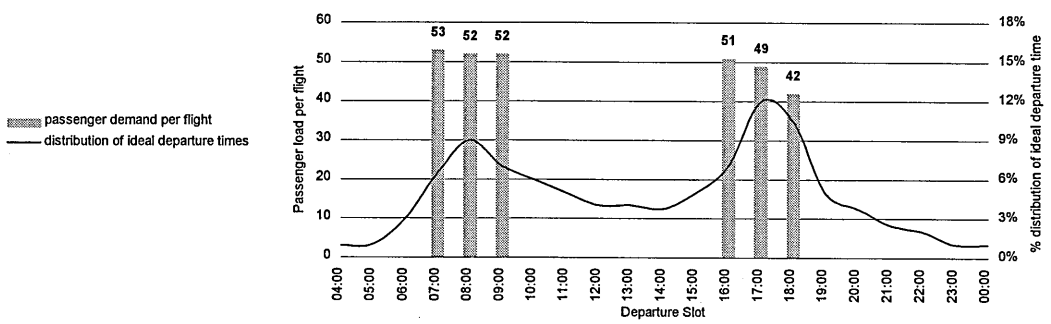
Total Demand=100



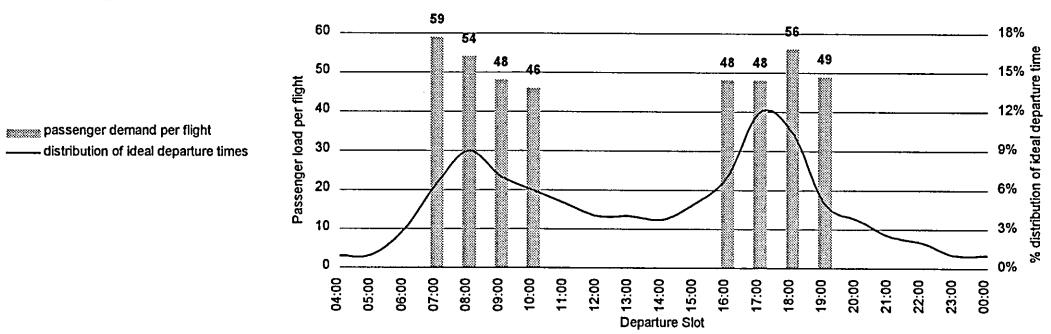
Total Demand=200



Total Demand=300



Total Demand=400



assumed to be 400 passenger trips, the simulation model generates eight flights, all occupying peak-time slots.

The precise patterns of scheduling and the distribution of passengers between individual flights is due to the influence of passenger choice model coefficients within the simulation model. If choices are purely deterministic and rational and both β^{se} and β^{sl} are utility symmetrical then, one would expect the flights at 08:00 and 17:00 to be the busiest, because they are the most popular departure times. However, the probabilistic element in choice behaviour represented by the scale parameter β^{0}, and the low value of β^{se} relative to β^{sl}, passengers are firstly, less inclined to select a flight scheduled at their ideal time and more inclined to select flights at other departure slots, particularly those scheduled at earlier times. For example, when total demand is 400, a flight is scheduled at 07:00, with 59 passengers compared to the 54 at 08:00, which is a more popular departure time.

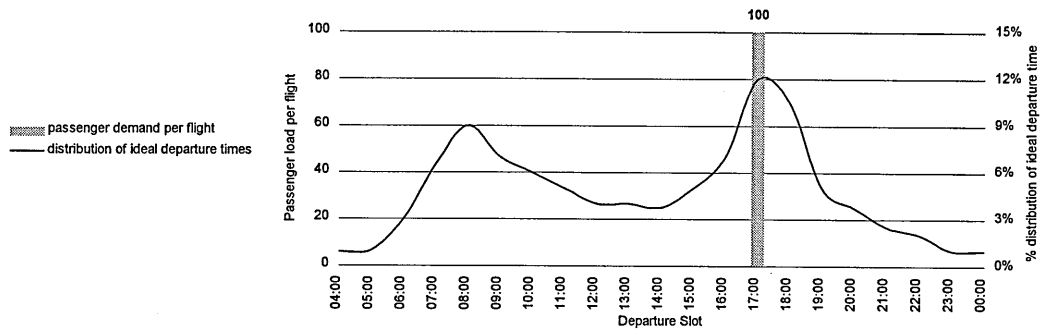
7.3.2 100-seat jet

In seeking to identify patterns of departure time scheduling using a 100-seat jet, the model is simulated on exactly the same basis as the 65-seat turboprop, four intervals of total passenger demand: 100, 200, 300, and 400 one-way passenger trips per day. Within each iteration, departure slots are evaluated by individual operators using a 100-seat jet aircraft, each setting a fare of £55.

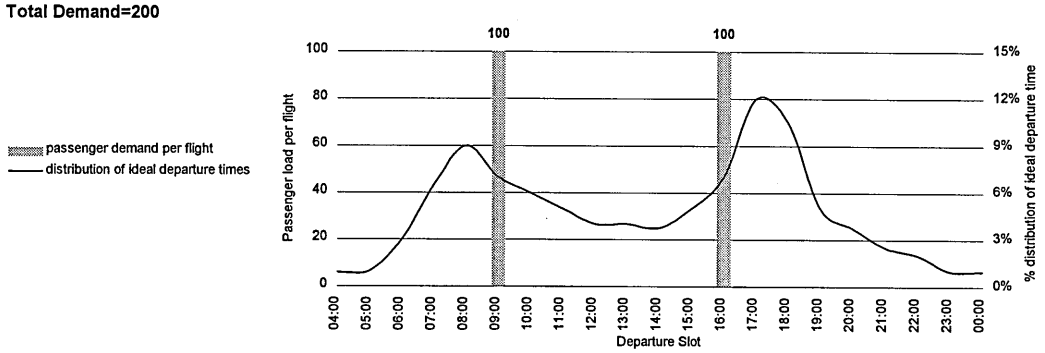
Assuming total daily demand is 100 trips, the simulation model generates one flight at 17:00. This is the most popular departure time measured by the distribution of ideal departure time preferences. As total demand is equal to seating capacity, all passengers are allocated to this flight. When total demand increases to 200 trips per day, the model schedules two flights. With variation in the density of preferences, fixed fares across departure times, and given the relative magnitudes of the passenger choice model parameters, this leads to excess demand at slot 09:00. The model generates two flights, one at 09:00, the other at 16:00. However, 105 passengers select the flight at 09:00, whilst 95 choose 16:00. Relaxation of the fixed fare assumption and allowing fares to increase by £1 for each iteration, excess demand is eventually eliminated and equilibrium between supply and demand is restored. This

Figure 7.2: Flight time scheduling and passenger load per flight when demand = 100, 200, 300, 400 and $\partial f = 0$: 100-seat jet

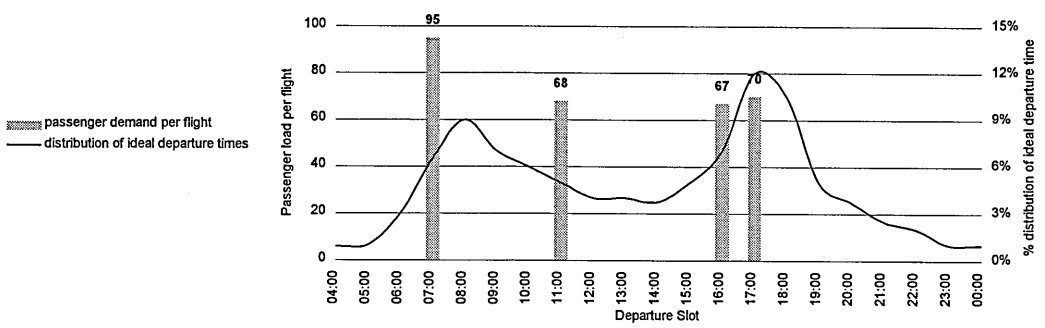
Total Demand=100



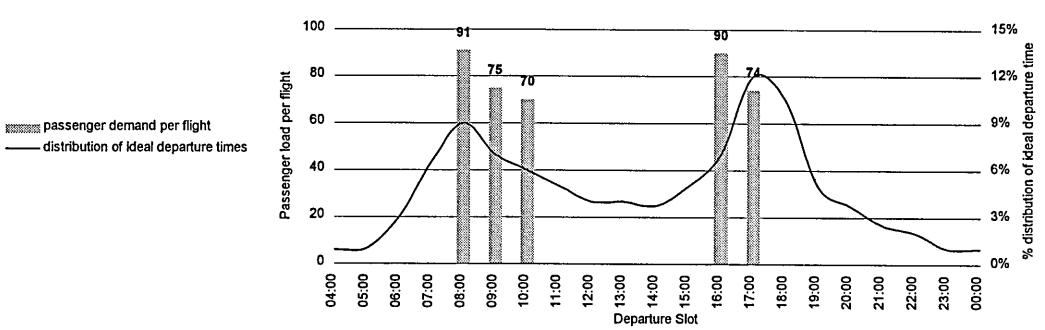
Total Demand=200



Total Demand=300

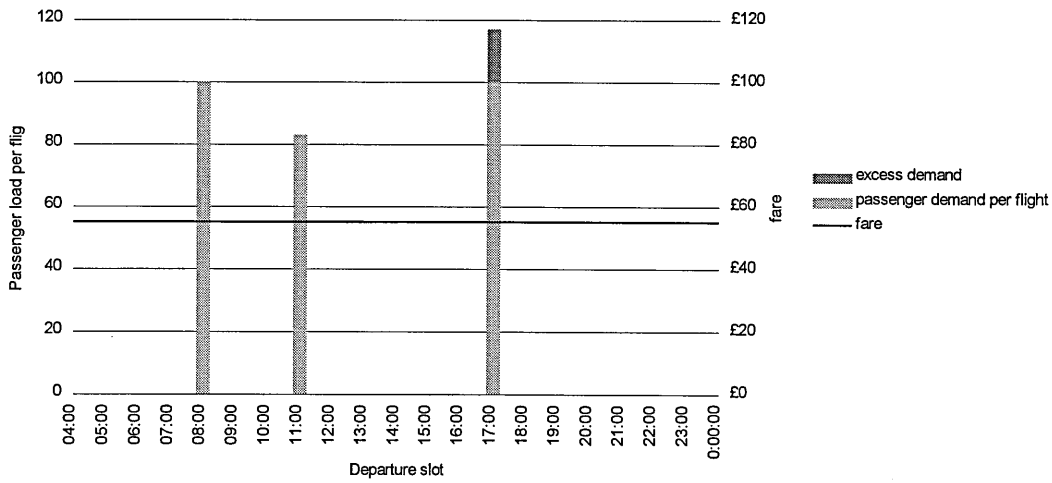


Total Demand=400



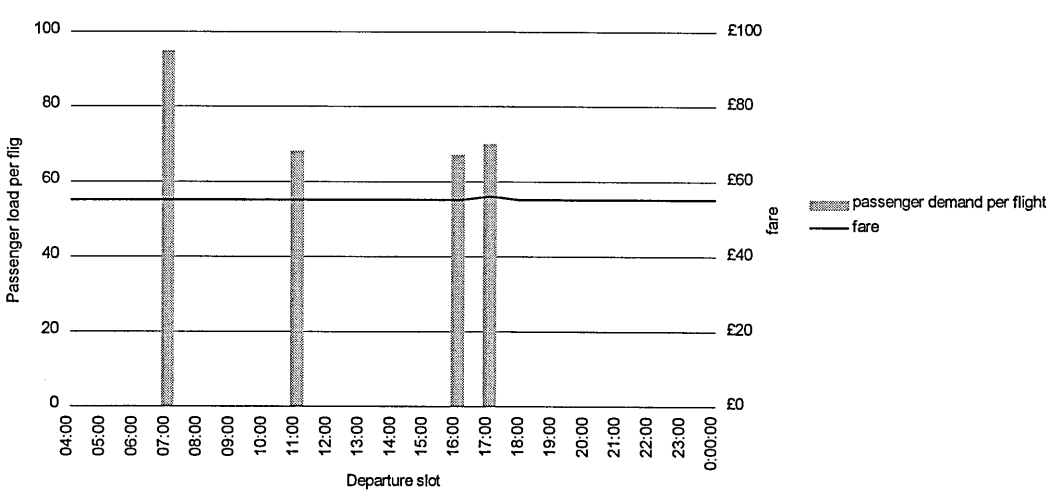
was achieved by two iterative £1 fare increases at 09:00, from £55 to £57. As a consequence of the increased cost of departing at 09:00, five passengers are re-allocated to the flight at 16:00.

Figure 7.3: Passenger load per flight disequilibrium: $\partial f = 0$, demand =200: 100-seat jet



When daily one-way demand increases from 200 to 300 trips, the problem of excess demand re-emerges. Assuming that fares remain fixed, the model generates three flights. There is one flight scheduled at 08:00 with 100 passengers, followed by one at 11:00 with 83 passengers, and then finally one at 17:00 with 117 passengers, as shown in Figure 7.3 above.

Figure 7.4: Passenger load per flight equilibrium: demand = 200 and $\partial f \neq 0$: 100-seat jet



Through permitting fare at 17:00 to increase in order to restore equilibrium between

supply and demand, this simultaneously creates an opportunity for an additional operator to schedule a flight at 16:00, which offers a cheaper fare of £54. The combined effect of increasing fare at 17:00, from £55 to £56, and the scheduling of a cheaper service, one hour earlier at 16:00, eliminates excess demand to travel at 17:00, thereby restoring equilibrium between supply and demand as shown in Figure 7.4 on the previous page.

Assuming one-way passenger demand increases from 300 to 400 one-way trips, the market is able to accommodate a fifth flight. The simulation model generates five flights at: 08:00, 09:00, 10:00, 16:00 and 17:00, all at peak departure times, with the busiest flight scheduled at 08:00 followed by 16:00 and the least busiest at 10:00 with 70 passengers.

7.3.3 37-seat turboprop

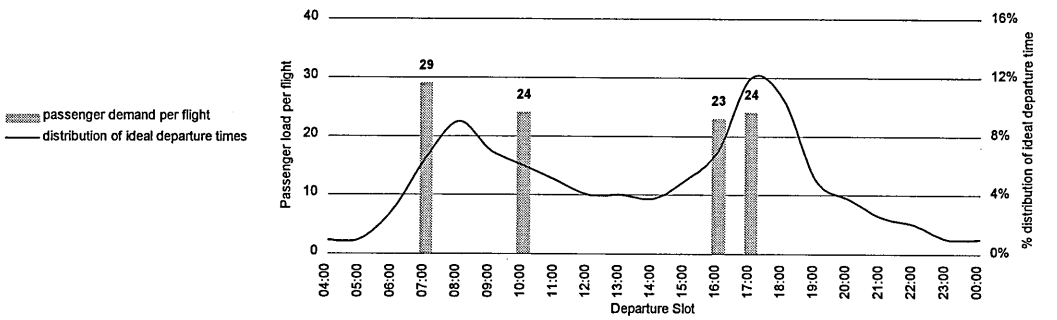
In seeking to identify patterns of departure time scheduling using the smallest aircraft type considered, a 37-seat turboprop, the number of flights generated at each interval of total demand exceeds that generated by the two larger aircraft types.

With fares restricted to £55 on any flight, the simulation model generates four flights when total daily passenger demand is 100 one-way trips, as shown on the first chart in Figure 7.5 below.

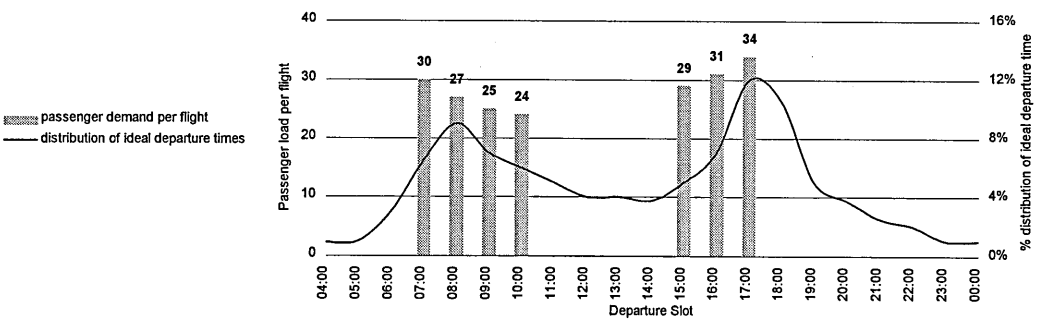
Flights are scheduled at 07:00, 10:00, 16:00 and 17:00, with the busiest at 07:00 attracting 29 passengers, a load factor of 78%. As demand increases to 200 passenger trips, additional flights are scheduled at 08:00, 09:00 and 15:00. When total demand increases to 300 trips, the simulation model generates ten equilibrium flights, which cluster around the two peak periods. With total demand at 400 passenger trips, 12 flights are scheduled, 7 at each hourly slot between 05:00 and 11:00 and 5 between 14:00 and 18:00. Measured against the percentage distribution of ideal departure times, the two flights at 15:00 and 16:00 are busier in terms of passenger load than the flight scheduled at 17:00, which is the most popular departure time. Furthermore, the simulation model, also schedules a flight at 14:00 with 24 passengers. By contrast, the flight scheduled at 18:00 which is a more popular departure time, attracts fewer passengers. This is because, firstly, the value of the scale parameter β^{o}, randomises

Figure 7.5: Flight time scheduling and passenger load per flight when demand = 100, 200, 300, 400 and $\partial f = 0$: 37-seat turboprop

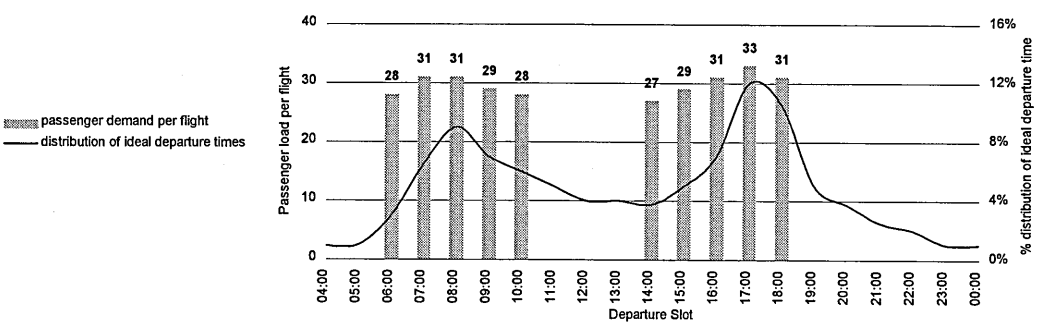
Total Demand=100



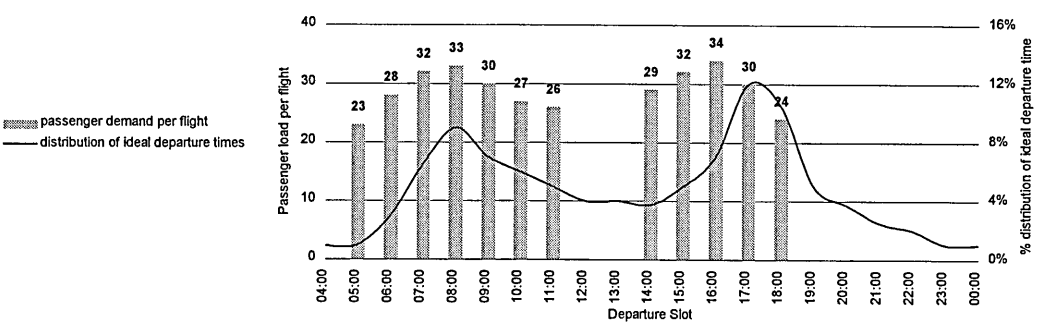
Total Demand=200



Total Demand=300



Total Demand=400

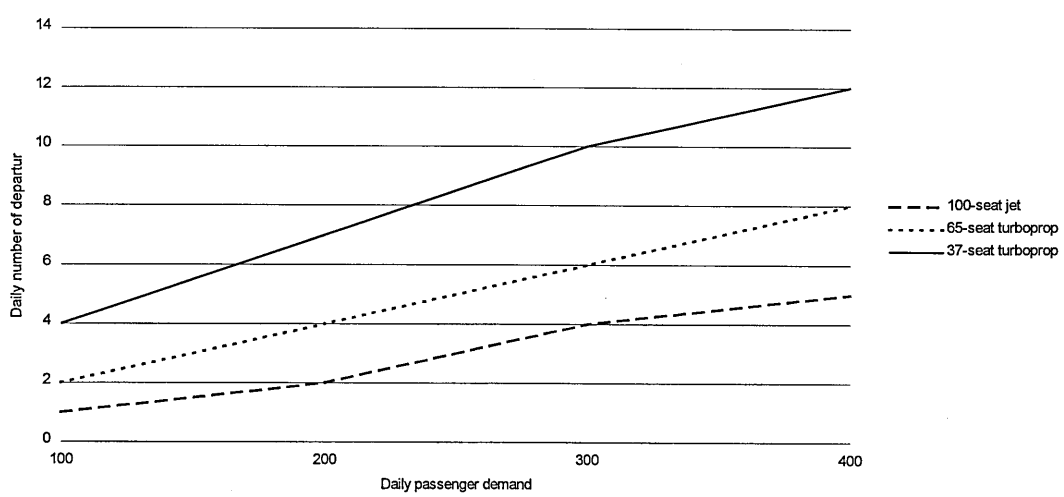


choice probabilities, and secondly, the low magnitude of the schedule delay early parameter β^{se} relative to the schedule delay late parameter β^{sl}, encourages passengers to select earlier departure time options. This is also the case when assessing the pattern of flights scheduled during the morning peak period. For example, whilst there is no flight scheduled at 12:00, the model generates a flight at 05:00, which is a less popular ideal departure time. This is because, for those passengers who select to depart during the morning peak period (07:00 to 09:00), the effect of the scale parameter β^{0} is to randomise choice probabilities towards earlier departure times, because of the large disincentive to depart at later times.

7.3.4 Frequency, passenger generalised costs and average profits per aircraft type

The general conclusion that can be drawn from the results in sub-sections 7.3.1, 7.3.2 and 7.3.3, is that the pattern of equilibrium flights for each of the three aircraft types is influenced by the values and magnitude of the passenger choice model parameters. Figure 7.6 below illustrates equilibrium levels of total daily service frequency by aircraft type, as total passenger demand increases from 100 to 400 daily trips. As expected, at each interval of demand, the smaller the aircraft, the higher the level of service frequency.

Figure 7.6: Daily service frequency against total demand by aircraft type ($\partial f \neq 0$)



Past research on evaluating the relative influence of various supply-side factors on passengers choice of airline, usually concludes that the single most important variable that determines airline market share on any route, is the volume of service frequency

that it is able to supply. Quantitative analysis on passenger's choice of airline by Kanafani and Ghobrial (1985), Hansen (1990) and others, confirms that passengers, when evaluating different airlines on a given route, attach greater weight to service frequency compared to other supply-side variables, such as fare and aircraft type. Although it is important to remember that the relative importance of service frequency will also depend on which specific segment of the market is being analysed.

However, one of the arguments of this thesis, as expanded in chapter two, is that insufficient consideration has been given to measuring the relative convenience of an airline's schedule, from a schedule delay perspective, as opposed to using absolute levels of service frequency.

On the basis of results outlined in Figure 7.6, the 37-seat turboprop provides the most convenient schedule, in that at each interval of demand, daily service frequency exceeds that of both larger aircraft types. From this perspective then one would expect the 37-seat turboprop to outscore other aircraft types in terms of the average schedule delay experienced by passengers. If passenger preferences are distributed uniformly across departure times, then this would indeed be the case. However, if the distribution is not distributed uniformly, and is in contrast, characterised by variation in the density of preferences, then average schedule delay time will depend on the precise timing of these flights and the values of both schedule delay early and schedule delay late time.

In light of these considerations, one approach would be to measure the average schedule delay per passenger for each of the three aircraft types at different intervals of demand. Furthermore, incorporating the relative convenience associated with schedules generated by each aircraft type can also be examined, to yield a measure of the average generalised cost per passenger for each of the three aircraft types. Indeed, from the stated preference analysis in Chapter five, in-flight time emerged as the most important product attribute which influenced respondent preferences.

In order to examine the relative inconvenience or disutility of a schedule generated by the simulation model, consider the generalised cost equation below:

$$GC_{ij} = f_{ij} + \frac{\beta^{se}}{\beta^{t}} se_{ij} + \frac{\beta^{sl}}{\beta^{t}} sl_{ij} + \frac{\beta^{t}}{\beta^{t}} t_{ij} \qquad (7.1)$$

Assuming that total daily passenger demand on the route x is represented by D_x, then the average generalised cost per passenger is as follows;

$$GC / pax = \frac{\sum_{n}^{j} GC_{ij}}{D_x} \qquad (7.2)$$

In-flight time associated with the 65-seat turboprop is assumed to be one hour given the sector distance of 177 miles. From the stated preference experiment, this was in actual fact the aircraft type supplied by the existing operator and represents the current flight option. The two alternatives: a 100-seat jet and 37-seat turboprop represent the hypothetical alternatives in the stated preference choice sets. Through departing on the 100-seat jet, passengers have the advantage of a 20 minute reduction in in-flight time. By contrast, the 37-seat turboprop is assumed to complete the 177 miles in sector distance, 20 minutes longer than the existing 65-seat turboprop. Although one would expect average schedule delay per passenger to be lower for the 37-seat turboprop, higher generalised costs due to a longer in-flight time, may in actual fact, eliminate any advantage it has in terms of the volume of service frequency supplied.

Figure 7.7: Average generalised cost per passenger against total demand by aircraft type

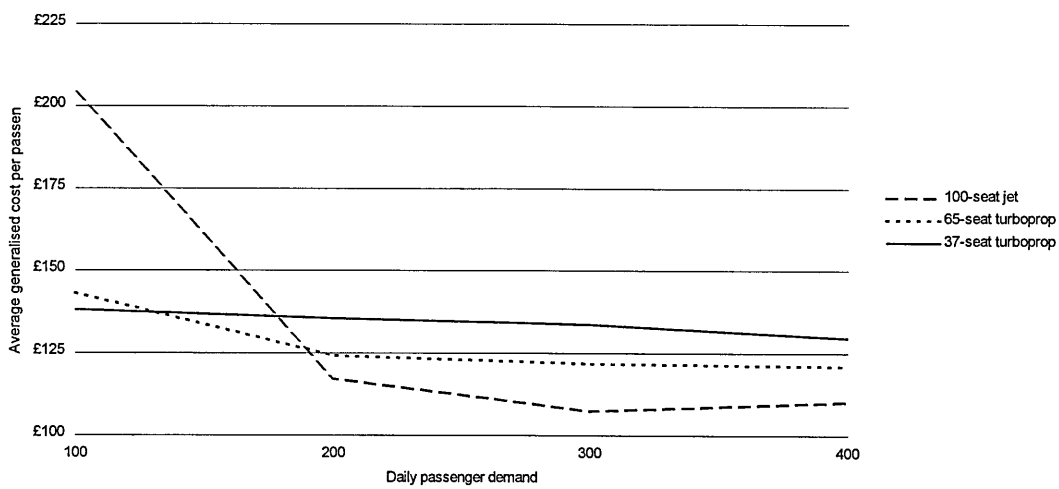


Figure 7.7 above, shows the average generalised cost per passenger associated with

schedules generated by the three aircraft types at the four levels of total daily passenger demand. When the model is run for the three aircraft types on the basis of 100 daily passenger trips, average generalised cost per passenger on the 100-seat jet is higher compared to the two smaller aircraft types. When total demand is 100, the model generates one flight scheduled at 17:00 when supplying services using a 100-seat jet. A large proportion of these passengers prefer to depart at earlier departure times. If a flight is scheduled at 17:00, they have to endure additional generalised costs because they have to depart at a time later than their ideal preference.

As demand increases to 200 passenger trips, average generalised cost per passenger decreases markedly with respect to the 100-seat jet. This is firstly because of the increased service frequency and secondly because the two flights scheduled are supplied at peak times, 09:00 and 16:00. This is particularly relevant for those passengers with ideal preferences during the morning peak, where under the assumption of one hundred daily passenger trips, they had to endure additional generalised costs of departing at 17:00. When total demand increases and a flight is scheduled at 09:00, average generalised cost for these passengers declines markedly.

By contrast, average generalised cost per passenger as a result of the schedules generated by the 37-seat turboprop, remains consistent at each level of demand. When total daily one-way passenger demand is assumed to be one hundred trips, average generalised cost per passenger is £138, compared to £204 generated by the 100-seat jet. However, as demand increases, there is no significant reduction in average generalised cost. This is because, despite the higher volume of service frequency, the greater weight attached by passengers to in-flight time, eliminates the additional convenience of high levels of service frequency.

Whilst measuring average generalised cost per passenger can provide a measure of the relative convenience or inconvenience experienced by passengers given different flight schedules generated by the model, examination of average profit per passenger can provide an assessment of levels of flight profitability associated with each schedule at different intervals of total daily demand.

Profit per flight at any departure time j is calculated as follows:

$$\pi_j = R_j - C_a \tag{7.3}$$

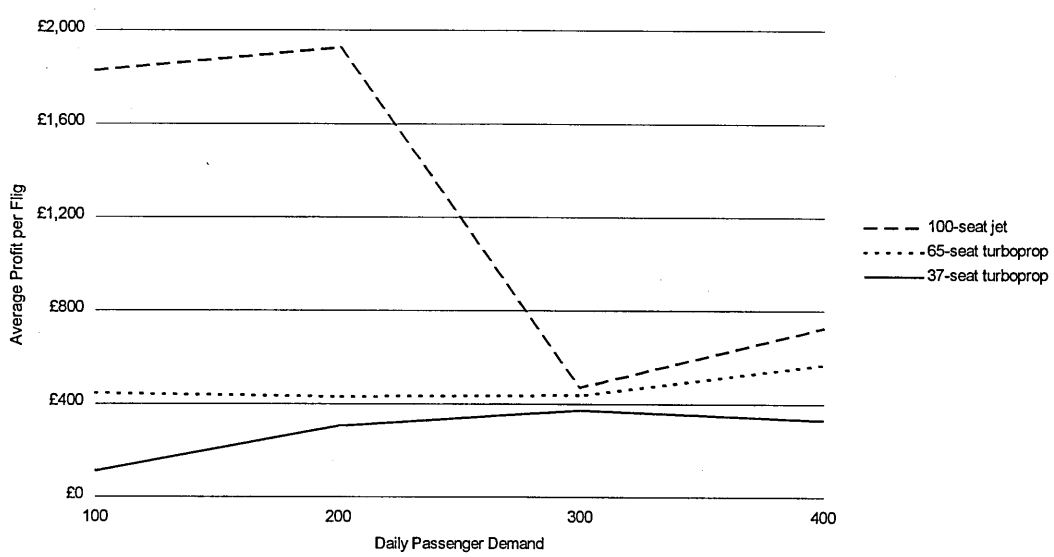
Average profit per flight, AVG(π) is calculated as follows:

$$AVG(\pi) = \frac{\sum_{n}^{j} \pi_{ij}}{F} \tag{7.4}$$

Where F represents total daily frequency.

Figure 7.8 below, illustrates average profit per flight generated by the simulation model at four levels of daily one-way passenger demand. When one-way passenger demand is 100 daily trips, average profit per flight is significantly higher with respect to 100-seat jet schedule generated by the simulation model. When demand increases to 200 trips average profit per flight increases from £1,828 to £1,928. By contrast average profit per flight generated by the 37-seat turboprop is significantly lower at £307. When total daily demand increases to 300 trips, average profit per flight for the 100-seat jet operators, falls markedly to £471, as two additional flights are scheduled. When demand is 400 trips, average profits per flight for the three different aircraft types are broadly comparable.

Figure 7.8: Average profit per flight against demand by aircraft type ($\partial f \neq 0$)



Section 7.3 illustrates patterns of scheduling for each aircraft type under certain assumptions regarding fare and passenger demand. The following section focuses firstly, on deriving slot values from different aircraft types, and secondly how much passengers are prepared to pay at each departure time interval. Therefore, the assumption of fixed fares between departure times is relaxed in order to permit fares to vary according to how highly passengers value departing at different times of the day.

7.4 Slot value model analysis assumptions

The basic principle underlying slot value estimation, is that the value of a given slot is a function of the maximum profit that is generated over one year from operating a flight at a specific departure time.

The simulation model generates equilibrium flights for three different aircraft types. For each aircraft type, the model is run on different intervals of ∂f. In other words, when flights are scheduled at unoccupied slots, fare is reduced by ∂f, and if passenger demand on any flight exceeds seating capacity, then in the following iteration, fare is increased by ∂f. The magnitude of ∂f remains the same throughout each iteration, until equilibrium is achieved.

When equilibrium is achieved, in any run of the model, a set of flights is generated, which are scheduled at specific departure slots. These flights are associated with a level of passenger demand and level of fare. Therefore, for different intervals of ∂f, variation in patterns of scheduling, demand per flight and fare can be observed. The hypothesis is that by increasing the value of ∂f, the costs to passengers of departing at different times of the day will vary, and that patterns of scheduling, profits per flight and the slot values obtained will be reflected in the different values passengers attach to departing at certain times of the day. The value of a slot therefore, is assumed to be the maximum profit generated at a specific departure slot from different runs of the model at different levels of ∂f. In the following section, slot values generated by the model for the three aircraft types are considered and evaluated. Within this context, patterns of flight scheduling, levels of equilibrium fares, and profits for each departure slot are examined and interpreted at each interval of ∂f. The

simulation model is calibrated on a total daily route demand of 400 one-way passenger trips and each flight is assumed to be supplied by an individual operator.

7.5 Slot value model results

7.5.1 100-seat jet

Table 7.2 on the following page, illustrates equilibrium patterns of scheduling generated by the simulation model at different intervals of fare variation ∂f (£1, £2, £3, £4, £5, £6), and assuming that flights are supplied and slots evaluated by 100-seat jet operators. Thus, in calibrating the model for each run, the basic fare is permitted to vary by ∂f. Once equilibrium has been achieved, the model is re-calibrated on a different level of ∂f.

The rectangles on Table 7.2 represent flights supplied by individual operators. Where there is no rectangle, no flight was scheduled at this time when the simulation model achieved equilibrium. The number on the left-hand side of each rectangle represents passenger load on the flight, while the figure on the right hand side represents equilibrium fare. For each run of the model, which represents a different interval of ∂f, there is an equilibrium solution, in terms of departure slots selected, passenger load per flight, and fare for each flight. Equilibrium being the point at which there are no further incentives for additional flights to be scheduled at other times with different fares, and passengers are satisfied with their choice of flight and level of fare.

When ∂f = £0, the simulation model generates a set of equilibrium flights at the following departure slots: 08:00, 09:00, 10:00, 16:00 and 17:00. Passenger load is higher on those flights generated at 08:00 and 17:00, As ∂f = £0, the equilibrium fares associated with each flight remain fixed £55.

When ∂f = £1, i.e when fares are permitted to change by £1, the model generates five equilibrium flights at the same departure times. However, in terms of pricing, three out of the five flights set a reduced fare of £54. When ∂f = £2, the pattern of scheduling changes. Two flights are scheduled at 08:00 and 09:00, and three flights are scheduled in the late-afternoon / early evening period, at 15:00, 16:00 and 17:00. The fare set at 08:00, 15:00 and 16:00 is £53, compared to £57 and £59 at 09:00 and 17:00 respectively. As ∂f increases in magnitude, equilibrium fare levels increase at

Table 7.3 Demand and fare equilibrium results by change in fare ∂ *f*: 100-Seat Jet (total demand = 400)

	change in fare ∂ *f*													
	£0		£1		£2		£3		£4		£5		£6	
	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare
4:00														
5:00														
6:00									72	63	76	75	79	73
7:00													79	85
8:00	90	55	90	55	97	53	96	61						
9:00	75	55	74	55	89	57	76	61	75	59	86	70		
10:00	70	55	71	54										
11:00									76	51				
12:00														
13:00							72	52						
14:00							72	55	81	55	76	65	77	67
15:00					71	53							83	67
16:00					72	53	84	61					82	73
17:00	90	55	90	54	72	55								
18:00	74	55	74	54					96	55	84	70		
19:00											77	75		
20:00														
21:00														
22:00														
23:00														
24:00														

Dem = Passenger Demand

Fare = Equilibrium Fare

peak times, whilst those at off-peak periods tend to be lower. For example, when $\partial f =$ £3, the model generates five flights, Three of these, scheduled at 08:00, 09:00 and 17:00 set a fare of £61, whilst lower fares of £52 and £55 are set at 13:00 and 14:00 respectively. Relaxation of the fixed fare assumption and increasing the magnitude of ∂f, creates opportunities for cheaper flights to be scheduled during off-peak periods, since they are able to attract passengers from more expensive peak time flights. By contrast, higher fares are generated at peak intervals, this is reflected in the higher value passengers place on departing at those times. At peak periods, because of the concentration of passenger preferences, excess demand on certain flights emerges as the simulation model passes different iterations. When this occurs, fares are increased in order to balance supply and demand on each flight.

As ∂f increases further, the pattern of scheduling becomes less stable. Passengers at this point are reacting to ever higher increases and reductions in fare. The model, therefore, has to pass through an increasing number of iterations to achieve equilibrium. When $\partial f =$ £4, a flight is scheduled at 09:00. Because of the presence of cheaper flights during the off-peak period, i.e. the flight scheduled at 11:00 with a fare of £51, the fare at 09:00 is £59 as opposed to £61 in the previous run of the model (∂f = £4).

At higher intervals of ∂f, patterns of slot scheduling become less stable as passengers are offered fare changes of greater magnitude. When $\partial f =$ £6, the model generates five flights, scheduled at 06:00, 07:00, 13:00, 14:00 and 15:00. Interestingly, four of these departure times would not normally be considered as peak time slots. Equilibrium fares generated by these flights are: £73, £85, £67, £67 and £73 respectively. The highest of these fares were associated with flights scheduled at 07:00 and 15:00. These slots are positioned closer to peak departure times. Compared with those results generated by the model on the assumption of fixed fares ($\partial f =$ £0), there is a shift in scheduling to those departure slots positioned before the peak periods. This is because, when fares were fixed passengers selected only on the basis of schedule delay time. When this assumption is relaxed, those passengers also evaluate the fares set at each departure slot. As preferences are clustered within two peaks, those passengers tended to prefer those cheaper flights scheduled at those slots

positioned before the peak slots, given the relative magnitude of the early schedule delay time coefficient β^{se} and β^{sl}. Furthermore, the magnitude of the scale parameter β^{0} also affects choices by dispersing probabilities away from ideal departure times. This becomes ever more apparent when ∂f increases in magnitude. Thus, for example, a passenger who prefers to depart at 17:00, is more inclined to select, given the values of β^{se} and β^{0}, a cheaper flight scheduled at 15:00.

The simulation model was calibrated on £1 intervals of ∂f within a range of £1 to £6. When the model was calibrated on values higher than £6, an equilibrium solution could not be attained. At this point the model loses stability, with fares increasing in significant magnitude through each iteration. When total demand is fixed, and fares are not subject to the influence of factors exogenous to the model, such as competition from alternative modes of transportation, beyond a certain interval of ∂f, the model loses stability and enters a state of permanent disequilibrium. The issue as to why this should be the case is discussed in light of results produced by other aircraft types in Section 7.4.

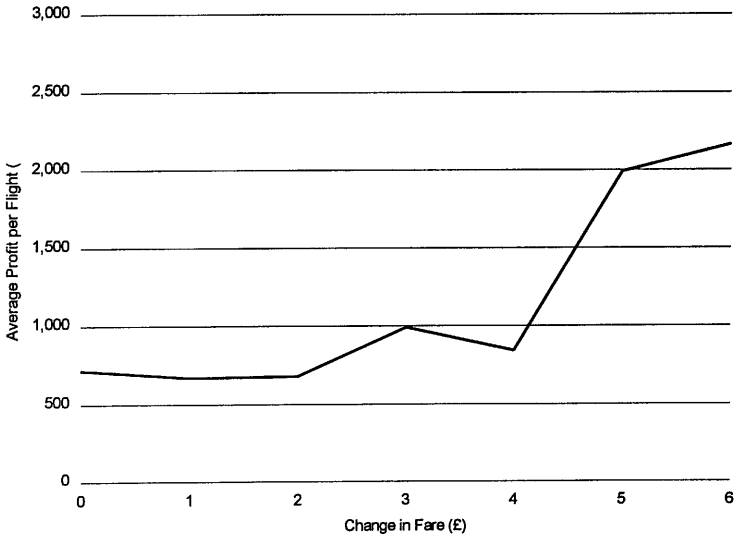
Table 7.3 Equilibrium profit per flight by level of ∂f: 100-seat jet

	change in fare ∂f						
	£0	£1	£2	£3	£4	£5	£6
4:00							
5:00							
6:00					£864	£2,028	**£2,095**
7:00							**£3,043**
8:00	£1,278	£1,278	£1,469	**£2,184**			
9:00	£453	£398	£1,401	£964	£753	**£2,348**	
10:00	£178	£162					
11:00					**£204**		
12:00							
13:00				£72			**£1,487**
14:00				£288	£783	£1,268	**£1,889**
15:00			£91				**£2,314**
16:00			£144	**£1,452**			
17:00	**£1,278**	£1,188	£288				
18:00	£398	£324			£1,608	**£2,208**	
19:00						**£2,103**	
20:00							
21:00							
22:00							
23:00							
00:00							

Table 7.3 outlines the profits generated by each flight at different intervals of ∂f. The maximum profits at each departure slot are highlighted in bold. Figure 7.9, shows the average profit per flight at each interval of ∂f.

Average profit per flight is significantly higher when ∂f = £6, compared to when ∂f = £0. Observation of Figure 7.9, indicates that when the magnitude of ∂f increases average profit levels initially decline. This shows the effect of fare competition between flights and the absence of excess demand.

Figure 7.9: Average profit per flight by against ∂f (total demand = 400): 100-seat jet



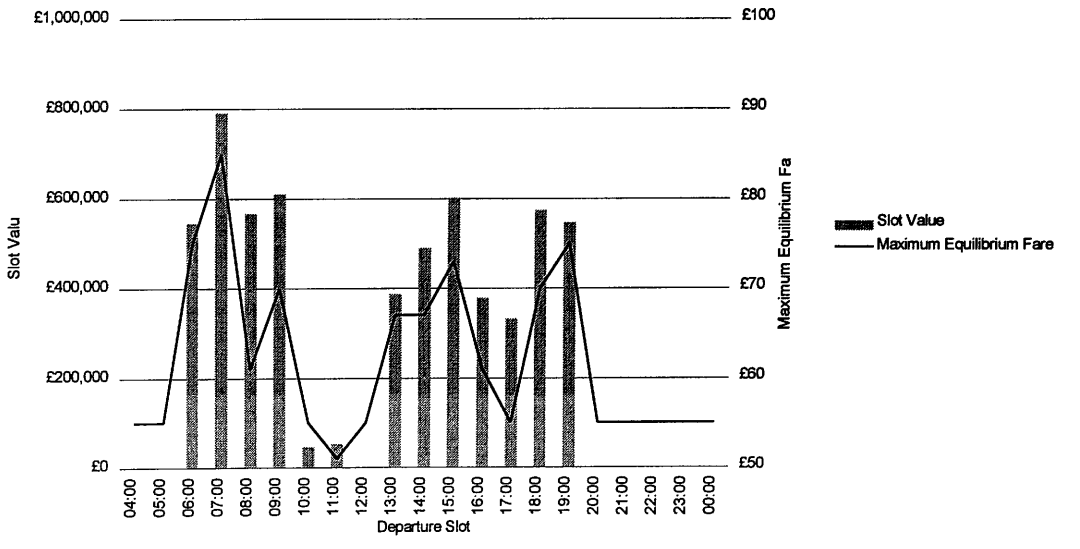
However average profit increases when ∂f = £3. Cheaper flights are scheduled during off-peak departure slots. For example, when ∂f = £4, a flight is scheduled at 14:00, generating a profit of £204. This generates excess demand at peak periods hence the higher fare and profits at 18:00. Interestingly, profits at slot 17:00 decline, as the magnitude of ∂f increases to the point where it is no longer profitable to operate a service at that time. This is due to the combined effect of both the scale parameter and the schedule delay time early coefficients, which encourages those passengers who prefer to depart at this slot, to be less inclined to select a flight at this time, and more inclined to select flights scheduled at earlier times such as 15:00 and 16:00.

Using the maximum profits obtained from Table 7.3 above, and multiplying these figures by 260 days, this generates the maximum profits at each departure slot for a

whole scheduling season, and therefore the monetary value of each departure slot. Figure 7.10, on the following page, shows, firstly, the pattern and scale of slot values, and secondly, the distribution of maximum equilibrium fares levied at each slot.

Those departure slots that could not support a profitable flight, such as at 05:00 and at 21:00 have no value. Departure time 07:00, valued at around £791,000 per year, is the most valuable slot. By contrast, the least valuable slots are at 10:00 and 11:00; valued at £46,280 and £53,040 respectively.

Figure 7.10: Slot Values and maximum equilibrium fares by departure slot (demand = 400): 100-seat jet



Ideally, one would expect the pattern and scale of slot values to closely correspond to the distribution of ideal departure time preferences. For example, since slots 16:00 and 17:00 are associated with two of the most popular departure times, in terms of passenger preferences, one would anticipate correspondingly high slot values and maximum equilibrium fares. However, the distribution of slot values in Figure 7.10 suggests that slot values generated at both 16:00 and 17:00 are comparatively low relative to other departure slots. One explanation for this apparent inconsistency is related to the magnitude of the scale parameter β^0 within the passenger choice model function. Given the low magnitude associated with this parameter relative to generalised costs, passengers are more inclined to select departure times which are less than optimal in relation to their ideal preference. Furthermore, given the low

value of schedule delay early time compared to schedule delay late time, passengers are also more inclined to select flights offered at earlier departure times. For example, those passengers who originally preferred 17:00 and 18:00 as their ideal departure time, are more inclined to choose flights offered at earlier departure times. The combined effect of both parameters therefore is effectively to shift the peak in preferences to earlier times. For example, slot 15:00 is more valuable than slot 17:00 and slot 07:00 is more valuable than slot 08:00.

The distribution of maximum equilibrium fare, mirrors the pattern of slot values described in Figure 7.10. Maximum equilibrium fare by departure slot ranges from £85 at 07:00, £73 at 15:00 and £75 at 19:00 to £51 at 11:00. The costs of travelling, in passenger terms are indeed lower during off-peak periods compared to peak departure times. Although equilibrium fares are in general higher at peak times, there are two inconsistencies: the £61 and £55 fares levied at 08:00 and 17:00, two of the most popular periods of the day in terms of passenger ideal preferences. This is again a function of the relative magnitudes of both parameters mentioned above. During each iteration of the model, at high values of ∂f, since passenger preferences incline towards earlier slots, this generates excess demand during these periods, hence the higher equilibrium fares at those times.

7.5.2 65-seat turboprop

Table 7.4, on the following page, illustrates equilibrium patterns of scheduling generated by the simulation model at different intervals of fare variation (∂f), with regard to the 65-seat turboprop aircraft. As expected, with total demand fixed at 400 one-way passenger trips, the number of daily departures generated by the simulation model is greater than the level of frequency supplied by the 100-seat jet.

Table 7.4 illustrates patterns of departure time scheduling, demand per flight and equilibrium fare generated at each interval of ∂f. When fares are assumed to be fixed between departure slots, i.e. when ∂f = £0, the model generates eight flights, four scheduled at each departure slot between 07:00 and 10:00, and the remaining four scheduled between 14:00 and 17:00. The busiest flights, in terms of passenger load, are those departures scheduled at 07:00 and 08:00 with 59 and 54 passengers

Table 7.5 Demand and fare equilibrium results by change in fare ∂: 65-seat turboprop (total demand = 400)

	change in fare ∂ f																			
	£0		£1		£2		£3		£4		£5		£6		£7		£8		£9		£10	
	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare
04:00																						
05:00																					58	85
06:00									50	51	52	50	60	49	61	48	62	47	63	46	54	95
07:00	59	55	60	54	61	53			50	55	50	57	57	55	57	55	57	55	55	55		
08:00	54	55	51	56	50	57	63	52							51	62	49	63				
09:00	48	55	49	54	50	53	48	58	54	51	58	50	60	55					57	55		
10:00	46	55	47	54	47	53	47	55	51	51	56	50									56	95
11:00							49	58														
12:00																					63	85
13:00													57	49	61	48	63	47	60	46		
14:00	48	55									60	60										
15:00	49	55	48	54	48	53	48	52	49	51	64	55	51	55	52	55	53	55	51	55	54	95
16:00	50	55	49	54	49	53	49	52	50	51	62	55			58	62	58	55	56	55		
17:00	46	55	51	54	51	53	51	52	51	51			56	55					57	55	60	95
18:00			46	54	46	53	46	52	46	51			60	49	58	55	58	55				
19:00																						
20:00																					54	65
21:00																						
22:00																						
23:00																						
00:00																						

Dem = Passenger Demand

Fare = Equilibrium Fare

respectively. Of those flights scheduled in the late afternoon period, the departure at 16:00 is the busiest with 50 passengers.

When ∂f = £1, the simulation model generates eight flights, four between 07:00 and 10:00 and four between 15:00 and 18:00. When ∂f = £1, there is no longer a flight scheduled at 14:00. The flight at 08:00 levies a fare of £56. All other flights set a reduced fare of £54. When ∂f increases further there is little change in the basic pattern of scheduling. When ∂f = £4, all four flights scheduled between 15:00 and 18:00 set a fare of £51, which is £4 below the basic fare. The level of demand and degree of competition between flights appears to have left little scope for flights scheduled during the peak periods to increase fare. This is particularly relevant for flights scheduled during the late-afternoon period where, with four flights scheduled, seating capacity is more than sufficiently accommodating passenger demand.

When ∂f = £5, the model generates seven departures, as opposed to eight when ∂f = £4. Given the withdrawal of one departure during the late afternoon period, these passengers are re-allocated to the three remaining services scheduled during this period, at 14:00. 15:00 and 16:00. Given the emergence of excess demand during iterations of the model, the flight at 14:00 sets a fare of £60, and both flights at 15:00 and 16:00 set fares at £55. When the magnitude of ∂f increases further, stability is maintained in the pattern of scheduling. The model also generates higher equilibrium fares during peak periods. However, in particular runs of the model. some peak slots are left unoccupied. For example, when ∂f = £9, slot 08:00 is left unoccupied. By contrast, slot 13:00, which is one of the least desirable in terms of passenger preferences, is able to accommodate a profitable departure, but having to set a lower one-way fare of £46, which is £9 below the basic fare. The pattern of scheduling, as in the example of the 100-seat jet, loses stability when ∂f = £10. The simulation model generates seven flights, but the positioning of these departures and equilibrium fare levels are significantly different from the pattern of departures and fares generated by the model when ∂f = £0. For example, the simulation model generates a flight at 20:00, attracting 54 passengers and setting a fare of £65. Those scheduled at 06:00, 11:00, 15:00 and 17:00 set a fare of £95, an increase of £40 on the basic one way fare.

Interpretation of these results, inevitably focuses on the instability of the model. Why, given the relative popularity of departure slots 07:00, 08:00 and 09:00, should the simulation model generate flights at other times ?

One explanation focuses on the relative magnitudes of the schedule delay early coefficient and the randomising effect of the scale parameter. The combined effect of both is to, firstly, induce passengers to choose flights scheduled at departure times other than their ideal preferences, and secondly, to bias these choices to earlier departure times.

Table 7.5: Equilibrium profit per flight by level of ∂f: 65-seat turboprop

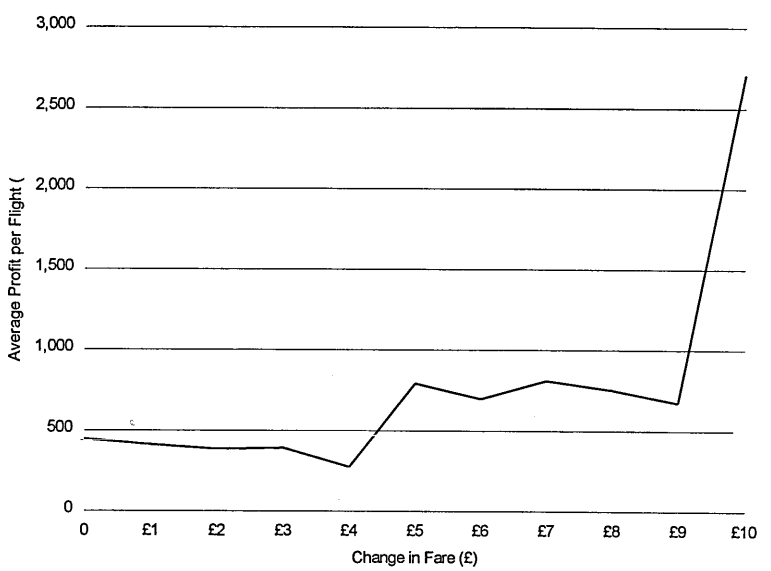
	change in fare ∂f										
	£0	£1	£2	£3	£4	£5	£6	£7	£8	£9	£10
4:00											
5:00											**£2,625**
6:00					£245	£295	£635	£623	£609	£593	**£2,825**
7:00	£940	**£935**	£928		£445	£545	£830	£830	£830	£720	
8:00	£665	£551	£545	**£971**				£857	£782		
9:00	£335	£341	£345	£479	£449	£595	**£995**			£830	
10:00	£225	£233	£186	£280	£296	£495					**£3,015**
11:00				£537							
12:00											**£3,050**
13:00							£488	£623	**£656**	£455	
14:00	£335					**£1,295**					
15:00	£390	£287	£239	£191	£194	£1,215	£500	£555	£610	£500	**£2,825**
16:00	£445	£341	£292	£243	£245	£1,105		**£1,291**	£885	£775	
17:00	£225	£449	£398	£347	£296		£775			£830	**£3,395**
18:00		£179	£133	£87	£41		£635	£885	**£885**		
19:00											
20:00											**£1,205**
21:00											
22:00											
23:00											
00:00											

The instability is also caused by the high value of ∂f. During each iteration of the model, when flights are being scheduled at unoccupied slots, fare is reduced by £10. If passenger demand exceeds seating capacity, in the following iteration, fare is increased by £10. These pricing decisions, generate volatility in both the scheduling of services and in choice of flight, as passengers are tempted by significantly lower fares offered at other departure times. Whilst at those departure times where

demand exceeds supply, fare is increased by £10. At peak departure slots, this leads to a sequence of escalating fares until it becomes no longer profitable to operate a service at those times.

Table 7.5 illustrates, at each interval of ∂f, equilibrium profit levels associated with each flight, with the maximum profits at each slot represented in bold. Figure 7.11 below, illustrates average profit per flight at each interval of ∂f. As ∂f increases, average profits initially decline. When ∂f = £5, the model generates one less flight. As a consequence, there is a marked increase in average profit per flight. This is because, the loss of one flight, leads to excess demand at some slots, and hence higher fares. The level of average profit remains stable, until when ∂f = £10, where there is a marked increase.

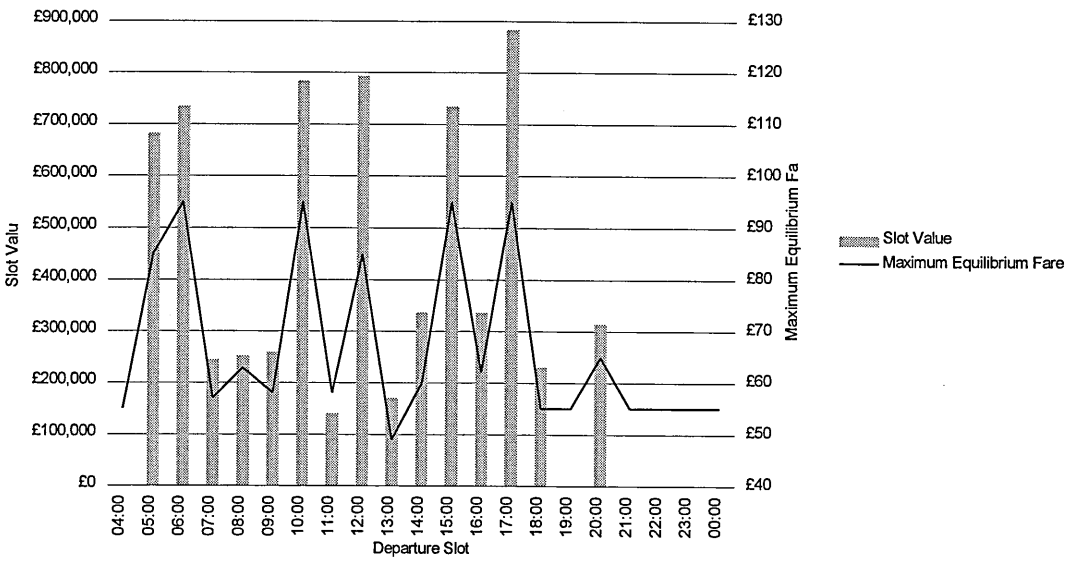
Figure 7.11: Average profit per flight by against ∂f (demand = 400): 65-seat turboprop



Slot values and maximum equilibrium fare trends are shown in Figure 7.12. By taking the maximum profit generated at each slot over one year (260 days), results appear to mirror those conclusions drawn from the experience of the 100-seat jet. Despite the fact that the most popular departure time 17:00 is associated with the higher slot value; £882,000, the general pattern of slot values does not appear to closely conform with the distribution of passenger ideal departure time preferences. The pattern and scale of these values suggests that the combined effect of the scale

parameter value and the low magnitude of β^{se} relative to β^{sl} has increased the values of those slots not normally associated with passenger departure time popularity.

Figure 7.12: Slot Values and maximum equilibrium fares by departure slot (demand = 400): 65-seat turboprop



For example, slots 05:00 and 06:00 are valued at around £700,000, whilst slot 08:00 is only valued at between £200,000 and £300,000. Because of the combined effect of both β^{0} and β^{se} within the passenger departure choice model, passengers are less inclined to select their ideal preference if a flight is scheduled at that time, and secondly, are more inclined to select earlier departure time options, hence the large number of flights scheduled before 10:00, compared to the few flights scheduled after 18:00. Indeed slot 12:00, which is valued at £800,000, is not one of the most popular departure times for passengers especially compared to 16:00, which is valued at just over £600,000.

Maximum equilibrium fare trends also closely mirrors the distribution of slot values, with a maximum fare of £63 at 08:00, compared to £85 at 12:00. On the other hand, the high maximum equilibrium fare at 17:00 of £95, shows that, to some extent, the model is conforming with *a priori* expectations. Nevertheless, inconsistencies with a priori expectation do appear given the particularly high maximum equilibrium fares at 05:00, 10:00 and 12:00.

7.5.3 37-seat turboprop

Running the simulation model on the assumption that individual flights are operated by a 37-seat turboprop aircraft, and total daily demand is four hundred one-way passenger trips, generates a higher level of service frequency relative to the two larger aircraft types already examined, as shown in Table 7.6, on the following page.

When ∂f = £0, the model generates 14 departures, 7 scheduled at each slot between 05:00 and 11:00, and the remaining 7 scheduled between 13:00 and 19:00. With each flight charging the same fare, the busiest flights are those scheduled at slots 08:00 and 17:00. The least busiest are those scheduled at 05:00 and 19:00, both considered off-peak periods in terms of passenger departure time preferences. When the fixed fare assumption is relaxed, and ∂f increases in magnitude from £1 to £10, there is little change in the pattern of scheduling. However, there are changes in the distribution of passengers between flights, and the level of equilibrium fare across departure slots. When the fixed fare assumption is relaxed, the fares charged vary by time of day, with those flights scheduled during peak periods setting higher fares compared to those scheduled at less popular departure slots. For example, at slots 07:00, 08:00, 16:00 and 17:00, the fares set are higher than at other times. When ∂f = £5, the fares set at 07:00, 08:00 and those set at 16:00 and 17:00 are higher compared to off-peak periods. However, the highest fare set is £65 at 07:00, whilst at other peak slots, operators are content to set the basic fare, which is £55. At off-peak periods, such as at 05:00, 13:00 and 19:00, the fares charged are £50. The difference between peak and off-peak equilibrium fares is in most cases only £5. This suggests that the volume of frequency supplied and degree of competition between flights appears to have had the effect of keeping fares low. When ∂f increases in magnitude beyond £5, the model generates thirteen flights, as one operator exits the market. When ∂f = £10, those flights scheduled at 07:00, 08:00 and 09:00 set a fare of £65. The model also generates a flight at 04:00. Because of the relatively more expensive flights scheduled during the mid-morning period, this slot is able to sustain a flight with a fare of £45, which is £20 cheaper than departing at the peak times. Passengers departing during the late afternoon-early evening period on the other hand, are paying £55 to depart at those times. This suggests that because of the scale of competition and the proximity

Table 7.7 Demand and fare equilibrium results by change in fare ∂: 37-seat turboprop (total demand = 400)

	Change in Fare																					
	£0		£1		£2		£3		£4		£5		£6		£7		£8		£9		£10	
	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare	Dem	Fare
04:00																					36	45
05:00	23	55	24	54	24	53	25	52	26	51	27	50	37	49	34	55	33	55	35	55		
06:00	28	55	28	55	28	55	28	55	28	55	28	55										
07:00	32	55	31	56	30	57	29	58	28	59	28	60	34	61	36	55	34	63	36	64	35	65
08:00	33	55	33	55	33	55	33	55	33	55	34	55	34	55	36	62	33	63	31	64	35	65
09:00	30	55	30	55	30	55	30	55	30	55	31	55	36	49	31	55	37	55	36	55	30	65
10:00	27	55	27	55	27	55	27	55	27	55	28	55	32	49	34	55	32	55	29	55	37	55
11:00	26	55	26	55	25	55	25	55	25	55									29	55		
12:00											30	55	32	55	35	55	33	47			30	55
13:00	25	55	26	54	27	53	27	52	28	51	31	50	32	55	35	48	33	47			30	55
14:00	27	55	26	55	26	55	26	55	26	55			32	55			28	55				
15:00	29	55	29	55	30	55	29	55	28	55	31	50	33	55	33	55	32	55	33	55	33	55
16:00	32	55	32	55	32	55	32	55	31	55	33	55	35	55	35	55	37	55	35	55	35	55
17:00	34	55	34	55	34	55	33	55	33	55	35	55	36	49	30	55	34	55	37	55	35	55
18:00	30	55	31	54	31	53	32	52	33	51	33	50	27	49	32	55	33	47	31	55	36	55
19:00	24	55	34	55	34	53	25	52	25	51	27	50			31	55			31	46	30	55
20:00																					32	45
21:00																						
22:00																						
23:00																						
00:00																						

Dem = Passenger Demand

Fare = Equilibrium Fare

of flights there is less scope to increase fare. Furthermore, given the volume of flights generated, the level of capacity supplied is sufficiently accommodating demand, making it less likely that excess demand emerges during the passing of each iteration, and therefore, less need for increased fares to eliminate excess demand. The model at this magnitude of ∂f, is also able to generate a flight at 20:00 with an equilibrium fare of £45.

Table 7.7: Equilibrium profit per flight by level of ∂f: 37-seat turboprop

	Change in Fare										
	£0	£1	£2	£3	£4	£5	£6	£7	£8	£9	£10
4:00											**£356**
5:00	£1	£32	£8	£36	£62	£86	£549	£606	£551	**£661**	
6:00	£276	£276	£276	£276	£276	**£276**					
7:00	£496	£472	£446	£418	£388	£416	£810	£716	£878	**£1,040**	£1,011
8:00	£551	£551	£551	£551	£551	£606	£606	£968	£815	£720	**£1,011**
9:00	£386	£386	£386	£386	£386	£441	£500	£441	**£771**	£716	£686
10:00	£221	£221	£221	£221	£221	£276	£304	£606	£496	£331	**£771**
11:00	£166	£166	£111	£111	£111					**£331**	
12:00						£386	£496	**£661**	£287		£386
13:00	£111	£140	£167	£140	£164	£286	**£496**	£416	£287		£386
14:00	£221	£166	£166	£166	£166		**£496**		£276		
15:00	£331	£331	£386	£331	£276	£286	£551	£551	£496	£551	**£551**
16:00	£496	£496	£496	£496	£441	£551	£661	£661	**£771**	£661	£661
17:00	£606	£606	£606	£551	£551	£661	£500	£386	£606	**£771**	£661
18:00	£386	£410	£379	£400	£419	£386	£59	£496	£287	£441	**£716**
19:00	£56	£606	£538	£36	£11	£86		**£441**		£162	£386
20:00											**£176**
21:00											
22:00											
23:00											
00:00											

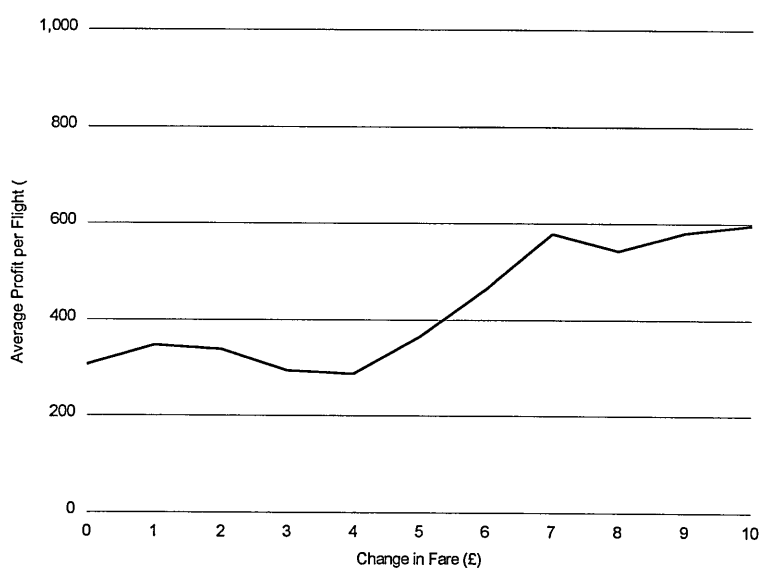
Table 7.7 outlines equilibrium profits generated by each flight at different intervals of ∂f, and Figure 7.13 illustrates average profit per flight at each interval of ∂f. As the fixed fare assumption is relaxed, there is a small reduction in average profit per flight, as some operators, particularly during the off-peak periods, are setting lower fares. When $\partial f =$ £5, there is a marked increase in average profit per flight as the model generates thirteen departures, as opposed to fourteen. When $\partial f =$ £10, the average profit per flight is £597, compared to £338 generated by the model under the fixed

fares assumption. Profit at slot 08:00 increases from £551 when ∂f = £0 to £1,011 when ∂f = £10.

As daily demand is high relative to seating capacity, the model generates flights at most departure slots. When ∂f increases in magnitude, this creates opportunities for the scheduling of flights during off-peak periods. For example at slot 05:00, for each interval of ∂f, equilibrium fare is consistently lower than the fare levied at 08:00. This enables slot 05:00 to sustain a service.

Figure 7.14 below, illustrates the scale of slot values associated with each departure slot generated by the model. To a greater extent than other aircraft types, the values of each slot are more closely related to the distribution of ideal passenger departure time preferences.

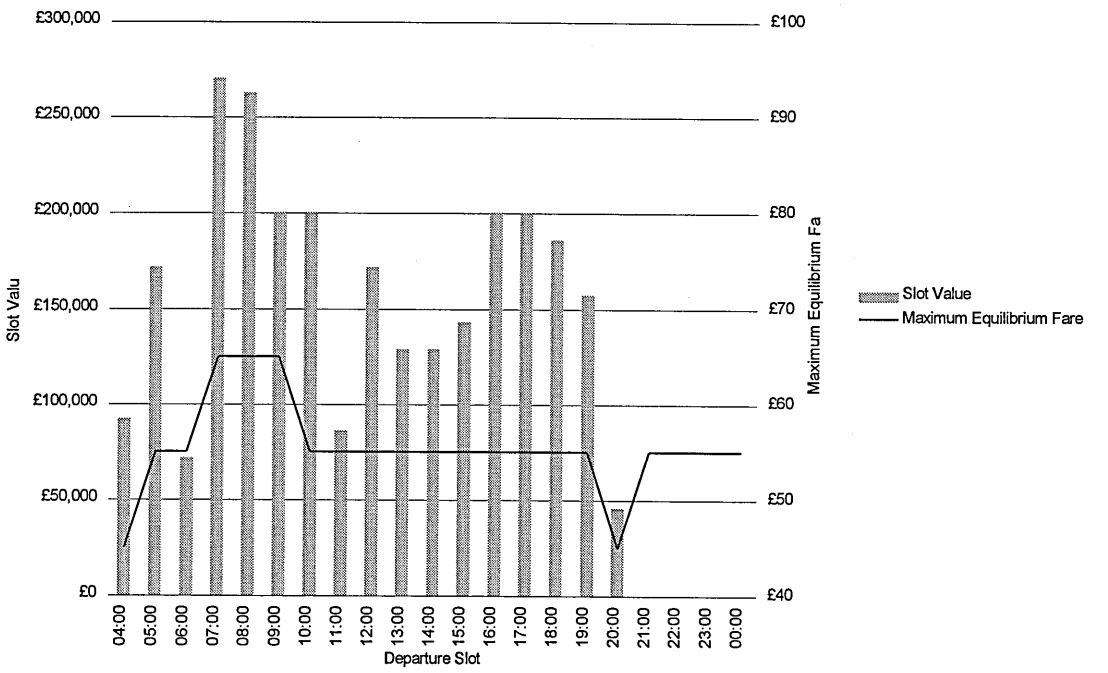
Figure 7.13: Average profit per flight against ∂f (demand = 400): 37-seat turboprop



For example, the most valuable slots are those located at 07:00 and 08:00 both times very popular in terms of passenger preferences, compared to other morning departure times. These slots are valued at £262,860 and £200,460 respectively.

During the late afternoon-early evening period, slots 16:00 and 17:00 are more valuable than other departure times, both valued at £200,460. By contrast, at those slots times that are least popular, the value of slots is significantly lower.

Figure 7.14: Slot Values and maximum equilibrium fares by departure slot (demand =- 400): 37-seat turboprop



For example, at slot 04:00 during the early morning the value of the slot is £92,560 whilst at 20:00, it is even lower at £45,760. What is also apparent from these results and is consistent with results generated by the model with regard to the two other aircraft types, is the tendency for higher than expected slot values at shoulder periods such as 15:00 and in particular 06:00, which is the most valuable slot at £270,400.

In terms of equilibrium fare trends, there is less variation by time of day when compared with both the 100-seat jet and 65-seat turboprop results. This suggests that because of the number of flights generated, the level of competition was such that individual operators were less inclined to increase fares. The highest fare set is only £65, whereas for the remaining slots that were selected, passengers were either paying the basic fare of £55, whilst at some off-peak slots the fares are lower, £45 at 04:00 and 20:00.

7.6 Validation of slot value simulation model results

Having examined and interpreted results generated by the simulation model for each of the three different aircraft types, this section focuses on evaluating the validity of

these results in light of *a priori* expectations regarding the pattern of scheduling and the scale of slot values anticipated.

The hypothesis is based on an expectation that the value of slots should closely correspond to the value passengers attach to departing at different times of the day. Any inconsistencies generated by the model with regard to the hypothesis, must inevitably focus on the basic performance of the model regarding its structural assumptions, and secondly, on the suitability or validity of the passenger choice model parameters. Therefore, there are two issues that need to be considered, to what extent do the results validate the hypothesis ? and if not, can these inconsistencies be explained ?

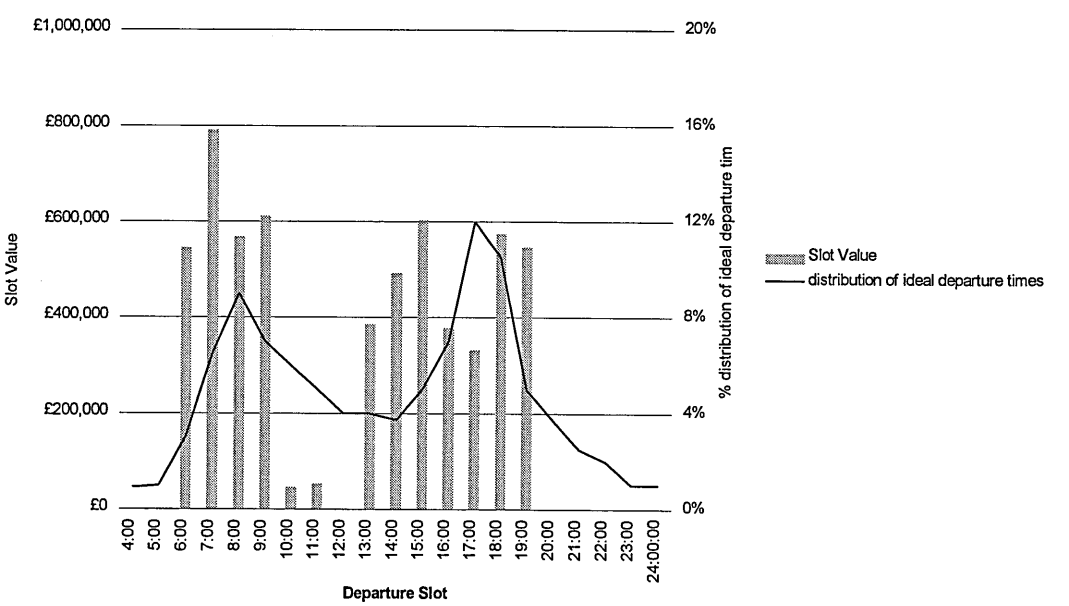
As far as patterns of scheduling and pricing behaviour generated by the simulation model is concerned, the results showed, that as the fixed fare assumption is relaxed, equilibrium fares increase during peak periods. Furthermore, the ability to set different fares according to the value passengers attach to travelling at those times, creates opportunities for the scheduling of cheaper flights during off-peak periods. The slot values derived from these runs of the simulation model are generally consistent with a priori expectations in that higher slot values tended to be generated at the most popular departure slots.

For example, 07:00, 08:00, 09:00, 16:00, 17:00 and 18:00 were generally associated with high slot values. By contrast, given the low value passengers attach to departing, during off-peak periods, the value of slots at these times was correspondingly lower. Indeed, the opportunity to schedule profitable flights after 20:00 and before 05:00 proved to be extremely limited given the low level of demand to travel at these times and the high penalty, in generalised cost terms, associated with selecting flights at these times. When flights were generated during off-peak periods, the equilibrium fares tended to be lower than those set by peak period flights. In this regard the model can also be considered as robust in that it conforms with the *a priori* expectation that flights scheduled during less popular departure times, are required to set lower fares in order to attract passengers from flights scheduled at popular times, but paying a higher fare. In this sense, passengers, as in the case of the respondents to the stated preference questionnaire, were trading- off between convenience of departure time

and level of fare, and that the values of schedule delay early and schedule delay late time appeared to be reflected in those decisions taken by passengers when calibrating the model.

There were however, a number of inconsistencies. Whilst there appeared to be some degree of positive relationship between slot values and the distribution of passengers ideal departure time preferences, in some instances, the model generated higher than expected slot values at less popular departure times. For example, with the 65-seat turboprop, the 12:00 slot is valued at £793,000. By contrast and in the same example, the slot at 16:00, which is considered as a peak time slot is only valued at £335,000. One would expect given the hypothesis that the most popular departure times i.e. 08:00 and 17:00 would be associated with higher slot values. On the other hand the model appears to generate higher values at those slots positioned just before peak departure times, i.e 07:00, 15:00 and 16:00. Figure 7.15, below, provides an example of these inconsistencies.

Figure 7.15: Slot Values and % distribution of passenger ideal departures times: 100-seat jet



The pattern of slot values and distribution of ideal departure time preferences shown in Figure 7.15 with respect to the 100-seat jet, shows that despite slot values being higher during peak periods compared to off-peak periods, those values associated with the most popular departure times do not necessarily conform with the relative

popularity of these departure times in terms of passenger preferences. For example, despite the fact that 17:00 is valued highest by passengers, the money value of this slot is lower compared to 15:00 and 16:00. Similarly, slots 06:00 and 07:00, are more valuable than the slot at 08:00, which is the most popular departure time during the mid-morning period.

In accounting for these apparent inconsistencies, any explanation has to focus on two fundamental issues related to the passenger departure time choice model parameters. Firstly the value of the scale parameter and secondly the magnitude of the schedule delay early coefficient relative to the late schedule delay time coefficient.

The scale parameter influences the distribution of choice probabilities. A low value, relative to generalised costs, implies that choice behaviour is less deterministic and more probabilistic. This means that passengers are less inclined to select their ideal departure time if a flight is scheduled at that slot. Examination of the nature of error term variance in the stated preference experiment in chapter five revealed that the error term also incorporates variation in values of schedule delay and in-flight time combinations across the sample of respondents. Inconsistencies in passenger choice behaviour and the resultant slot value estimates can also be attributed to variation in values of time combinations across the sample of respondents.

The relative magnitudes of both schedule delay time coefficients, β^{se} and β^{sl}, also had a significant influence on the way passengers selected flights and on the pattern of slot value estimates. Both β^{se} and β^{sl} are asymmetrical in terms of their relative magnitudes. This does conform with *a priori* expectations, since passengers will tend to prefer earlier departure time options. On the other hand, later departure times have the added inconvenience of being more likely to disrupt destination activities or any onward trip schedule.

However, the main issue to consider is the relative magnitudes of both coefficients, which is approximately 1:4. The tendency and bias for passengers to select earlier departure times is clearly evident in the patterns of flights scheduling, levels of demand per flight, equilibrium fares and slot values. This also accounts for the complete absence of flights scheduled later than 20:00, since there is a large penalty in

terms of additional generalised cost to departing at these times. However the question to consider is should one expect such a difference between the values of schedule delay early and schedule delay late time. Indeed, what would be the effect of making both β^{se} and β^{sl} more utility symmetrical ? The effect of increasing β^{se} relative to β^{sl} would be to increase the penalty in generalised cost terms, of departing at earlier times. As a consequence fewer flights would be scheduled during off-peak periods. The effect of increasing β^{se} relative to β^{sl} , on patterns of scheduling, equilibrium fare and slot values is considered in the following sub-section.

Furthermore there is also a degree of uncertainty regarding the magnitude of the scale parameter β^{o}. The issue of concern focuses on whether such a degree of error in passenger choices actually exists in reality and whether it is valid to transfer scale parameter values derived generated from disaggregate to aggregate data.

Uncertainty over the precise values of both the scale parameter β^{0}, and the magnitude of β^{se}, therefore, weakens the validity of these results. If the magnitudes of both β^{0} and β^{se} should indeed be higher than those empirically derived, then perhaps, one should expect slot values generated by the simulation model to more closely correspond to the distribution of ideal departure items. Firstly, because passengers would be more inclined to select their ideal departure time if a flight is scheduled at that slot and secondly, there would be additional generalised costs associated with selecting an earlier departure time.

As far as comparing slot values obtained from past research is concerned, two authors Hulet (1991) and Blore (1992) have sought to estimate the value of slots at London Heathrow. Although it is very difficult to compare these estimates with those results generated from this thesis, because of the different context, it is nonetheless important to at least specify those values obtained from past research and to comment on any similarities or differences. In doing so, those figures obtained from the other studies were adjusted for inflation, in order to make them comparable to those estimates generated in this thesis. Hulet (1991), in an examination of different slot allocation methods suggests, that the value of a domestic slot over one year at London Heathrow is £145,600. Although the author did not state precisely the means by which this estimate was derived, this value is in line with the average estimate across departure

slots, generated using the 36-seat turboprop, which is £129,517. As far as international slots are concerned, Hulet (1991) suggests that the average value would be £2,912,000. The difference in scale with the domestic slot value is considerable, and probably, correct, given that this covers a wide range of routes including highly profitable long-haul services. In the sensitivity analysis considered in the following section, slot values were derived on the basis of flights being scheduled by 150-seat jet operators and total demand being 1,400 one-way trips per day. The average slot value derived is £510,256, although the route is still considered domestic.

Blore (1992) in an evaluation of the effects of slot pricing on route structure calculates slot values on a selection of major short to medium haul intra-European routes, also out of London Heathrow. His estimates do vary by route, from £591,300 on slots used for Amsterdam services to £3,547,800 on slots used for services to Paris Charles de Gaulle. Slots used on international services, compared to regional routes are more valuable for two reasons: firstly, if total passenger throughput is higher and secondly fares are usually significantly higher than on domestic routes, even when considering international routes of similar sector distance. It is difficult to draw comparisons with results generated from the thesis, since the assumptions used to derive these estimates and the context applied are very different. Nevertheless they do show, that the results derived are broadly consistent with those developed by Hulet (1991). In the following section, the model is generated on the assumption that flights are supplied by 150-seat operators on a heavily trafficked route. The slot values generated are within the range generated by Blore (1992).

As far as the performance of the simulation model itself is concerned, one consistent feature that emerged common to all three aircraft types was the degree of instability generated beyond a certain interval of ∂f, in that the model did could not find an equilibrium solution. Fares generated by individual flights, as a consequence, increased with the passing of each iteration.

The difficulty with using simulation models, especially those that are closed or captive, is that they will almost invariably tend to disequilibrium. This was recognised and acknowledged as a deficiency when developing the simulation model in the previous chapter. With total demand fixed, and the market not subject to

exogenous factors such as competition from alternative modes of transportation, there is a tendency for fares at individual slots to rise to infinity.

There appeared to be a threshold level of ∂f, within which equilibrium solutions are generated, and beyond which, the model loses its stability. A state of permanent disequilibrium occurs when there remains within each iteration of the model, opportunities for the scheduling of additional flights at other departure slots and that passengers are continuously altering their preferences in response to these decisions. When ∂f is low, the model appears to readily generate an equilibrium solution. However, at high intervals of ∂f, beyond £6 for the 100-seat jet and beyond £10 for the two smaller aircraft, where flights are being scheduled at unoccupied slots, the fares set by these new flights are significantly lower than those fares levied at occupied slots. At those departure slots where passenger demand exceeds seating capacity, fares are increased by a similar margin. As there is significant variation in fare by the passing of each iteration, both flight scheduling and pricing behaviour becomes more volatile. In all three cases considered, the model tended toward permanent disequilibrium above certain values of ∂f. The thresholds with respect to the 100-seat jet is lower, because of the reduced volume of frequency, and therefore the greater scope and opportunity for the scheduling of new flights. Thus, if aircraft seating capacity is high relative to total demand, then the volume of service frequency is lower. Applying high values of ∂f, leads to frequent shifts in passenger choices by the passing of each iteration. Since average schedule delay is high, because of the distance between services, large changes in fare lead to frequent shifts in passenger choices. As a consequence, new flights are being continuously supplied and existing services withdrawn. On the other hand, the model is much more stable at high intervals of ∂f, when seating capacity is low relative to total demand, since the volume of service frequency is higher, and therefore the scope for scheduling new flights is that much less.

The slot values generated by the model, are based on equilibrium solutions. In the following section, the transferability of the model to alternative operating assumptions will be considered within the context of a series of sensitivity tests.

7.7 Sensitivity analysis

7.7.1 Assumptions

Results outlined in Section 7.5, are based on: empirically derived passenger choice model parameters, an assumed distribution of ideal departure time preferences, and specific aircraft types. The objective of the sensitivity analysis is to evaluate and examine the transferability of the model as a result of changing some of the model input assumptions as mentioned above.

Three separate sensitivity tests were considered. The first test involved estimating the sensitivity of slot values and maximum equilibrium fares, as a result of increasing the magnitude of the scale parameter β^{0} and the schedule delay early time parameter β^{se}. The second test involved calibrating the simulation model on a uniform distribution of ideal departure times, leaving the passenger choice model parameters unchanged. And finally, the third test involved evaluating results generated by the model on the basis of a larger aircraft type, on a different route with higher total daily demand.

7.7.2 Sensitivity test 1: doubling the value of β^{0} and β^{se}

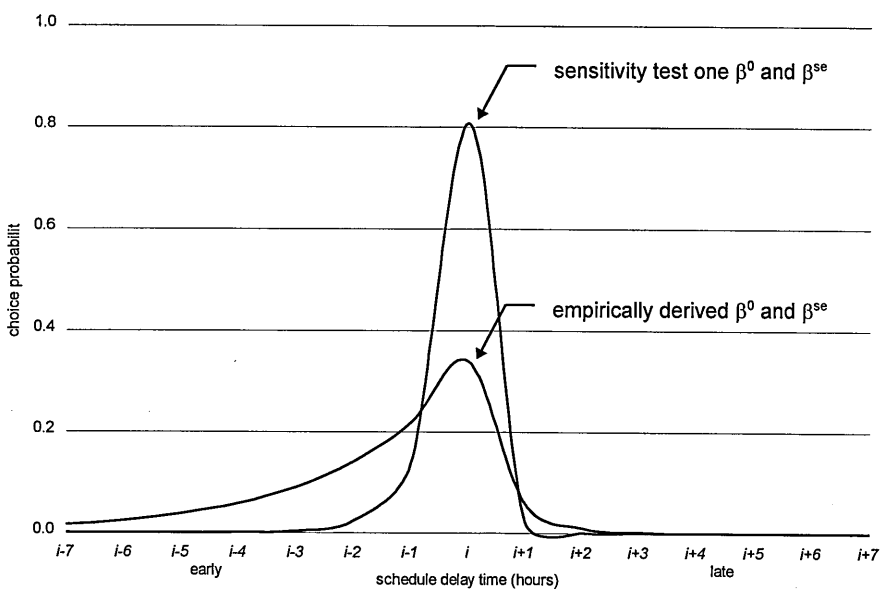
The slot values and maximum equilibrium fare results generated in Section 7.5, were derived by calibrating the model on empirically derived passenger choice model parameter estimates. However, there appeared to be a degree of uncertainty over the magnitude of the schedule delay early parameter β^{se}. This was due to deficiencies associated with the early departure time choice options in the stated preference experiment. There was also an issue over the magnitude of the scale parameter β^{o}, which measures the degree of error in responses to the stated questionnaire and variation in the value of schedule delay and value of in-flight time combinations across the passenger sample. To what extent, therefore, is the scale parameter a true reflection of the scale of error found in real passenger markets ?

Given uncertainty over these values, the first sensitivity test involves calibrating the simulation model on the basis of doubling the magnitudes of β^{0} and β^{se}. The hypothesis is, that by increasing the value of both parameters, slot values and maximum equilibrium fares should more closely correspond to the distribution of passenger ideal departure time preferences. This is because, passengers will be more

select a flight which is scheduled at their ideal departure time given the higher value of β^0 and they will be less inclined to select earlier flights given the increase in β^{se}. Figure 7.16 below, compares the choice probability distributions generated by the empirically derived choice model parameters and those used for the sensitivity test for passengers who prefer to depart at an ideal departure time *i*.

From Figure 7.16, given empirically derived values of β^0 and β^{se}, 34% of passengers who prefer to depart at *i*, would select to depart at this time, if a flight is scheduled at this slot. For those passengers who do not select their ideal time, there is a bias or tendency to choose earlier departure times. Assuming both β^0 and β^{se} are doubled in value, then the proportion of passengers who select to depart at *i* increases to 81%, and there is less tendency amongst passengers to depart at earlier times.

Figure 7.16: Passenger choice probabilities generated by empirically derived and sensitivity test 1 parameters

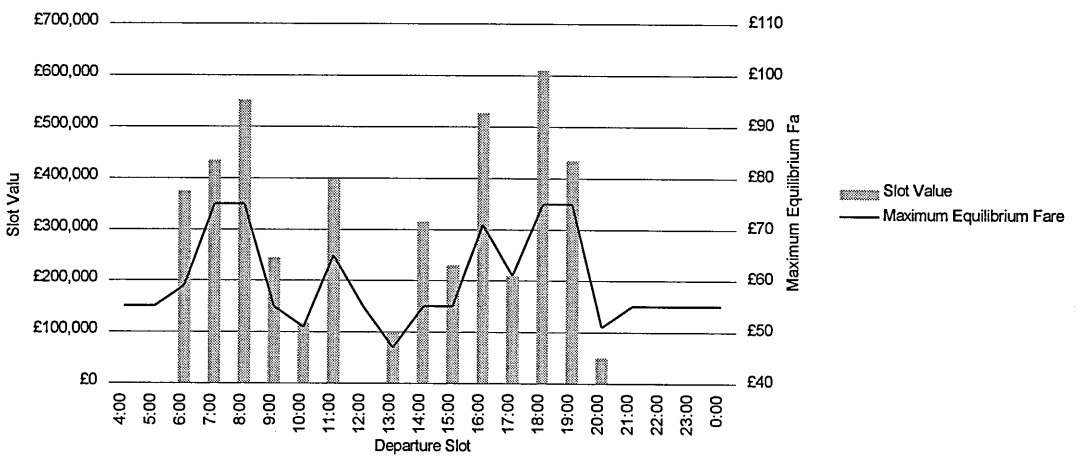


Thus, the hypothesis is that by increasing the magnitude of both parameters, a higher proportion of passengers select their ideal departure time if a flight is scheduled at this slot, therefore the value of slots and equilibrium fares will more closely reflect the distribution of passenger ideal departure times throughout the day.

The pattern of slot values generated on the basis of sensitivity test 1 parameter values outlined above, ranges from a maximum of £609,700 generated at 18:00 to £50,400 at

departure slot 20:00. During the mid-morning period, the most valuable slot appears to be at 09:00 where the slot value generated is £551,200. Observation of the scale and distribution of these slot values, does appear to confirm the hypothesis that increasing the magnitude of both β^0 and β^{se} generates slot values that more closely mirrors the distribution of ideal departure time preferences.

Figure 7.17 Sensitivity test 1 slot values and maximum equilibrium fares: 65-seat turboprop

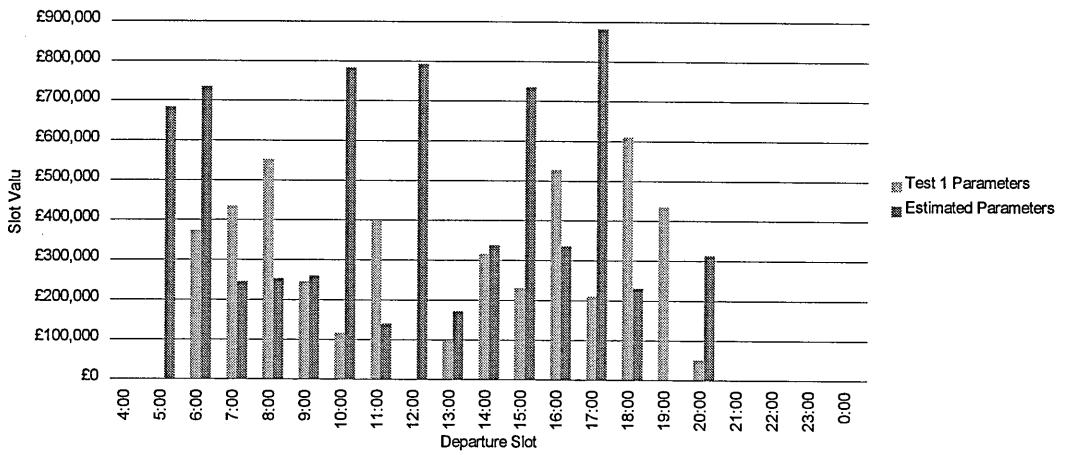


For example, during the most popular departure times, slot values are higher compared to less popular departure times. For example, from 07:00 to 09:00, slot values are higher, compared to those generated at 12:00 and 13:00. The sensitivity of the simulation model to changes in the magnitude of both parameters is also reflected in the pattern of maximum equilibrium fares across departure slots. For example, at those departure slots that are considered popular, i.e. 07:00, 08:00, 16:00 and 18:00, equilibrium fare is higher, £75 in all cases. However, despite increasing the magnitude of β^0, some inconsistencies in the results do remain, such as the relatively high slot values at 11:00, and 14:00, which suggests that passenger preferences continue to be biased to earlier departure times since, both β^{se} and β^{sl} remain utility symmetrical.

Comparing these results with those obtained from empirically derived passenger choice model parameters, as shown in Figure 7.18 below, confirms that the pattern of slot values generated under sensitivity test one assumptions more closely mirrors the distribution of ideal departure time preferences. Indeed at peak slots such as 08:00,

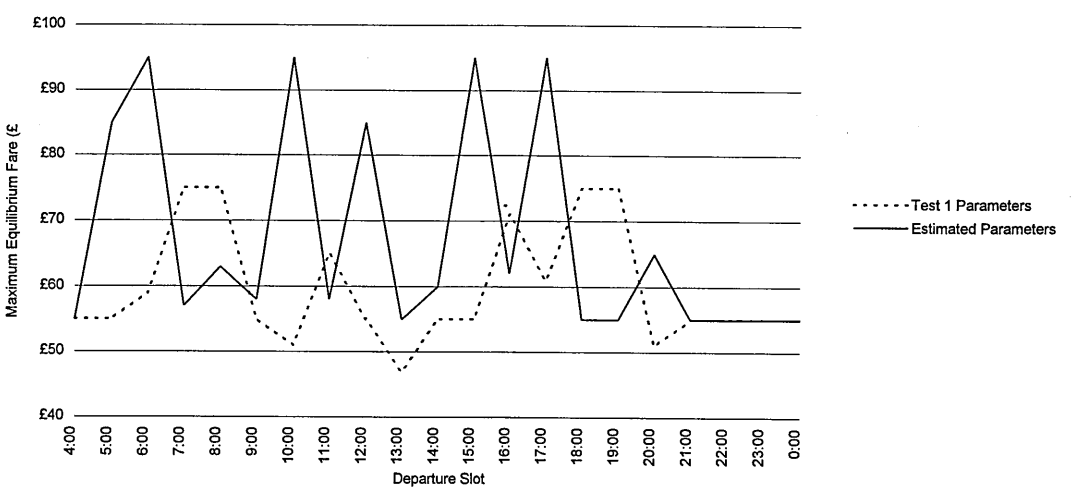
09:00, 16:00 and 18:00, the slot values are higher than those generated by the simulation model under empirically derived parameter input assumptions.

Figure 7.18 Difference in slot values between model and sensitivity test 1 results by departure slot: 65-seat turboprop



Comparing the pattern of maximum equilibrium fares as shown in Figure 7.19 indicates that firstly, the pattern is more stable and more closely reflects the distribution of ideal departure time preferences.

Figure 7.19 Difference in equilibrium fares between model and sensitivity test 1 results by departure slot: 65-seat turboprop



The reason as to why the pattern is more stable is that as passenger choices are more deterministic and there is less dispersion in choice probabilities, selection of departure time is more deterministic and model equilibrium is achieved though fewer iterations

of the simulation model. The hypothesis that by increasing the magnitude of the scale parameter and the early schedule delay time coefficient, the pattern of slot values and maximum equilibrium fares should more closely correspond to the distribution of ideal departure time preferences is indeed confirmed by the sensitivity test.

7.7.3 Sensitivity test 2: Uniform distribution of ideal departure time preferences

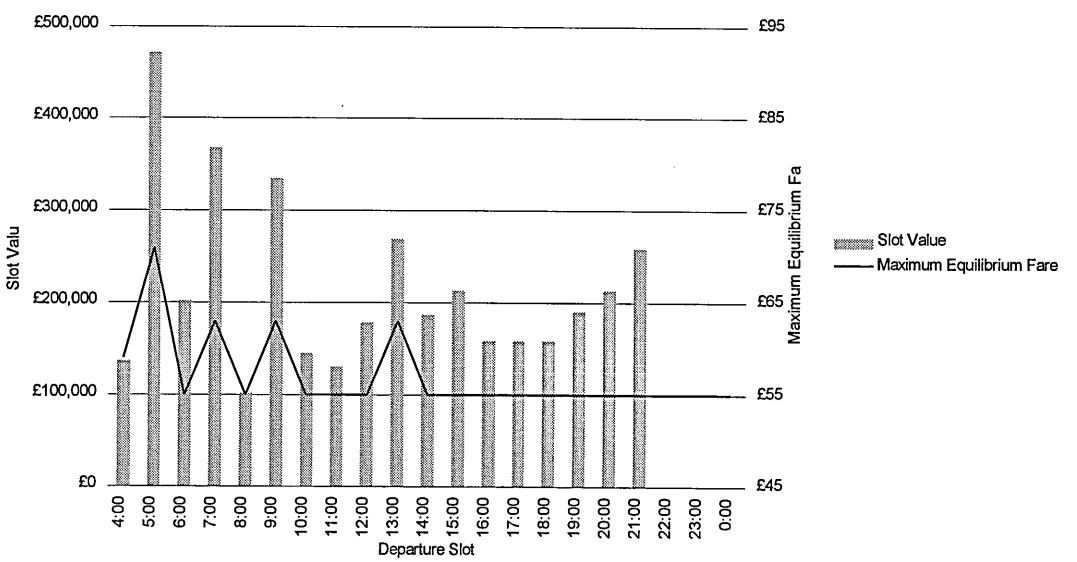
The daily distribution of passenger ideal departure times by slot was obtained from Jessiman et al (1970). The distribution used refers to a short-haul city-pair market in the United States. The distinctive features of this distribution is the existence of two daily peaks in demand, during the mid-morning, followed by another peak period during the late-afternoon early evening period. In some markets, the distribution will vary. For example, in long-haul routes, which involve significantly greater in-flight times compared to short-haul flights, optimal arrival time is probably more important relative to departure time. On transatlantic services from Europe, for example, most departures are scheduled between 12:00 and 15:00. Airlines seek slots at those times so that, taking into account in-flight times and time-zone changes, flights can arrive in North America at around 16:00. This enables passengers to access connecting services to onward destinations. Therefore, there may only be one peak in departure preferences, between 12:00 and 15:00. In other markets, the distribution may be more uniform, i.e. charter markets or on those routes with a very high percentage of leisure passengers.

The second sensitivity test seeks to evaluate results generated by the model on the assumption that the daily distribution of passenger ideal departure times is uniform (does not vary) across departure slots. Leaving the parameter values of the passenger choice model unchanged, and with operators using a 65-seat turboprop aircraft, the hypothesis is that there will be little variation in the scale of slot values and maximum equilibrium fares by departure slot.

Figure 7.20 below illustrates the pattern of slot values and maximum equilibrium fares generated by the simulation model as a result of altering the distribution of ideal departure time preferences and leaving all other input parameters unchanged.

These results appear to confirm the hypothesis that by assuming there is no variation in passenger preferences by time of day, then there will be little variation in the scale of slot values and equilibrium fares. Closer examination reveals that slot values associated with departure times after 13:00 are broadly consistent in that there is little variation by departure slot. By contrast some slots during the early morning period, do appear to be associated with higher slot values.

Figure 7.20 Sensitivity test 2 slot values and equilibrium fare by departure slot: 65-seat turboprop



For example, the most valuable slot is at 05:00, with the maximum profit over one year generated at this time, being £471,380. This is due to the low value of β^{se}. Incidentally, this bias and the dispersion of choice probability remains, since the magnitudes of parameters that cause these effects remain unchanged.

The pattern of maximum equilibrium fare is also broadly consistent with the pattern of slot values. The highest equilibrium fare is £70 at slot 05:00. For the majority of slots, there is no change from the basic fare (£55). Figure 7.21 below compares the results generated by the sensitivity analysis with those results generated using the original distribution.

The pattern of slot values associated with the actual distribution is clearly different from those values generated by assuming a uniform distribution of departure time

preferences. Indeed, the scale of slot values is significantly higher, because demand is concentrated within two peak periods.

Figure 7.21 Difference in slot values between model sensitivity test 2 slot by departure slot: 65-seat turboprop

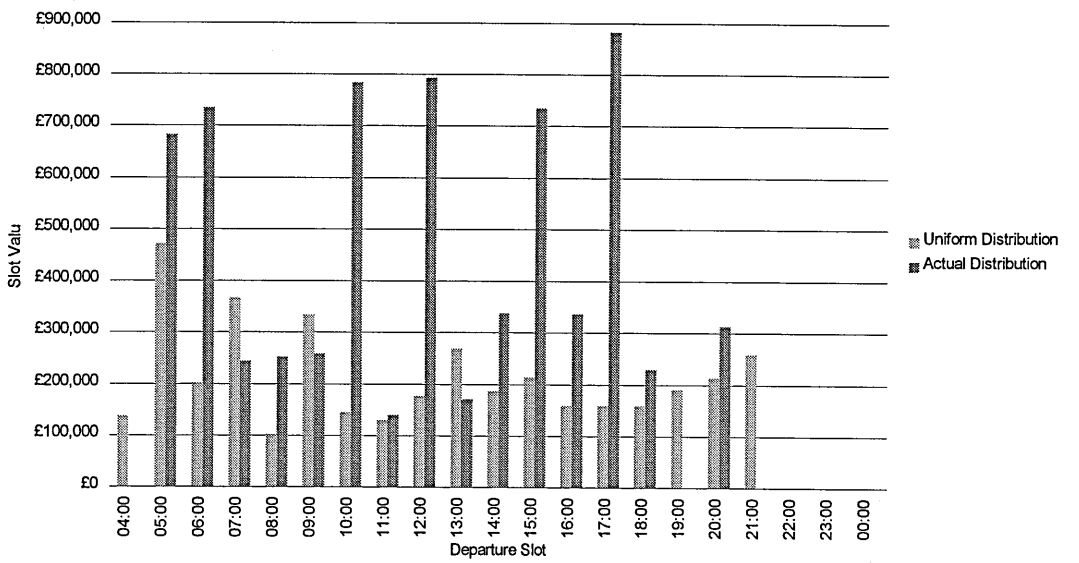
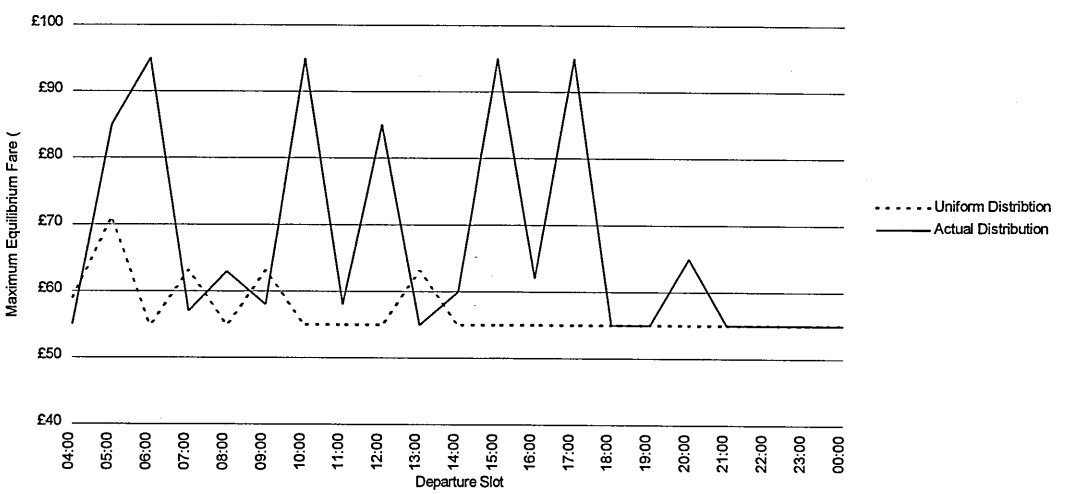


Figure 7.22 Difference in equilibrium fares between model and sensitivity test 1 results by departure slot: 65-seat turboprop



As a consequence, when flights are scheduled during these periods, fares and therefore, profits are more likely to be higher relative to fares set during off-peak periods, because of the greater likelihood that passenger demand will exceed seating capacity on some flights. If demand is uniformly distributed, profits and fares are less

likely to increase, given that excess demand, because of the absence of peaks in preferences, is less likely to emerge.

Figure 7.22 above, compares maximum equilibrium fare levels generated by the model under both scenarios. As mentioned earlier, if there are peaks in demand throughout the day, then equilibrium fares are higher.

Whereas, if preferences are uniformly distributed, then fare will be much lower. Although there are cases where at some departure slots, maximum equilibrium fares is higher, for example, at 05:00. This is because, passengers are biased in their choices towards earlier departure times. As a consequence during calibration of the simulation model, prior to equilibrium, excess demand may arise, hence leading to increased fares.

7.7.4 Sensitivity test 3: 150-seat aircraft and total demand = 1,400

As a method for estimating the value of a departure slot, to what extent is the simulation model transferable to other routes and aircraft sizes? The stated preference model coefficients were derived from a sample of passengers on a short-haul city-pair market in the United Kingdom. The extent to which these values are transferable onto a long-haul transatlantic city-pair market is limited, since values of in-flight and schedule delay time for these routes are likely to be lower (see Yoo 1995).

Nevertheless, it is possible to apply the model to a busier route with operators scheduling flights with a larger aircraft. The third sensitivity test, therefore, involves calibrating the simulation model on a 150-seat jet and assuming the route is 153 miles in length and total daily demand is 1,400 one-way passenger trips as opposed to four hundred. This figure was selected because it represents the daily one-way demand on a route with a passenger throughput of one million passengers per year. As far as the parameter estimates and distribution of departure preferences are concerned, these remain unchanged. Table 7.8 below outlines the assumptions used for the third sensitivity test.

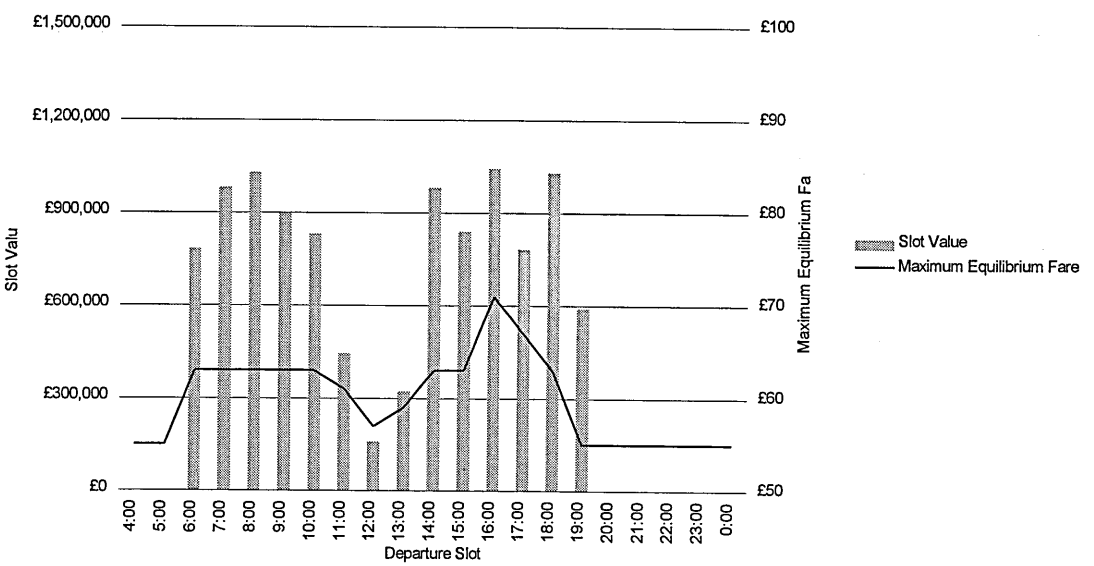
Appendix J shows the equilibrium results in terms of demand and fare generated at each interval of ∂f. The maximum profits generated at each slot from the table in Appendix J is used to represent the value of a departure slot. Figure 7.23 illustrates

patterns of slot values and maximum equilibrium fares generated by the simulation model at each departure time interval.

Table 7.8: Sensitivity test 3 model input assumptions

	Normal	Sensitivity Test 3
Aircraft Type	146	A320
Seating Capacity	100	150
Total costs per flight	£3,672	5,407
Route Distance	177	153
Total Daily Demand	400	1,400

Figure 7.23 Sensitivity test 3 slot values and equilibrium fare by departure slot: 150-seat jet



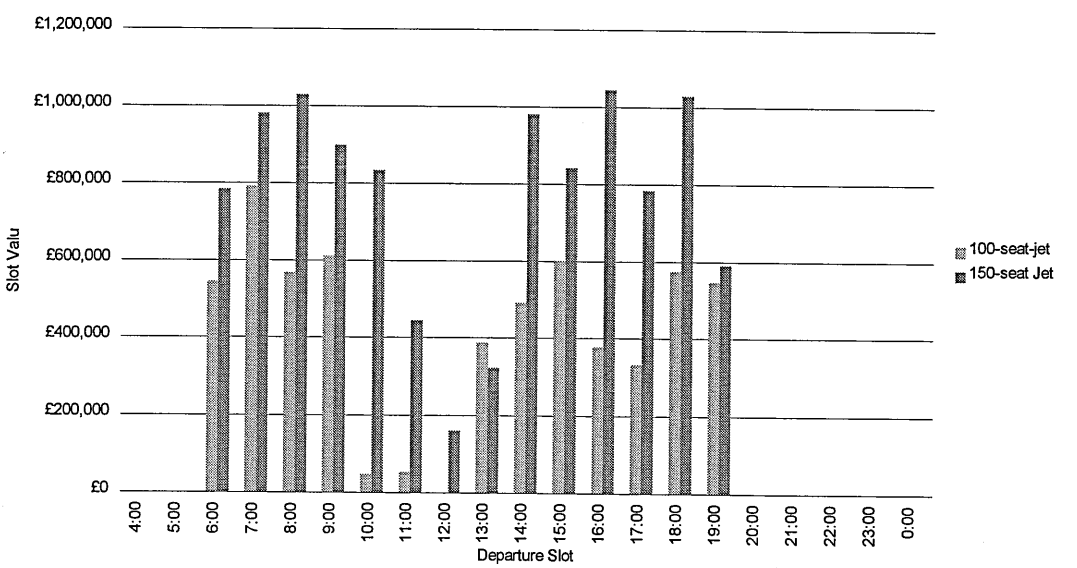
Because of the lack of demand to travel before 06:00 and after 19:00, no flights were scheduled at that time. Flight scheduling is concentrated during the period 06:00 to 19:00.

Given the increased level of total daily demand and the larger aircraft type, the model generates higher slot values and maximum equilibrium fares during peak periods. The most valuable slots are 07:00, 08:00, 14:00, 16:00 and 18:00. These values are: £980,000, £1,029,080, £980,000, £1,044,000 and £1,029,080 respectively. The least valuable slots are at off-peak periods, 11:00, 12:00 and 13:00.

Maximum equilibrium fares are similarly higher in peak departure slots compared to off-peak slots. The highest fare charged, for example, is £71 at slot 16:00. At other departure slots, particularly those during the mid-morning period, the fares are £63. The 12:00 slot, because it is considered less desirable by passengers the maximum equilibrium fare is £57, whilst the maximum equilibrium fare set at slot 19:00 is even lower at £55.

Comparing these results with equilibrium slot values generated by the 100-seat jet on the pervious model input assumptions, reveals and indeed confirms, that the scale of slot values generated is significantly higher assuming flights are supplied by 150-seat jet operators on a busier route.

Figure 7.24 Difference in slot values between 100-seat jet and sensitivity test 3 (150-seat jet)



This raises some important slot allocation policy implications which will be addressed in the following section. For example, referring to Figure 7.24 above, at 08:00, a flight supplied by a 100-seat jet operator will yield, at most in terms of profits over one year, £567,840.

By contrast, a flight supplied at this slot by a 150-seat jet operator on busier route yields a maximum profit of £1,029,080. Similarly, at other peak time slots such as 17:00, the difference is just as significant, with a 150-seat jet operator able to generate £783,380, compared to £332,280. valued by a 100-seat jet operator.

7.8 Policy implications

Given the methodology developed and results generated, to what extent are there any significant policy implications, in so far as the issue of slot allocation is concerned ?

In chapter two, various alternative slot allocation proposals were considered and their associated advantages and disadvantages described. Some of these methods involve the implementation of the pricing mechanism as the basis for rationing slots. One of those methods examined was auctioning, where the airport auctions both departure and arrival slots to the higher value bidder. If such a system were to be implemented, airlines would need to establish a method of measuring the value of departure slots.

The method developed in this thesis is a first step in establishing a system of enabling airlines to measure the value of departure slots. Implicit in the methodology developed, is an assumption that the value of a departure slot is a function of how highly passengers value travelling at different times of the day. In many city-pair markets, demand varies by time of day. If an airline is seeking to measure the value of a slot, then it must generate an estimate of the maximum profits generated from operating a flight at that time. Existing fare structures on many routes do not explicitly contain differential fares with respect to time of day. By employing such a method of pricing, the true value of each slot can be determined.

The airport operator, based on how highly airlines value various departure slots, can determine the true value of access to certain departure slots, and can therefore allocate accordingly.

Doganis (1992) argues that aeronautical charges levied at both London Heathrow and London Gatwick do not give a satisfactory indication as to the value airlines attach to operating services at these times. Even though peak and off-peak charges are levied at these airports, they are set on the basis of long-run marginal costs rather than on the different values airlines place on operating services at different times of the day. Cost-based pricing involves setting airport charges to reflect the higher marginal costs operators place on using airport facilities during busy periods. The problem with this method, especially at BAA-managed airports, is that the scale of airport charges are not reflected in the scarcity value of these slots, since it does not ensure that those

airlines who value departing at certain times the most, pay the scarcity value. One of the main reasons peak and off-peak charges have failed to ration slots efficiently or to transfer demand to off-peak periods, is that value airlines attach to operating services at certain times of the day exceeds long-run marginal costs, and secondly, the higher charges that are currently levied during peak periods are not passed onto passengers. As this thesis demonstrates, passengers place a different value to departing at different times of the day. If these different values are reflected in the fares airlines set, those passengers who value departing at peak times may be prepared to pay additional fares whereas, those passengers who are largely indifferent to flight timing, may be prepared to pay less in order to travel at an off-peak period.

Although demonstrated on the basis of rather simplistic assumptions, the model shows that by varying fare by time of day, operators can price their services on the basis of the different value passengers attach to travelling at different times of the day, and that some passengers are prepared to endure travelling at less appealing times in return for lower fares. Thus a method of auctioning slots on the basis of how highly operators value scheduling flights at particular times, can encourage greater use of off-peak runway capacity, since some passengers can be encouraged to travel at off-peak times if time of day pricing is introduced.

Assuming that a form of slot auctioning is introduced, where allocation is based on the highest value bid principle, does this place certain airlines at an advantage over other operators ? Conclusions drawn from past research summarised in chapter two, suggest that in theory, the implementation of the pricing mechanism as a more effective means of rationing slots will firstly, disadvantage those airlines who operate smaller aircraft, and secondly, those airlines operating on thinly trafficked routes. Are these conclusions borne out by the results generated in this thesis ?

As far as the issue of smaller aircraft operators is concerned, this is indeed confirmed by the results generated. The reasoning behind this argument is that, given lower seating capacity and higher frequency supplied by small aircraft operators on a given route, their value of a slot will be lower than those operators who schedule larger aircraft types. This is because, the average profit per flight operated by a larger aircraft is that much higher than that generated from a small aircraft. As such, the

larger aircraft operator is at an advantage within a slot auction, in that the airline attaches a greater value to operating flights at certain slots.

Regarding the issue of low and high traffic density routes, it is argued that if slot auctioning is implemented, and different airlines operating on different routes compete for the same slots, those airlines who generated higher profits from using their slots on high density routes, would be able to out-bid those airlines who operate services on thinly trafficked routes. For example, in the third sensitivity test, slot values generated by assuming that flights are scheduled by 150-seat aircraft operators on a route with a daily one way passenger throughput of 1,400, are higher than those generated by 100-seat aircraft operating in a city-pair market with only 400 one-way passenger trips, at each departure slot, except one. The scale of these differences at some slots is quite significant (see Figure 7.24). This raises the spectre of the loss of many thinly trafficked regional routes, since airlines who are scheduling flights on these routes, would be unable to successfully compete in a straight slot auction against those carriers who operate on heavily trafficked routes, and are able to bid substantially higher sums for the same slots.

7.9 Summary and Conclusions

The purpose of chapter seven was to demonstrate the model developed in chapter six, and to generate patterns of equilibrium flights, fares and slot values for a range of departure slots using three different aircraft types. Key points that emerge from Chapter seven are summarised below.

- Section 7.3, was designed primarily to demonstrate the performance of the simulation model with regard to patterns of flight scheduling generated for each aircraft type. The model was calibrated, for each aircraft type, at different intervals of total demand and on the assumption that fares are fixed across departure slots.

- As expected, the volume of daily service frequency generated by the 37-seat turboprop is highest followed by the 65-seat turboprop and 100-seat jet. Evaluation of the precise nature of scheduling behaviour shows that with demand increasing, additional flights are scheduled. Because of the peaking of passenger

departure time preferences, these flights cluster within the peak periods. This mirrors competitive scheduling behaviour in real airline markets where carriers schedule flights close to the departure times of competing operators. With fares fixed, passengers are selecting on the basis of schedule delay time only and flights are therefore scheduled during peak periods only.

- In measuring the generalised cost experienced by passengers with respect to the schedules generated by the three aircraft types, results indicate that as demand increases, average generalised cost declined with regard to the 100-seat jet. This is because, as demand increases and additional flights are supplied, this reduced average schedule delay time combined with the additional convenience associated with a lower in-flight time. As far as the smaller aircraft types are concerned, especially those flights supplied by 37-seat turboprop operators, average generalised cost declines to a lesser extent, because any increases in generalised cost as a result of increased frequency, is eliminated by the disadvantages of a longer in-flight time.

- In generating equilibrium slot values and hence the maximum amount operators of the three aircraft types valued specific departure slots, the simulation model was run on an assumed level of demand of 400 passenger trips per day for each aircraft type. Furthermore, operators were permitted to vary fares at departure time intervals thereby pricing services on the basis of the different values passengers attach to departing at various slots.

- Calibrating the model on the assumption that flights are supplied by 65-seat turboprop and 100-seat jet operators, results show that by pricing their services on the basis of how high passengers value different departure times, flights are scheduled during off-peak periods, at lower fares. The slot values generated are generally reflected in the distribution of passenger departure time preferences, with peak periods associated with high slot values compared to off-peak periods.

- Slot values associated with 37-seat operators are significantly lower than that achieved by both the 100 and 65-seat aircraft, because of the lower profit per flight generated by the simulation model.

- Although the results appear to conform with a *priori* expectations, there are some inconsistencies. Uncertainty over the magnitudes of the passenger departure time choice and schedule delay early parameters, β^{0} and β^{se}, generate some inconsistencies in the model results. The low value of β^{se} relative to β^{sl} and the low magnitude of β^{o} relative to the generalised cost in the choice model, biased choice probabilities towards earlier departure times. This was reflected in some off-peak departure slots being associated with high slot values e.g. 05:00, 06:00, 11:00, 12:00, 14:00 and 15:00. The model also appears to lose stability at particularly high values of ∂f. As such, equilibrium solutions could not be attained, because of the scale of fare changes involved. This deficiency was recognised when developing the simulation model in Chapter six.

- In order to examine the performance of the model under different operating assumptions, three sensitivity tests were carried out. The first test, given uncertainty in the values of both β^{0} and β^{se}, involved doubling the magnitudes of both parameters. This produces a set of equilibrium slot values which more closely conforms to the distribution of passenger ideal departure time preferences. The second test involved assuming that the distribution of passenger preferences was uniform. The simulation model generates, as expected, little variation in slot values by departure slot. The third test involved calibrating the model using an aircraft type with greater than 100 seats and on a higher level of total demand, 1,400 as opposed to 400. The model generates, as expected, equilibrium higher slot values compared to the smaller aircraft types.

- Two policy implications arise from these results. Firstly, time of day pricing of services, makes greater use of off-peak departure times. Since, by setting fares and scheduling flights on the basis of how passengers trade-off between fare and schedule delay time, some passengers can be re-allocated to cheaper off-peak flights. Secondly, if slot pricing is introduced, and airlines are required to bid for slots, because larger aircraft operators and airlines operating on heavily trafficked routes, their value of a slot is that much higher than small aircraft operators, who because of the fact that their valuation of slots is lower, would be unable to successfully match larger bids.

CHAPTER 8

Summary and Conclusions

8.1 Introduction

The aim of chapter eight is to summarise the main findings of the thesis, to evaluate any significant contributions to the existing research area, to acknowledge weaknesses and deficiencies in the methodologies applied, and to make suggestions for further research.

The primary aim of this thesis was to establish a methodology whereby estimates of the monetary value of departure slots can be estimated. Within this context, the research objectives, as outlined in chapter one, were defined as follows:

- To select and apply a method to estimate the value passengers place on departing at different times of the day.
- To establish behavioural decision-rules which define how passengers choose at what time to travel and how operators schedule flights and price their services at different departure slots.
- To use both sets of decision-rules to build a simulation model which can generate a set of flight departure times with their passenger demands and fares
- To generate slot values by using the simulation model on a specific route with a given level of demand, and with different aircraft types.

8.2 Summary of the findings

In seeking to examine the issue of passengers' choice of departure time and to estimate how highly passengers value travelling at different times of the day, stated preference analysis was selected as the most appropriate analytical technique.

The use of stated preference analysis involved asking a sample of passengers departing to a specific destination at Manchester airport, how highly they rated a set of hypothetical travel options in terms of their current journey, i.e the flight which they are just about to take. In identifying the value of different departure times,

respondents were presented with hypothetical flights scheduled at different departure times, with lower fares and different levels of in-flight time compared to their current flight.

The process of establishing the number of hypothetical flights to be evaluated, the hypothetical levels of fare, departure times and in-flight times with regard to each hypothetical flight, involved careful consideration of which combination of hypothetical levels was likely to generate the most statistically significant parameter estimates. An orthogonal design with zero correlation between product attributes was preferred to a non-orthogonal design, with collinearity between product attributes. The non-orthogonal design had the advantage of being able to capture a wider range of values of time in the sample, but the disadvantage of generating statistical bias in the coefficients through correlation between product attributes.

Passengers were asked to rate each response along a five-point scale indicating the strength of their preference. Using this measure as a dependent variable, a variety of statistical estimation techniques based on linear regression and maximum likelihood methods were applied to identify the relative importance of the product attributes in passenger's evaluation of each option. Overall, the estimates were robust between different techniques.

Applying a linear regression model to the sample of responses, the value of schedule delay early time generated was of the order of £7 per hour, whilst the value of late schedule delay time estimated was of the order of £30 per hour. The results strongly confirmed that that passengers were more inclined to prefer those flights scheduled earlier than their ideal preference compared to those flights scheduled later than their ideal preference. This is in line with *a priori* expectations regarding the relative magnitudes of both values of schedule delay time.

As with all stated preference experiments, it is necessary to validate results through a comparison with those obtained from past research. Although no previous examples could be identified where values of schedule delay time were estimated separately, for air travel, values of in-flight time generated generally conforms with those estimated from previous studies e.g. (Yoo 1995).

The issue of examining error was also considered and results from the stated preference experiment were interpreted. The linear regression model yielded an R^2 of 0.17, which is in line with comparable estimates generated from other stated preference experiments. This magnitude of R^2 does raise some important issues regarding the scale of error in responses and interpretation of the R^2 statistic generated from stated preference experiments. Two factors influenced the magnitude of R^2: error and inconsistencies in responses, and variation in the values of time between respondents in the sample. Lexicographic techniques were applied to the sample of responses by firstly, removing those respondents who did not switch or trade their preferences between the current and alternative flight options, and secondly, those inconsistent or irrational responses in the sample.

When non-trading responses were removed, improvements in the R^2 statistic and in parameter *t*-ratios were recorded. Furthermore, removal of irrational respondents, defined as those individuals who chose one alternative over another which logically dominates it in product attributes levels, further improved model statistical significance, generating an R^2 of 0.46. However, removing both non-trading and irrational responses, did not account for the remaining unexplained variation in the dependent variable. Variation in the values of schedule delay and in-flight time across the sample of respondents, accounts for this unexplained variation.

Those parameters generated from the whole sample were selected for passenger choice model calibration. Error in passenger choice decision-making and variation in values of time across the sample were represented in the choice model by the scale parameter β^0, which was derived from the estimation procedure used to identify the magnitude of error term variance which is able to reproduce those parameters derived from the stated preference experiment.

Having established how passengers value departing at different times of the day, the next step was to establish behavioural decision-rules which define how passengers choose at what time to travel and how operators schedule flights and price their services at different departure slots.

Within the context of a city-pair market, the analysis consisted of initially evaluating patterns of flight scheduling for three aircraft types on the assumption that fares remain fixed between flights and at four levels of demand: 100, 200, 300 and 400 passenger trips respectively. As expected, patterns of flight scheduling appeared to concentrate during peak periods. However, the precise positioning of flights was also influenced by the passenger departure time choice model parameters. Passengers tended to select those flights scheduled earlier rather than later than their ideal departures time preferences.

The next stage derived the value of departure slots generated by the simulation model for each of the three different aircraft types considered. In this instance, the assumption of fixed fares was relaxed in order to permit equilibrium fares associated with scheduled flights to vary by flight.

The simulation model generated a pattern of slot values and equilibrium fares for each individual departure slot at a fixed level of total daily demand and with respect to each of the three aircraft types considered.

Those slot values generated by the model for larger aircraft types were higher than those generated on the assumption of a lower aircraft size. This is because total daily passenger demand was concentrated between fewer flights, and because of less competition between flights, equilibrium fares tended to be higher.

Slot values generated by the simulation model had a similar shape to the distribution of ideal departure times, which confirms the relationship between passenger departure time preferences and the value of a departure slot. However, changes occur with respect to the magnitude of the scale parameter and the relative difference between the schedule delay early coefficient and the schedule delay late coefficient. The magnitude of the scale parameter influenced the degree of dispersion in choice probabilities. The lower the value, in relation to the difference in generalised costs, the greater the dispersion. If the scale parameter increases in magnitude relative to the difference in generalised cost, then choices became more deterministic and passengers, are more concentrated in their choice of flight. This influences the bias towards earlier departure times.

The combined effect of both factors, is to generate higher slot values during off-peak periods, specifically during "shoulder" periods i.e at those departure slots positioned just before, peak times. As far as equilibrium fare is concerned, the model generated a variation in fares across departure times according to the value placed on departing at different slots. However, as in the case of the slot values, equilibrium fares at each departure slot was also influenced by the magnitude of the passenger choice model parameter estimates. As far as the profit generated at different times is concerned, this is influenced by higher passenger departures and higher fares.

Three sensitivity tests were carried out in order to measure the performance and evaluate the output of the simulation model based on variation in the model input assumptions. The first test involved doubling the magnitude of both the schedule delay early coefficient and the scale parameter. The effect of these changes, generated, as expected, a closer relationship between the distribution of passenger ideal departure times and slot values. This is because, the effect of increasing the scale parameter is to make choices more deterministic, hence less dispersion in probabilities and to reduce bias towards earlier departure times, through increasing the magnitude of β^{se}. The second test involved assuming a uniform distribution of ideal departure time preferences, without changing any of the parameter values. As expected the model does not generate any significant variation in both slot values and equilibrium fares between departure slots. The third and final test involved evaluating slot values and equilibrium fares by the model on a higher level of demand, on a different route, and assuming that flights are scheduled using a larger aircraft type with associated costs and seating capacity. Results showed that the model is transferable to alternative operating assumptions and indeed, confirmed that slot values are higher the larger the aircraft size and on routes with a higher level of passenger demand.

8.3 Contribution to knowledge

Few attempts have been made in the past to firstly, undertake an empirically based analysis of passenger departure time choice decision-making within an air transport context, and secondly, to establish a method whereby the monetary value of a slot can be derived.

Past research in passenger choice behaviour in air transportation often neglected the importance of schedule delay time in measuring the convenience of an airline's schedule. The concept of measuring schedule delay time has been mainly confined to research undertaken in the field of urban transportation. Studies by Small (1992) and Mannering and Hammed (1990), for example, examine schedule delay time within the context of commuter departure time choice behaviour using examples from the United States. Previous studies on identifying those factors which influence passengers choice of airlines, use total service frequency as a measure of schedule convenience. Whilst there is no dispute with the general conclusions of these studies, they have tended, in the main, to neglect to consider the importance of schedule delay time. Douglas and Miller (1974), in evaluating modal choice behaviour within inter-city markets in United States, do incorporate schedule delay time in their analysis. Alamdari (1989), in an analysis of airline strategic behaviour in Europe, similarly incorporates schedule delay time when developing a passenger choice model. However, both authors assume that there is a uniform distribution of passenger departure time preferences and that there is no difference in generalised cost terms between those flights scheduled later and earlier than a passenger's ideal preference. However, Alamdari (1989) recognises this point when discussing shortcomings in her passenger choice model.

A more refined analysis of schedule delay time was undertaken by this thesis. Using stated preference analysis, it was possible to generate an estimate of how highly passengers value those flights scheduled later than their ideal departure time and those flights scheduled earlier than their ideal departure time. The results obtained, correctly conform with *a priori* expectations regarding the relative magnitude of schedule delay early and schedule delay late time, making a contribution to understanding how passengers value travelling at different times of the day. One of the problems involved in validating these results was that they could not be compared with comparable values of time derived from past research, since the author could not identify previous studies that had undertaken an examination of schedule delay time to such a refined extent. Indeed, the extent to which, stated preference analysis has been applied to air transportation problems has been limited to analysis by Yoo (1995) on

evaluating Korean passengers choice of carrier, a paper by Whelan (1995) on evaluating passengers choice of mode between air and rail in UK inter-regional markets and a paper by Hencher and Louviere (1983) on examining passengers choice of air fare. Stated preference analysis has been more widely applied to research problems in urban transportation such as for example, estimating commuter values of in-vehicle time and examining passengers choice of surface transport mode. Recognising that there are deficiencies associated with using stated preference analysis (see chapter 3), it has nevertheless proved to be a useful technique in evaluating how passengers perceive hypothetical service levels, and therefore has contributed in some measure to the growing library of research in this field.

Two particularly valuable contributions has been the analysis of error and the issue of lexicographic responses. Because of the hypothetical nature of these experiments, the scale or error is significant, especially compared to revealed preference methods. This is a property that is inherent in stated preference techniques. Experimental conditions at the time of interview, failure on the part of the respondent to understand or appreciate the experiment will affect the magnitude of error in respondent choices. The scale of error, identified through a simulation process, was incorporated into the passenger departure time model. Lexicographic analysis, otherwise known as data cleaning, involves removing those responses that are regarded as inconsistent or irrational and those respondents who consistently select one preference when evaluating each choice set. By removing these responses from the sample, the statistical significance of the coefficients improved. The use of lexicographic techniques has, however, been neglected in some applications of stated preference analysis. The issue was covered in some detail, in chapter five and raised some important questions regarding the decision of whether to include or exclude irrational and non-trading responses. Consideration of this issue has made some contribution to stated preference literature, and may prompt a more refined and in-depth analysis of stated preference results in future studies.

Airport slot allocation is one of the most topical issues in aviation. In light of the airport capacity crisis facing the industry, policy-makers have considered and indeed implemented various methods designed to alleviate the problem. The issue of slot

pricing has also been widely considered within the context of this debate. This thesis has made an important contribution to research in the economics of slot allocation, more specifically in developing a method where the value of slots can be estimated. Literature on this subject, has tended to focus on establishing qualitative judgements on the likely impact of such a policy on the air transport industry. Whilst there is no fault in their conclusions, any quantitative or empirical analysis has been neglected. Contributions by Zacca (1990), Blore (1992) and Hulet (1991) have focused on empirically deriving estimates of the value of slots. Whilst there can be little criticism of their analytical approach or the results generated, they have neglected to consider or incorporate schedule delay time and variability in the distribution of passenger's ideal departure times in the models applied. The author does, however, recognise that in two of the above mentioned studies, the time constraints involved limited the scope of their research to making restrictive assumptions regarding passenger ideal departure time preferences.

The method developed in this thesis involved combining decision-rules which define passenger's choice of departure time and secondly, the scheduling of flights at departure slots, to determine the maximum profits generated at each departure slot, used as a proxy for the money value of slots. The author could not identify other studies which sought to establish a method of deriving the value of slots. Some previous studies have sought to simulate a slot auction. But elements of realism have been removed, since no consideration was given to how passengers value travelling at different times of the day.

8.4 Weaknesses and deficiencies

The author acknowledges that there are shortcomings in the methodologies applied and uncertainty over the validity of some of the results.

As far as the use of stated preference analysis is concerned, there are two issues that need to be considered. First, the validity of the statistical estimation technique which was applied to generate the model parameters, and second, choice set design-related deficiencies.

In chapter five, linear regression on an ordered dependent variable (choice preference) was selected to estimate the model parameters. Whilst there is no debate regarding the efficiency and statistical validity of using this method on continuous dependent variables, the application of this method on an ordered or restricted dependent variable can raise some important questions regarding the statistical validity of the estimated parameters. The issue of concern focuses on the assumption of equally spaced intervals between the dependent variables i.e whether the difference between the differently prefer current flight and probably prefer current flight is the same as difference between probably prefer current flight and cannot decide. If these intervals are equally spaced, some argue such as Long (1997), that the application of the linear regression method can be justified. On the other hand, there is less justification for applying this method to ordered dependent variables that are not equally spaced, in that it can generate some misleading results. Under these circumstances, it is perhaps more appropriate to apply models and estimation methods that are specifically designed for ordered dependent variable parameter estimation, such as ordered logit and ordered probit, both based on maximum likelihood methods. The problem focuses on the different distributional assumptions of the errors between linear regression and methods based on maximum likelihood techniques. Use of the linear regression method assumes that the errors are homoscedastic, in other words, the error terms are identically distributed for each observation and that that these distributions have the same variance. On the other hand, the errors can be considered heteroskedastic, where the error term variances are not equal between sample observations. i.e. if error term variance increased or decreased as the level of an independent variable changes.

Although results produced by both methods, as revealed in chapter five are broadly consistent, with lower standard errors generated by the linear regression method for three our of the four coefficient estimates, the author recognises that there are deficiencies associated with using linear regression, in particular the standard errors may be incorrect, and advises that when estimating parameters using data with ordered dependent variables, other methods such as logit and probit should also be considered. There is a wide spectrum of diverse opinions on the suitability of using

linear regression on ordered dependent variables, between those who consider it acceptable to use and those that consider it inappropriate. In seeking to apply the most suitable method, these diverse opinions should be considered and any results generated should be carefully interpreted.

The results showed that there was variation in levels of statistical significance between coefficient estimates, especially between the schedule delay early and schedule delay late parameters. The former with associated with a low *t*-ratio.

The reduced level of statistical significance was due to stated preference design-related deficiencies. The questionnaire, associated with earlier departure time choice set options (see Appendix F), did not capture or identify respondent trade-off behaviour. As such, the levels of the independent variables were such that many respondents could not trade between both flights, and as such, accurate values of time could not be obtained.

In developing the simulation model in chapter six, several assumptions were established with regard to decision-rules which govern passenger choice of flight and the scheduling of profitable services. As with all simulation models, deficiencies regarding the extent to which it mirrors actual "real-life" behaviour was noted and acknowledged.

Deficiencies with regard to assumptions made regarding passenger choices are: firstly, the model considers only departures, but does not incorporate the issue of when passengers return. Secondly, within each flight all passengers are assumed to pay the same fare. Given substantial product differentiation, airlines usually set different fares with varying terms and conditions according to different segments of the passenger market. The model assumes that the market is not segmented but homogenous.

As far as flight scheduling decision-rules are concerned, one weakness in the assumptions applied is the absence of supply inelasticities. Choice of slots and the ability to schedule profitable services are, in reality, constrained by operational limits in the extent to which aircraft can be readily available, such as the need to satisfy network-wide scheduling requirements. The model, on the other hand, assumes that there is perfect elasticity in the supply of departures in that there are no restrictions in

the availability of both arrival slots and aircraft. In this regard, an element of realism is removed. There is also the assumption of free entry and exit, which is rather difficult to justify especially given the fact that in entering new markets, airlines are often required to bear significant sunk costs such as marketing, promotion and the purchase of ground resources. Although elements of these indirect costs were incorporated, but they probably underestimated the scale of these expenditures.

As far as the general performance of the model is concerned, two weaknesses should be noted: Firstly, the model assumes that total daily one-way passenger demand is fixed. Therefore, as the demand for different flights varies by departure slot, total demand is not linked to overall fare levels and is therefore held constant. In this sense, the market is captive, and perhaps the weakness is that the effect of competing transportation modes on total demand and fares is not incorporated in the model.

The second point regarding the general performance of the model is the issue of stability. Equilibrium solutions for the three aircraft types were achieved under different values of ∂f. However beyond a certain value of ∂f, the model losses its stability and equilibrium was very difficult to achieve. This was due to the inherent instability associated with significant increases and decreases in fare as flights are scheduled and departure slots evaluated. This led to constant changes in passenger choices and the withdrawal and re-scheduling of flights. Although equilibrium solutions generated seem realistic and plausible, it should be noted that under certain assumptions, the model loses its stability making it difficult to achieve equilibrium.

The robustness of the simulation model was also affected by the magnitudes of the choice model parameter estimates, as revealed in the second sensitivity test. The high value of the scale parameter and the low value of the schedule delay time coefficient compared to the schedule delay time late coefficient appears to have reduced the stability of the simulation model at high intervals of ∂f. When these values were changed for the sensitivity test and the model was calibrated on new values of these parameters, firstly equilibrium was achieved more readily and secondly, slot values and equilibrium fares corresponded more closely to the pattern of ideal departure time preferences

8.5 Suggestions for further research

Given the main findings of the thesis, and associated strengths and weaknesses outlined in the previous sections, there are significant opportunities for further research in the following directions.

As far as literature on stated preference is concerned, there is scope for additional applications of this technique to other policy issues in air transportation. For example, evaluating the viability of new regional airports or using stated preference analysis to evaluate consumer spending behaviour in airports and to assess the potential impact of the loss of duty and tax-free revenues, perhaps qualified by a parallel revealed preference study.

As far as assessing the validity of stated preference analysis is concerned, additional work can be undertaken, on a more refined evaluation and interpretation of error in respondent choices, through perhaps a more refined examination of lexicographic techniques. This would substantially enrich existing literature on stated preference analysis.

As far as the field of research on slot allocation is concerned, future work on slot pricing can focus on incorporating the network-wide scheduling considerations and supply inelasticities as mentioned in section 8.4. Future research can perhaps take this thesis one step further to estimating how much an airline would pay in slot prices. This could take the form of an auction where other airlines are also bidding for the same slots.

REFERENCES

ABC (1994a)

ABC World Airways guide, November ed (blue book), Reed Travel Group, Dunstable, UK.

ABC (1994b)

ABC World Airways guide, November ed (red book), Reed Travel Group, Dunstable, UK.

Alamdari, F (1989)

Airline deregulation: an analysis under different regulatory and operating environments , PhD Thesis, Cranfield University, UK.

Anderson , H and Kraus, (1980)

"Quality of service and the demand for air travel", *Review of Economics and Statistics,* Vol 1, pp 533-39.

Anderson , P. B, Moeller, J and Sheldon, R.J (1986)

"Marketing DSB rail services using a stated preference approach", *PTRC Summer Annual Meeting*. Brighton.

Ashford, N and Benchemam, M, (1987)

"Passengers" choice of airport: an application of the multinomial logit model", *Transportation Research Record, 1147*, pp 1-5.

Barrett, S.D. (1992)

"Barriers to contestability in the deregulated European aviation market, *Transportation Research*, Vol 26A No 2, pp 159-165

Bates, J (1984)

"*Vales of time from stated preference data*" Paper H12 PTRC Annual Summer Meeting, Brighton

Bates, J and Roberts, M (1983)

"Recent experience with models fitted to stated preference data", *1983 PTRC Annual Summer Meeting*. Brighton

Ben-Akiva, M and Lerman, S. (1985)

Discrete choice analysis: theory and application to travel demand. MIT press, Massachusetts.

Berkson , J (1953)

"a statistically precise and relatively simple method of estimating the bioassay with quantal response based logistic function" *Journal of the American Statistical Association*, Vol 48, pp 565-599.

Black, I and Towriss, J. (1993)

Demand effects of travel time variability. Department of Transport, HMSO, London.

Blore, D. (1992)

An evaluation of the effects of Slot Pricing on Airline Route Structure, MSc Thesis, Cranfield University, UK.

Borenstein, S. (1988)

"The efficiency of competitive markets for operating licenses". *Quarterly Journal of Economics*, Vol 16, No 4, pp 357-385.

Bradley, M. (1988)

"Realism and adaptation in designing stated preference hypothetical travel concepts". *Journal of Transport Economics and Policy*, Vol 22, No 1, pp 121-137

Brander, J.R.G, Cook, B.A and Rowcroft, J.E. (1989)

"Congestion concentration and contestability: the case of the airline industry". *Transportation Research Record*, Vol 1214, pp 37-42.

Brooke, A.S, Caves, R.E and Pitfield, D.E (1994)

"Methodology for predicting European short-haul air transport demand from regional airports: an application to East Midlands International Airport". *Journal of Air Transport Management*, Vol 1 , No 1, pp 37-46

CAA (1985)

Air traffic distribution in the London area - a consultation document, CAP 510, Civil Aviation Authority, London.

CAA (1989)

Traffic distribution policy for airports serving the London area CAP 559, Civil Aviation Authority, London.

CAA (1993a)

Access to congested airports for regional services, CAP 615, Civil Aviation Authority, London.

CAA (1993b)

Passengers at Central England Airports, CAP 618, Civil Aviation Authority, London.

CAA (1994)

Slot Allocation: a proposal for Europe's airports, CAP 644, Civil Aviation Authority, London.

Cattin, P and Wittink D, R (1976)

"A Monte-Carlo study of metric and non-metric estimation methods for multi-attribute models". Research paper No 34, Stanford University Graduate School of Business, Stanford University

Caves, R (1992)

"Modelling UK regional Airport Traffic: the relevance of the Civil Aviation Authority's traffic distribution model to UK regional airports forecasting". *Transportation Planning and Technology,* Vol 16, pp 283-289.

CEC (1991)

Proposal for a Council regulation on common rules for the allocation of slots at Community airports, COM 90, 576 Final, Commission of the European Communities Brussels.

CEC (1993)

Council regulation (EEC) No 95/93 on common rules for the allocation of slots at community airports, Official Journal of the European Communities Commission of the European Communities, Brussels.

Dagazano, C.F (1979)

Multinomial Probit: Theory and Application to Demand forecasting, Academic Press, New York.

Dobson, G and Lederer, P.J. (1993)

"Airline Scheduling and Routing in a Hub and Spoke System". *Transportation Science* , Vol 27, No 3, pp 281-297.

Doganis ,R, Dennis, N and Graham, A (1988)

Interaction of airport congestion and supply and demand, Department of Transport Seminar Paper, pp 193-243

Doganis, R. (1992)

The Airport Business, George Allen and Unwin, London.

Donne, M (1991)

"IATA focuses on need to tackle airport congestion. *Financial Times Business Air Travel Survey, 08/91*, pp 9-10.

Douglas, and Miller, (1974)

The Economic Regulation of Air Transport; Theory and Practice, Brookings Institution, Washington.

Fawcett, S A. and Fawcett, S E. (1988)

"Congestion at Capacity Constrained Airports: A Question of Economics and Realism". *Transportation Journal*, Summer, pp 42-54

Fowkes, H and Wardman, M (1988)

"The design of stated preference travel choice experiments with special reference to interpersonal taste variations", *Journal of Transport Economics and Policy*, Vol 22, No 1, pp 27-44.

Fowkes, H (1991)

"Recent developments in stated preference techniques in transport research", *1991 PTRC Annual Summer Meeting Brighton*

Furuichi, M and Koppelman, F.S. (1994)

"An analysis of air travellers departure airport and destination choice behaviour", *Transportation Research*, Vol 28 No 3, pp 187-195.

Gagnon, G (1967)

"A model for flowing passengers over airline networks", *Transportation Science*, Vol 1, No 3, pp 232-248

Green, P.E and Srinivasan, V (1978)

"Conjoint analysis in consumer research: issues and outlook", *Journal of Consumer Research*, Vol 5, pp 232-248

Ghobrial, A (1993)

"An Aggregate Demand Model for Domestic Airlines", *Journal of Advanced Transportation*, Vol 126, No 2, pp 105-119

Gordon, H and De Neufville, R. (1973)

"Design of Air Transportation Networks". *Transportation Research*, Vol 7, pp 202-207.

Grethner, D, Isaac, R M, and Plott, C R. (1989)

The Allocation of Scarce Resources: *Experimental Economics and the Problem of Allocating Airport Slots*, Boulder, Colorado.

Grethner, D.M, Isaac, R M, and Plott, C R. (1981)

"The Allocation of Landing Rights by Unanimity Among Competitors", *American Economic Review,* Vol 71, pp

Gunn, H.F, Bradley, M.A, and Hencher, D.A (1992)

"High-speed rail market projections: survey design and analysis *Transportation,* Vol 19, pp 117-139

Hamzawi, S.G (1992)

"Lack of Airport Capacity: an explanation of alternative solutions". *Transportation Research, 08/91*, Vol 24B No 1, pp 47-58

Hansen, M and Kanafani, M (1988)

"International airline hubbing in a competitive environment". *Transportation Planning and Technology*, Vol 13, pp 3-18.

Hansen, M. (1990)

"Airline competition in a hub dominated environment". *Transportation Research*, Vol 24B, No 1, pp 27-43.

Harvey, G (1987)

"Airport choice in a multi-airport region". *Transportation Research*, Vol 21A, pp 439-449.

Hencher, D.A., Barnard, P.O. and Truong T.P. (1988)

"The role of stated preference methods in studies of travel choice", *Journal of Transport Economics and Policy*, Vol 22, No 1, pp 45-58.

Hencher, D.A. and Louviere, J.J (1983)

"Identifying Individual Preferences for International Air Fares: an application of functional measurement theory", *Journal of Transport Economics and Policy*, Vol 17 , No2 , pp 225-245.

Hendrickson, C and Plank, E (1984)

"The flexibility of departure times for work trips". *Transportation Research*, Vol 18A, pp 25-36.

Holden, D. (1991)

Efficiency measures for stated preference experiments, UTSG working paper, Newcastle University.

Horowitz, J (1983)

"Statistical comparison of non-tested probablistic choice models". *Transportation Science*, Vol 17, pp 319-350

Hulet, J. (1991)

Study on Airport Slot Allocation, Department of Transport, London.

IATA (1991)

Scheduling Procedures Guide (9th ed.),International Air Transport Association ,Geneva.

Jessiman et al (1970)

Inter-city transportation effectiveness model, Peat, Marwick and Mitchell, Boston.

Jones, I, Viehoff, I and Marks, P. (1994)

"The Economics of Airport Slots, *Fiscal Studies,* Vol 14, No 4, pp 37-57.

Kanafani, A. (1983)

Transportation Demand Analysis, McGraw and Hill, Mass.

Kanafani, M and Ghobrial A. (1985)

"Airline hubbing: Some Implications for Airport Economics". *Transportation Research*, Vol 19A No 1, pp 15-27.

Kroes, H and Sheldon H, (1988)

"Stated preference methods: an introduction", *Journal of Transport Economics and Policy*, Vol 22 No 1, pp 11-25.

Labovitz, S (1967)

"Some observations on measurement and statistics", *Social Forces*, Vol 46, pp 151-160.

Labovitz, S (1970)

"The assignment of numbers to rank order categories", *American Sociological Review*, Vol 35, pp 515-524.

Levine, M.E. (1969)

"Landing fees and the airport congestion problem", *Journal of Law and Economics*, Vol 12, pp 79-108.

Lin, L.Y, Pioche, A and Stander, P (1986)

"Estimating sales volume potential for Innovative products with case histories". *Proceedings of 1986 ESOMAR Congress*, Monte Carlo.

Lisco, T (1967)

The Value of Commuters Travel Time: a study in Urban Transportation. PhD Thesis. Department of Economics, University of Chicago, Chicago ILL.

Long, J.S (1997)

Regression Models for Categorical and Limited Dependent Variables, SAGE, London.

Louviere, J.J (1988)

"Conjoint analysis modelling stated preferences: a review of theory, methods, recent developments and external validity", *Journal of Transport Economics and Policy*, Vol 22, No 1, pp 93-119.

Luce, R (1959)

Individual Choice Behaviour, Wiley, New York.

Manchester Airport (1994)

Proof of evidence to the Manchester Airport proposed second runway inquiry: submission by Britannia Airways Ltd, Manchester Airport.

Mannering, F and Hamed, M. (1990)

"Occurrence, frequency and duration of commuters work to home departure delay". *Transportation Research*, Vol 24B, pp 99-109.

Milan, J (1993)

"A model of competition between high speed rail and air transport". *Transportation Planning and Technology,* Vol 17, pp 1-23.

Miller, J. (1972)

"A time of day model for aircraft scheduling", *Transportation Science* ,Vol 6, No 3, pp 221-246.

Morrison, H and Winston, C (1985)

"An econometric analysis of the demand for inter-city passenger transportation", *Research in Transportation Economics* Vol 2, pp 213-237

O"Brien, R, M (1979)

"The use of Pearson's R with ordinal data", *American Sociological Review*, Vol 44, pp 851-857.

Ortuzar, J.D. and Garrido, R (1991)

"Rank, rate or choice : an evaluation of Stated preference methods in Santiago *1991 PTRC Annual Summer Meeting*. Brighton.

Ortuzar, J.D. and Willumsen, L.G. (1994)

Modelling Transport, 2nd ed. Wiley, London.

Rassenti, S J, Smith , V L and Buffin, R L. (1988)

" A Combinatorial Auction Mechanism for Airport Time Slot Allocation", *Bell Journal of Economics*, Vol 13, No 2, pp 402-417.

Sheldon, H and Steer (1982)

"The use of Conjoint Analysis in Transport Research". *PTRC Annual Summer Meeting*, pp 145-158.

Small, K. (1992)

Urban Transportation Economics, Irvine, University of California.

Starkie, D. (1991)

Slot Trading at United States Airport: a Report to the Director-General for Transport of the Commission of the European Communities, Pitnam Hayes and Bartlett, Washington D C.

Starkie, D. (1994)

The US Market in Airport Slots. *Journal of Transport Economics and Policy*, September, pp 325-329.

Swanson, H, Pearmain, D., and Loughead, K. (1993)

"New approaches to the design of stated preference experiments". *PTRC Annual Summer Meeting*, pp 99-108

Teodorovic, D. (1988)

Airline Operations Research, Gordon Breach, New York.

Teodorovic, D and Krcmar-Nozic, E. (1989)

"A multicriteria model to determine flight frequencies on an airline network under competitive Conditions", *Transportation Science,* Vol 23, No , pp 14 - 25.

Theil, H (1969)

"A multinomial extension of the logit Model". *international Economic Review"* Vol 10, pp 251-259.

Thompson, H and Caves, (1992)

"The projected market share for a new small airport in the North of England, *Regional Studies,* Vol 22, No 2, pp 137-147.

Wardman, M (1988)

"A comparison of revealed preference and stated preference models of travel behaviour", *Journal of Transport Economics and Policy,* Vol 22, No 1, pp 71-91.

Winship, C. and Mare, R.D (1984)

"Regression models with ordinal variables", *American Sociological Review,* Vol 49, pp 512-525

Whelan, G.A (1995)

"Air v. Rail in the UK Business Market: a disaggregate model choice model of stated preferences", *UTSG Annual Conference* Vol 2, Cranfield University.

Yance, J.V (1969)

"Movement time as a cost in airport operations", *Journal of Transport Economics and Policy,* Vol 3, No 1, pp 28-35.

Yoo, K.E. (1995)

A study of Korean air passengers" choice behaviour, PhD Thesis, Loughborough University, UK.

Zacca, G. (1991)

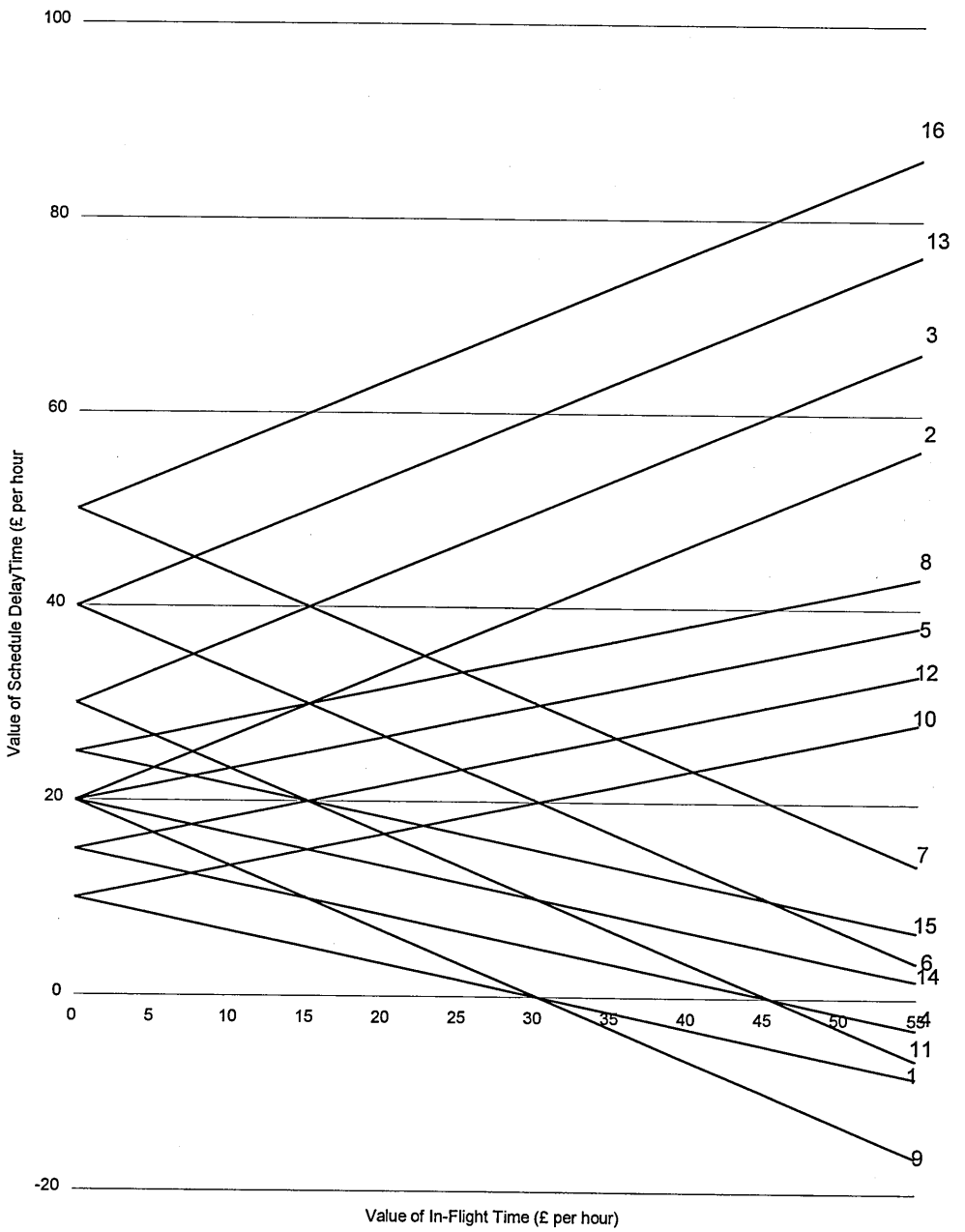
An evaluation of the effects of runway slot pricing on the air transport industry, MSc Thesis, Cranfield University, UK.

Appendices

Appendix A : Full Factoral Design

	Current Flight			Alternative Flight		
	fare (£)	schedule delay time (hours)	in-flight time (hours)	fare (£)	schedule delay time (hours)	in-flight time (hours)
choice 1	100	0	1	90	1	1.33
choice 2	100	0	1	90	0.5	0.67
choice 3	100	0	1	85	0.5	0.67
choice 4	100	0	1	85	1	1.33
choice 5	100	0	1	80	1	0.67
choice 6	100	0	1	80	0.5	1.33
choice 7	100	0	1	75	0.5	1.33
choice 8	100	0	1	75	1	0.67
choice 9	100	0	1	90	0.5	1.33
choice 10	100	0	1	90	1	0.67
choice 11	100	0	1	85	0.5	1.33
choice 12	100	0	1	85	1	0.67
choice 13	100	0	1	80	0.5	0.67
choice 14	100	0	1	80	1	1.33
choice 15	100	0	1	75	1	1.33
choice 16	100	0	1	75	0.5	0.67

Appendix B : Full Factorial Design Boundary Values



Appendix C : Orthogonal and Non-Orthogonal Designs

ORTHOGONAL DESIGN

	Current Flight			Alternative Flight		
	fare (£)	schedule delay time (hours)	in-flight time (hours)	fare (£)	schedule delay time (hours)	in-flight time (hours)
choice 1	100	0	1	90	1	1.33
choice 2	100	0	1	90	0.5	0.67
choice 3	100	0	1	85	0.5	0.67
choice 4	100	0	1	85	1	1.33
choice 5	100	0	1	80	1	0.67
choice 6	100	0	1	80	0.5	1.33
choice 7	100	0	1	75	0.5	1.33
choice 8	100	0	1	75	1	0.67

NON-ORTHOGONAL DESIGN

	Current Flight			Alternative Flight		
	fare (£)	schedule delay time (hours)	in-flight time (hours)	fare (£)	schedule delay time (hours)	in-flight time (hours)
choice 6	100	0	1	80	0.5	1.33
choice 7	100	0	1	75	0.5	1.33
choice 8	100	0	1	75	1	0.67
choice 9	100	0	1	90	0.5	1.33
choice 10	100	0	1	90	1	0.67
choice 11	100	0	1	85	0.5	1.33
choice 12	100	0	1	85	1	0.67
choice 13	100	0	1	80	0.5	0.67

Appendix D : Stated Preference Design Simulation Results

Chart 1 Combination 1: α^{sd} = £15 per hour α^{t} = £10 per hour

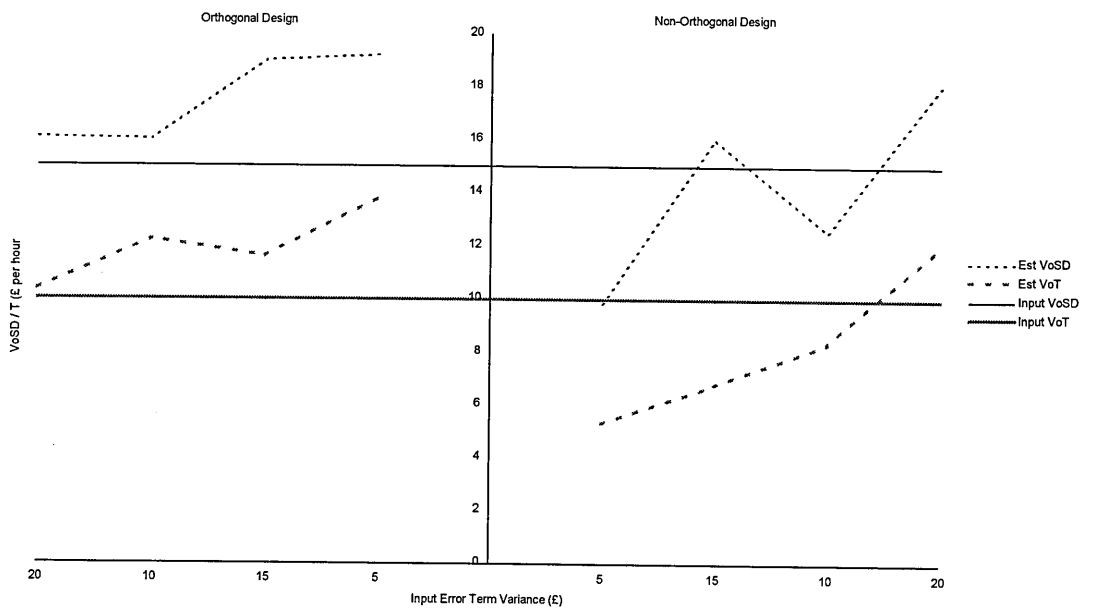


Chart 2 Combination 2: α^{sd} = £35 per hour α^{t} = £15 per hour

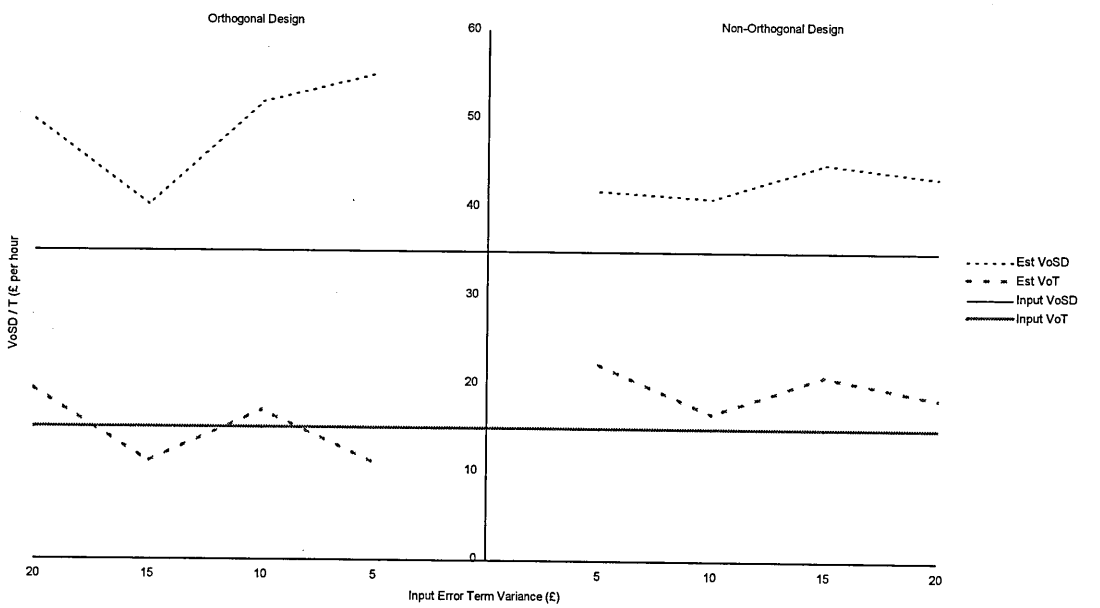


Chart 3 Combination 3: α^{sd} = £20 per hour α^{t} = £20 per hour

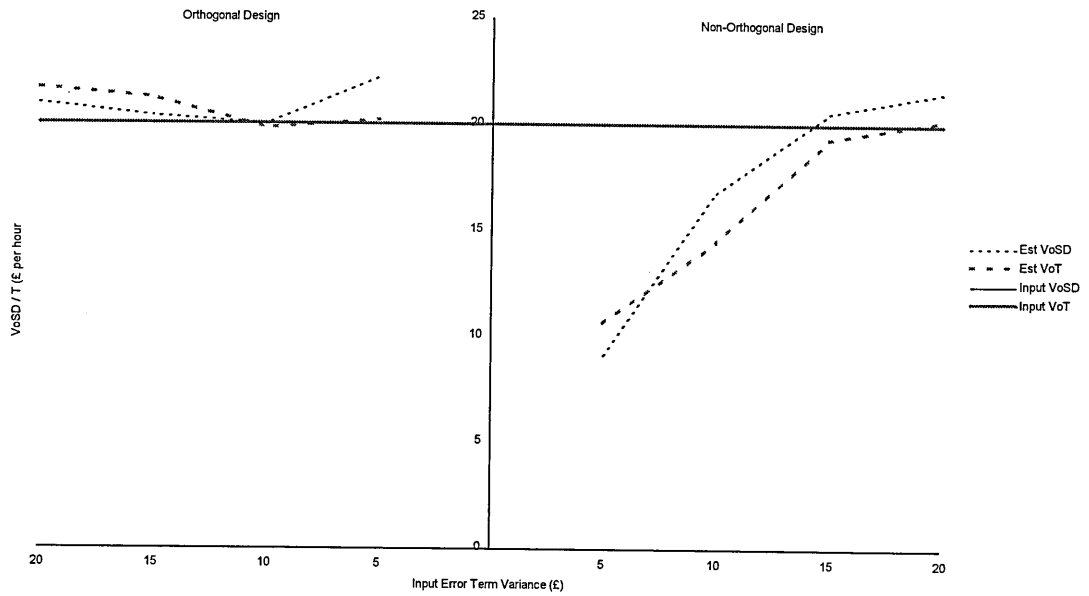


Chart 4 Combination 4: α^{sd} = £25 per hour α^{t} = £10 per hour

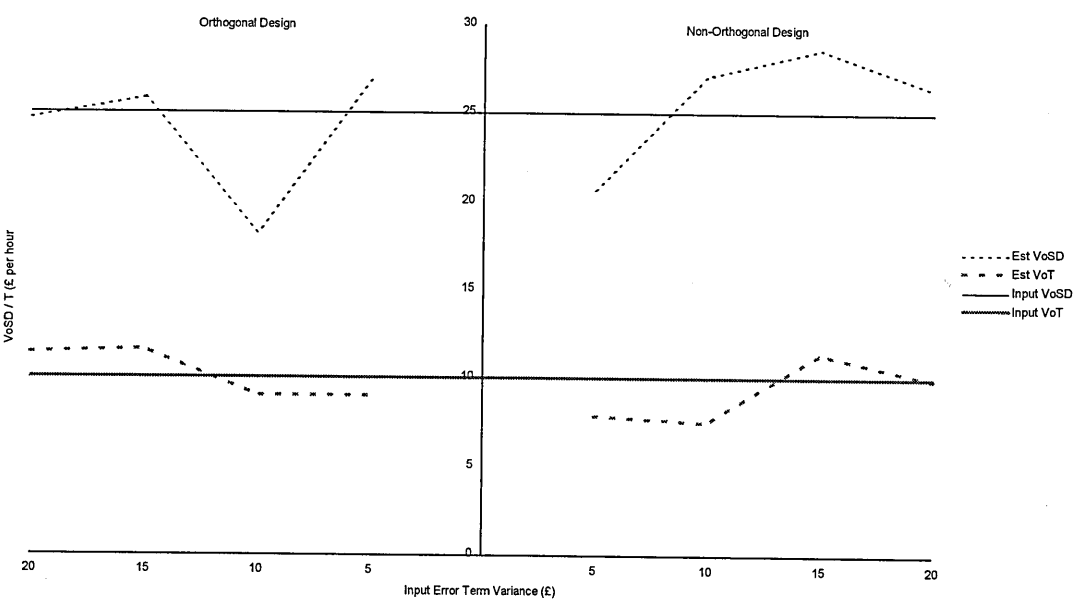


Chart 5 Combination 5: α^{sd} = £30 per hour α^{t} = £40 per hour

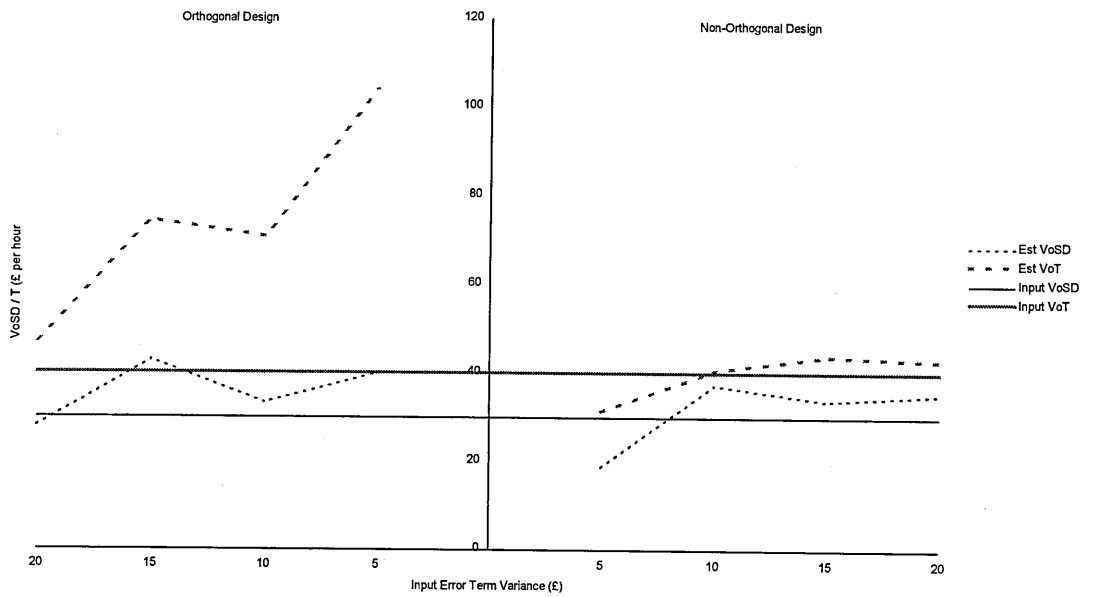
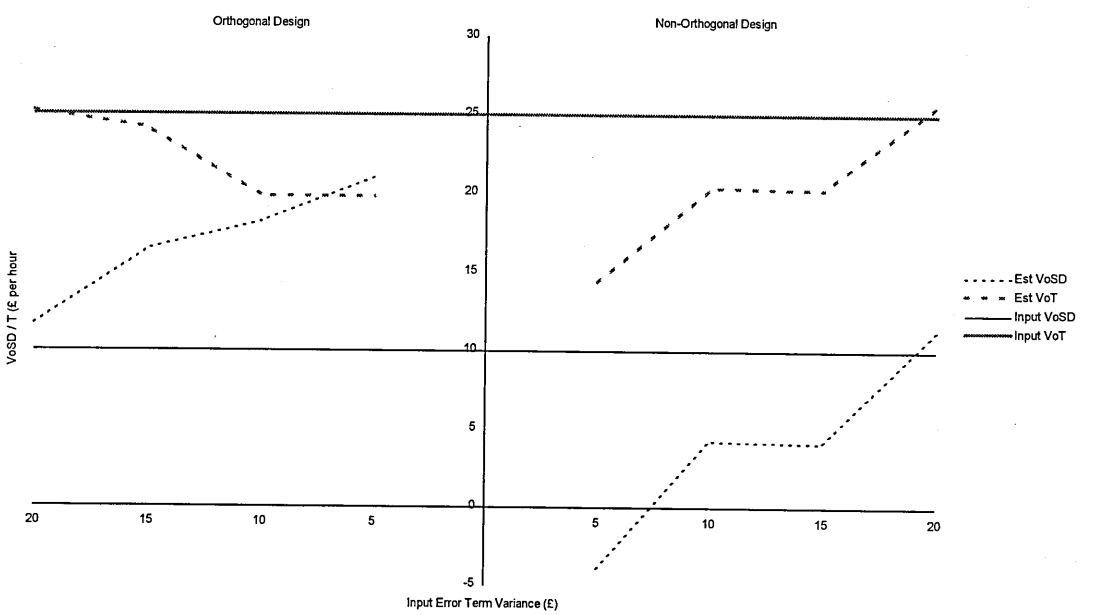


Chart 6 Combination 6: α^{sd} = £10 per hour α^{t} = £25 per hour



Appendix E :Late Departure Time Questionnaire

Interviewer . Subject Number ☐☐☐

Departure Time Airline

Q1 Where did you travel from to get to Manchester Airport for this flight

.....

Q2 What mode of transport did you use

Hire car	☐	private car as dri'r	☐	Taxi	☐
Bus	☐	private car as pax	☐	Rail	☐

Q3 Is this a return or outbound journey

Outbound	☐	*Go to Q3a*
Return	☐	*Go to Q3b*

Q3a When is your return journey

Today	☐	At what time does your return flight depart .....
Other day	☐	Date .....

Go to Q4b

Q3b When was as your outbound journey

Today	☐	At what time did your inbound flight arrive .....
Other day	☐	Date .....

Go to Q4b

Q4a What is the main purpose of your outbound trip

Business	☐	VFR	☐	Holiday	☐
Other	☐				

Go to Q5

Q4b What was the main purpose of your trip to Manchester

Business	☐	VFR	☐	Holiday	☐
Other	☐				

Q5 Where is your final destination today

.....

Q6 Following on form this flight which mode of transport will you use to reach your final destination

Hire car	☐	private car as dri'r	☐	Taxi	☐
Bus	☐	private car as pax	☐	Rail	☐

Q7 Who booked your flight

Yourself ☐

Someone else ☐

Q8 Who paid your fare

Yourself ☐

Someone else ☐

Q9 Was the cost of your fare higher or lower than £100

higher ☐

lower ☐

PART 2

Q10 how convenient would it be if your flight departed at the following times

	Less convenient	Indifferent	More Convenient
30 minutes later	☐	☐	☐
1 hour later	☐	☐	☐
1 hour 30 min later	☐	☐	☐
2 hours later	☐	☐	☐

Q11 If you could change the time of your destination activity, which of the following departure times would be most convenient for this journey.

0700	☐	1200	☐	1700	☐
0800	☐	1300	☐	1800	☐
0900	☐	1400	☐	1900	☐
1000	☐	1500	☐	2000	☐
1100	☐	1600	☐	2100	☐

I would like you to imagine that hen this flight was booked, you had a choice of alternative flights to this destination for this particular day

Each of these flights have a different departure time, flying time and air fare.

Assume you are BOOKING THE FLIGHT and take in to account TIME CONSTRAINTS associated with your current journey.

FOR EXAMPLE

SAMPLE CHOICE SET

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £10
Current departure time	Departure time 1 HOUR LATER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 40 MINUTES LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 1

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £25
Current departure time	Departure time 1 HOUR LATER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 40 MINUTES LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 2

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £10
Current departure time	Departure time 1 HOUR LATER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 1 HOUR 20 MINS LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 3

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £25
Current departure time	Departure time ½HOUR LATER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 50 MINUTES LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 4

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £10
Current departure time	Departure time ½ HOUR LATER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 10 MINUTES LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 5

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £15
Current departure time	Departure time 1 HOUR LATER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 1 HOUR 20 MINS LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 6

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £20
Current departure time	Departure time 1 HOUR LATER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 40 MINUTES LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 7

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £15
Current departure time	Departure time ½ HOUR LATER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 10 MINUTES LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 8

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current fare	Current fare MINUS £20
Current departure time	Departure time ½ HOUR LATER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 50 MINUTES LATER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

Appendix F : Early Departure Time Questionnaire

Interviewer . Subject Number ☐☐☐

Departure Time Airline

Q1 Where did you travel from to get to Manchester Airport for this flight

.....

Q2 What mode of transport did you use

Hire car	☐	private car as dri'r	☐	Taxi	☐
Bus	☐	private car as pax	☐	Rail	☐

Q3 Is this a return or outbound journey

Outbound	☐	*Go to Q3a*
Return	☐	*Go to Q3b*

Q3a When is your return journey

Today	☐	At what time does your return flight depart .....
Other day	☐	Date .....

Go to Q4b

Q3b When was as your outbound journey

Today	☐	At what time did your inbound flight arrive .....
Other day	☐	Date .....

Go to Q4b

Q4a What is the main purpose of your outbound trip

Business	☐	VFR	☐	Holiday	☐
Other	☐				

Go to Q5

Q4b What was the main purpose of your trip to Manchester

Business	☐	VFR	☐	Holiday	☐
Other	☐				

Q5 Where is your final destination today

.....

Q6 Following on form this flight which mode of transport will you use to reach your final destination

Hire car	☐	private car as dri'r	☐	Taxi	☐
Bus	☐	private car as pax	☐	Rail	☐

Q7 Who booked your flight

Yourself ☐

Someone else ☐

Q8 Who paid your fare

Yourself ☐

Someone else ☐

Q9 Was the cost of your fare higher or lower than £100

higher ☐

lower ☐

PART 2

Q10 how convenient would it be if your flight departed at the following times

	Less convenient	Indifferent	More Convenient
30 minutes later	☐	☐	☐
1 hour later	☐	☐	☐
1 hour 30 min later	☐	☐	☐
2 hours later	☐	☐	☐

Q11 If you could change the time of your destination activity, which of the following departure times would be most convenient for this journey.

0700	☐	1200	☐	1700	☐
0800	☐	1300	☐	1800	☐
0900	☐	1400	☐	1900	☐
1000	☐	1500	☐	2000	☐
1100	☐	1600	☐	2100	☐

I would like you to imagine that hen this flight was booked, you had a choice of alternative flights to this destination for this particular day

Each of these flights have a different departure time, flying time and air fare.

Assume you are BOOKING THE FLIGHT and take in to account TIME CONSTRAINTS associated with your current journey.

FOR EXAMPLE

SAMPLE CHOICE SET

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £10
Current departure time	Departure time 1 HOUR EARLIER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 40 MINUTES EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 1

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £25
Current departure time	Departure time 1 HOUR EARLIER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 1 HOUR 20 MINS EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 2

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £10
Current departure time	Departure time ½ HOUR EARLIER
Current flying time	Flying time 20 MINUTES EARLIER
Current arrival time	Arrival time 50 MINUTES EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 3

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £15
Current departure time	Departure time 1 HOUR EARLIER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 40 MINUTES EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 4

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £10
Current departure time	Departure time 1 HOUR EARLIER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 40 MINUTES EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 5

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £20
Current departure time	Departure time ½ HOUR EARLIER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 10 MINUTES EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 6

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £25
Current departure time	Departure time ½ HOUR EARLIER
Current flying time	Flying time 20 MINUTES GREATER
Current arrival time	Arrival time 10 MINUTES EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 7

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £15
Current departure time	Departure time ½ HOUR EARLIER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 50 MINUTES EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

CHOICE SET 8

CURRENT FLIGHT	ALTERNATIVE FLIGHT
Current Fare	Current fare MINUS £20
Current departure time	Departure time 1 HOUR EARLIER
Current flying time	Flying time 20 MINUTES LESS
Current arrival time	Arrival time 1 HOUR 20 MINS EARLIER

Definitely Current	Probably Current	Cannot decide	Probably Alternative	Definitely Alternative

Appendix G : Scale Parameter Derivation Simulation Results

Error term variance = 2.5

Iterations	$\hat{R}^2_{sim}$	$\hat{\beta}^{f}_{sim}$	$\hat{\beta}^{sl}_{sim}$	$\hat{\beta}^{t}_{sim}$	$\hat{\beta}^{se}_{sim}$
1	0.2036	0.0442	1.2117	2.2359	0.1666
2	0.1748	0.0374	1.0493	2.0595	0.0314
3	0.2005	0.0408	1.2250	2.1896	0.1032
4	0.1809	0.0471	1.1593	2.1010	0.2664
5	0.1532	0.0435	1.0642	1.7812	0.0409
6	0.1779	0.0486	1.2539	1.9719	0.2781
7	0.1799	0.0419	0.9823	2.1588	0.1040
8	0.1787	0.0605	1.4335	1.8727	0.5866
9	0.2164	0.0581	1.3142	2.2972	0.5858
10	0.1745	0.0449	1.0948	2.0734	0.2207
11	0.1783	0.0466	1.2341	2.0931	0.3073
12	0.1940	0.0332	1.2171	2.1731	0.1027
13	0.1704	0.0546	1.1934	1.8616	0.3170
14	0.1521	0.0463	1.1587	1.7973	0.2339
15	0.1876	0.0373	1.1042	2.1483	0.0026
MEAN	**0.1815**	**0.0457**	**1.1797**	**2.0543**	**0.2232**

Error term variance = 2.6

Iterations	$\hat{R}^2_{sim}$	$\hat{\beta}^{f}_{sim}$	$\hat{\beta}^{sl}_{sim}$	$\hat{\beta}^{t}_{sim}$	$\hat{\beta}^{se}_{sim}$
1	0.1453	0.03784	1.1629	1.6572	0.0251
2	0.1734	0.04125	1.1759	1.9328	0.0684
3	0.1809	0.04709	1.1593	2.1010	0.2664
4	0.1480	0.03705	1.0337	1.8285	0.0339
5	0.1799	0.04641	0.9800	2.2016	0.3298
6	0.1799	0.04962	1.0886	2.2198	0.4800
7	0.1784	0.05248	1.3102	1.9240	0.3552
8	0.1618	0.03201	0.9688	1.9362	0.0836
9	0.1885	0.05053	1.2433	2.2074	0.4915
10	0.2164	0.05651	1.5023	2.2364	0.5593
11	0.1696	0.04311	1.1260	2.0669	0.2526
12	0.1860	0.05256	1.2308	2.1216	0.4298
13	0.1538	0.03113	0.7298	2.0505	0.5932
14	0.2084	0.05836	1.2525	2.2094	0.4686
15	0.1749	0.04694	1.3069	1.9476	0.3038
Mean	**0.1763**	**0.045526**	**1.1514**	**2.0427**	**0.3161**

Error term variance = 2.7

Iterations	$\hat{R}^2_{sim}$	$\hat{\beta}^f_{sim}$	$\hat{\beta}^{sl}_{sim}$	$\hat{\beta}^t_{sim}$	$\hat{\beta}^{se}_{sim}$
1	0.1651	0.04156	1.1753	1.9150	0.0898
2	0.1706	0.05034	1.1865	2.0890	0.4099
3	0.1939	0.05624	1.2135	2.1430	0.4485
4	0.1680	0.04617	1.2997	1.9010	0.3096
5	0.1624	0.03899	1.1207	1.8860	0.0387
6	0.1501	0.04389	1.1216	1.8680	0.1841
7	0.1499	0.04759	1.2292	1.8120	0.2944
8	0.1488	0.05378	1.2118	1.8090	0.5223
9	0.1405	0.03244	0.8850	1.8630	0.0890
10	0.1867	0.04131	1.1765	2.1370	0.1518
11	0.1788	0.03749	1.0525	2.0870	0.0707
12	0.1420	0.03875	0.9190	1.8870	0.0196
13	0.1792	0.05163	1.0777	2.1950	0.5056
14	0.1415	0.03478	0.9860	1.7890	0.0155
15	0.1764	0.04826	1.1922	2.1470	0.4403
MEAN	**0.1636**	**0.04421**	**1.1231**	**1.9685**	**0.2393**

Error term variance = 2.8

Iterations	R^2_{sim}	β^f_{sim}	β^{sl}_{sim}	β^t_{sim}	β^{se}_{sim}
1	0.1861	0.05242	1.4160	2.0757	0.5260
2	0.1469	0.03932	1.0590	1.9319	0.2195
3	0.1649	0.04935	1.7130	2.0123	0.4044
4	0.1284	0.02687	0.6340	1.9071	0.0927
5	0.1772	0.05253	1.5120	2.0615	0.3915
6	0.1572	0.04395	1.2560	1.8360	0.2773
7	0.1496	0.03542	1.0520	1.8165	0.0342
8	0.1236	0.03393	1.0730	1.5033	0.0352
9	0.1342	0.04064	1.0340	1.7812	0.1327
10	0.1359	0.02947	0.7930	1.9042	0.0097
11	0.1348	0.04451	1.1580	1.7435	0.2677
12	0.1354	0.05087	1.1470	1.7243	0.4745
13	0.1264	0.03023	0.8310	1.7688	0.1031
14	0.1516	0.02784	0.9980	1.8914	0.1466
15	0.1875	0.039798	1.1180	1.9328	0.2013
MEAN	**0.1493**	**0.03981**	**1.1196**	**1.8594**	**0.2211**

Error term variance = 2.9

Iterations	R^2_{sim}	β^f_{sim}	β^{sl}_{sim}	β^t_{sim}	β^{se}_{sim}
1	0.1649	0.0447	1.1404	1.9748	0.2562
2	0.1638	0.0446	1.1335	1.9758	0.2638
3	0.1635	0.0445	1.1645	1.9713	0.2635
4	0.1597	0.0428	1.1304	1.9574	0.2426
5	0.1602	0.0432	1.1429	1.9669	0.2474
6	0.1599	0.0434	1.1509	1.9639	0.2614
7	0.1599	0.0429	1.1468	1.9609	0.2526
8	0.1583	0.0421	1.1376	1.9428	0.2373
9	0.1575	0.0414	1.1271	1.9411	0.2144
10	0.1572	0.0412	1.1217	1.9435	0.2098
11	0.1541	0.0414	1.1206	1.9204	0.2166
12	0.1516	0.0422	1.1262	1.8991	0.2403
13	0.1507	0.0417	1.1210	1.8921	0.2452
14	0.1490	0.0403	1.1163	1.8742	0.2241
15	0.1517	0.0406	1.1241	1.8827	0.2351
MEAN	**0.1575**	**0.0425**	**1.1336**	**1.9378**	**0.2407**

Appendix H : Operating Cost Model

The costs of operating a service consists of two basic elements; direct and indirect operating costs. Direct operating costs relates to those items of expenditure which vary with the operations of a specific aircraft type Indirect operating costs, on the other hand represent those expenses related to airline management such as sales ticketing, advertising, promotion and general administrative costs. Direct operating costs consists of the following elements, crew salaries and expenses, Fuel and oil costs, maintenance costs, insurance, depreciation and those costs associated with use of a particular airport i.e. those fees charged by the airport authority which cover use of the runway, terminal and ATC / navigational aid facilities. The costs will refer to those expenses involved in departing form an airport and those costs associated with operating a flight from the departing airport to the final destination. In order to avoid the distorting influence of the arrival costs at the destination airport, these expenses are excluded from the overall cost estimation.

One item of expenditure that typically represents around 10% of total operating costs is the labour costs per flight which generally covers expenses incurred by the cabin crew. This excludes however, labour costs associated with maintenance and ground handling which are included within the cost elements for maintenance and ground handling respectively. Typically labour cost will depend on varies by aircraft type since different aircraft types are associated with alternative seating configurations and hence varying crewing requirements. The labour cost per flight, associated with aircraft type a therefore, is calculated as follows.

$$L_{aj} = \frac{L_a^{bh}}{v_a} sl_x \qquad \text{(H-1)}$$

Where L_a^{bh} refers to the labour costs per block hour, v_a refers to block to block speed associated with aircraft type a and sl_x represents the sector distance between origin and destination on route x.

Fuel and oil is determined primarily by the sector distance over which an aircraft operates and the type of aircraft. The unit cost is generally determined by the supplier of fuel. The fuel and oil cost per flight F_a at any departure time j is derived as follows

$$F_a = \frac{F_a^{bh}}{v_a} sl_x \qquad \text{(H-2)}$$

Maintenance costs refers to those expenses incurred on maintenance of both the airframe and the engines. Generally the older the airframe and engines the greater the maintenance required. The costs per flight are calculated on the same basis as fuel and oil costs.

$$M_a = \frac{M_a^{bh}}{v_a} sl_x \qquad \text{(H-3)}$$

A significant component of operating costs refers to the cost of ownership. The depreciation costs consist of both depreciation of both the aircraft and its associated spares. Both are depreciated on a straight line bases to a residual value which represents 15% of the present value of the aircraft. The depreciation period which is consistent with the industry norm Doganis (1992) is assumed to be 10 years. The present value of spares is assumed to represent 10% of the present value of the aircraft also considered as an industry norm Doganis (1992). The aircraft depreciation cost per block hour L_a^{bh} is derived as follows:

$$D_{\mathrm{a}}^{\mathrm{bh}} = \frac{\frac{av_{\mathrm{a}}}{dp_{\mathrm{n}}} + \frac{as_{\mathrm{a}}}{dp_{\mathrm{na}}}}{u} \qquad \text{(H-4)}$$

Where av_a and as_a represent the value of the aircraft and the value of aircraft spares respectively. the depreciation period in years n is represented by dp_n whilst u represents the total annual aircraft utilisation in hours.

The depreciation cost per flight with respect to aircraft type a is therefore obtained as follows:

$$D_a = \frac{D_a^{bh}}{v_a} sl_x \qquad \text{(H-5)}$$

Airport turnaround costs incurred by the airline includes those expenses associated with usage of the airport facilities. The runway charge rp is set by the airport authority and is based on the maximum take-off weight of the aircraft. On the assumption that

the operator contracts out all passengers and ramp handling to an independent services provider a handling charge h_a is incurred depending on the type of aircraft a The total airport costs per departure is thus obtained from equation H-6 below.

$$At_a = h_a + rp_a\ MTOW_a \tag{H-6}$$

The total direct operating costs per flight departure tc is therefore calculated by summation of each of the individual expense component outlined above.

$$Tc_a = L_a + F_a + M_a + I_a + D_a + At_a \tag{H-7}$$

Indirect operating costs though difficult to allocate to a specific route given the system wide nature of these costs can be represented as a proportion of direct operating costs according to the International Civil Aviation Organisation (ICAO 1988) indirect operating typically represent 18% of total direct operating costs. Therefore on the assumption that indirect operating costs can be estimated as a ratio of Tc_a, the indirect operating costs per aircraft type are as follows.

$$Ti_a = 0.18\,Tc_a \tag{H-8}$$

The total costs Ca of operating a flight at a particular departure time is thus;

$$C_a = Tc_a + Ti_a \tag{H-9}$$

Appendix I : Aircraft Cost Data (in £)

	100-seat Jet	65-seat Turboprop	37-seat Turboprop	150-seat Jet
Operating assumptions				
Sector distance	177	177	177	153
Aircraft type	BAe 146-200	BAe ATP	Shorts 360	Airbus A320-200
In-flight time	40 minutes	60 minutes	80 minutes	60 minutes
Physical configurations				
Seating capacity	100	65	37	150
Maximum Tale-off Weight (t)	42	24	13	67
Aircraft-related costs				
Labour	126.46	145.00	103.64	309.12
Fuel and Oil	298.26	153.29	128.43	310.08
Depreciation	382.77	336.00	29.57	835.97
Maintenance	484.03	150.21	120.16	166.55
Insurance	145.82	128.00	13.52	318.46
Total	**1,437.25**	**912.81**	**401.23**	**1,940.18**
Airport-related costs				
Total	**1,186.59**	**711.04**	**489.32**	**1,972.43**
Indirect operating costs				
Total	**1,048.48**	**682.01**	**374.03**	**1,494.67**
COSTS PER FLIGHT	**3,672.43**	**2,305.86**	**1,264.58**	**5,407.28**

Appendix J : Sensitivity analysis data

Sensitivity Test 1 : Demand and Fare Equilibrium Results against Change in fare ∂f (65-seat turboprop, total demand = 400)

	∂f = £0		∂f = £2		∂f = £4		∂f = £6		∂f = £8		∂f = £10	
	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare
4:00												
5:00												
6:00	68	£55	63	£59								
7:00					62	£59	65	£55	53	£63	53	£75
8:00	52	£55	56	£53					59	£63	59	£75
9:00	58	£55	57	£53	59	£55	62	£49				
10:00					54	£51						
11:00							57	£49	50	£55	59	£65
12:00												
13:00									57	£47		
14:00	63	£55	64	£55							59	£55
15:00					58	£51	58	£55				
16:00	63	£55	59	£57	56	£55			61	£71		
17:00	53	£55	54	£55			51	£61			59	£56
18:00					60	£59	53	£55	57	£71	62	£75
19:00	43	£55	45	£53			51	£55	63	£63	53	£75
20:00					49	£51						
21:00												
22:00												
23:00												
24:00												

Sensitivity Test 2 : Demand and Fare Equilibrium Results against Change in fare ∂f (65-seat turboprop, total demand = 400)

	∂f = £0		∂f = £2		∂f = £4		∂f = £6		∂f = £8	
	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare
4:00	48	£55			48	£59				
5:00	52	£55	59	£55			52	£61	58	£71
6:00			56	£55						
7:00					50	£51	57	£49	59	£63
8:00					47	£51	55	£49	57	£63
9:00	51	£55								
10:00			54	£53	48	£51				
11:00	48	£55	51	£55						
12:00							61	£49		
13:00	49	£55							53	£63
14:00					48	£51	55	£55		
15:00			59	£53	47	£51				
16:00	48	£55							53	£55
17:00									53	£55
18:00			55	£53	50	£51				
19:00	49	£55					62	£49		
20:00	50	£55	59	£53	56	£51	52	£55		
21:00									60	£55
22:00										
23:00										
24:00										

Sensitivity Test 3 : Demand and Fare Equilibrium Results against Change in fare ∂f (150-seat Jet, total demand = 1,400)

	∂f = £0		∂f = £2		∂f = £4		∂f = £6		∂f = £8	
	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare	Demand	Fare
4:00										
5:00										
6:00	126	£55	133	£55	142	£55	146	£55	134	£63
7:00	135	£55	135	£57	136	£59	132	£61	146	£63
8:00	133	£55	135	£57	137	£59	134	£61	149	£63
9:00	120	£55	123	£57	127	£59	123	£61	141	£63
10:00	111	£55	114	£57	120	£59	118	£61	137	£63
11:00	107	£55					117	£61		
12:00			106	£57						
13:00					113	£59				
14:00	115	£55	114	£57	118	£59			146	£63
15:00	126	£55	126	£57	116	£63	142	£61	123	£63
16:00	137	£55	130	£59	130	£63	121	£67	133	£71
17:00	149	£55	141	£59	126	£67	124	£67		
18:00	138	£55	139	£57	133	£63	126	£61	149	£63
19:00							114	£55	140	£55
20:00										
21:00										
22:00										
23:00										
24:00										