Published paper

Preston, P.M. (1991) *Passenger Demand Forecasting for New Rail Services – Manual of Advice.* Institute of Transport Studies, University of Leeds. Working Paper 352

Working Paper 352

1991

PASSENGER DEMAND FORECASTING FOR NEW RAIL SERVICES

MANUAL OF ADVICE

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GLOSSARY

AD	=	Absolute Deviation
ASC	=	Alternative Specific Constant
ASDV	=	Alternative Specific Dummy Variable
ASM	=	Aggregate Simultaneous Model
BR	=	British Rail
EIL	=	Extended Incremental Logit
EMU	=	Expected Maximum Utility
Ep	=	Elasticity of demand with respect to price
FREQ	=	Frequency
GC	=	Generalised Cost
HL	=	Hierarchical Logit
IVT	=	In-Vehicle Time
MNL	=	Multi-Nomial Logit
NPV	=	Net Present Value
OVT	=	Out-of-Vehicle Time
RMSE	=	Root Mean Square Error
RP	=	Revealed Preference
RU	=	Random Utility
SE	=	Sample Enumeration
SI	=	Stated Intentions
SP	=	Stated Preference
TRM	=	Trip Rate Model
U	=	Utility
V	=	Value (in pence)
VOT	=	Value of Time

SECTION ONE

PASSENGER DEMAND FORECASTING FOR NEW RAIL SERVICES - THE ISSUES

1.1 INTRODUCTION

This Seminar reports on a research grant undertaken for the Economic and Social Research Council that commenced in January 1989 and is due to be completed in December 1991. The aims of the project are:

1. To develop forecasting approaches that are suitable for predicting the demand of new rail services.
2. To assess the accuracy of these approaches in terms of their predictions of current and future patronage.
3. By comparing the relative costs and accuracy of a range of forecasting approaches, the most appropriate methods for different levels of investment will be determined.
4. To produce a manual of advice.

The aim of this seminar is, quite, simply to present a draft version of this manual of advice and invite comments from practitioners. To this end we have invited to this seminar all those interested in developing new local rail services, including Central and Local Government, Rail Operators, Consultants, Academics and Pressure Groups. Feedback from participants will play a crucial role in this Seminar.

In the rest of this Seminar, we shall present our draft manual of advice. In doing so, we hope to demistify what can be a highly technical subject and provide useful advice on what techniques to use in particular circumstances.

In the rest of this section the issues surrounding the opening of new passenger rail services and stations will be examined. The Institute for Transport Studies has been researching this topic since 1982, when a Collaborative Award in Science and Engineering research studentship was set up by the Science and Engineering Research Council and the Leeds Division of British Rail (BR) to evaluate the programme of new local rail stations in West Yorkshire. This work was reported in detail in 1987 [1, 2].

When our research first started it did not seem to many as very topical. However, there has subsequently been something of a new stations and services 'boom'. Two main issues have dominated research. The first relates to forecasting. BR have developed a detailed forecasting methodology for existing services but it will be shown that this approach can not readily be extended to new stations and services. A new set of forecasting approaches have had to be developed. The second relates to assessing the most appropriate forecasting approach. New stations and services are generally modest investments (excluding underground railways) and, therefore, the appraisal methods deployed should not be too costly. However, a range of outputs are required to accurately assess new stations and services.

These issues will be set out at greater length in the rest of this introduction. In section two, a range of aggregate approaches, based on zonal data, will be described, including trip rate and direct demand models. In section three, a range of disaggregate approaches, based on data at the individual level will be described, including methods based on revealed preferences, stated preferences and a combination of the two. Lastly, in section four, some conclusions will be drawn with respect to the choice of appraisal methodology and the policy implications of some of our findings.

1.2 THE BOOM IN NEW STATIONS AND SERVICES

There has been an undoubted boom in the opening (or re-opening) of new stations and services. Such has been the extent of the boom that it is a non trivial task to collate exact figures. Between 1981 and 1991 161 stations have been added to the BR network, with the vast majority on the Regional Railways' network (between 1982 and 1990 135 stations opened and 11 closed). In addition, 15 new lines have been opened, although one (Kettering-Corby) has subsequently closed [3]. That this represents something of a policy U-turn is illustrated by Table 1. Monitoring work carried out by the author and others (in particular the Railway Development Society [4]) indicates that over 200 new stations have been opened on publicly owned passenger railways in Britain since 1970. Three phases may be detected. Up to the mid 1970s, station closures outweighed station openings as a result of the rationalisation programme initiated by Dr Beeching. The important threshold here was the 1974 Railways Act and the subsequent ministerial directive that services should be broadly comparable with those operated on 1 January 1975. This heralded a second phase in which only minor changes were made to the network, but with openings outweighing closures. A third phase, which began in the early 1980s has seen much more major changes to the network, with openings far exceeding closures. A number of factors contributed to this rise. In particular, the 1981 (Speller) amendment to the 1962 Transport Act, has facilitated the experimental opening of new stations and services that can subsequently be closed without undergoing the normal procedures. There may be some evidence that the 'boom', if not exactly ended, has certainly slowed down, at least as far as conventional rail is concerned (although light rail may continue the 'boom'). This slow-down is perhaps inevitable as the best sites have been developed, although recent rolling stock shortages may have also played a part. However, it is unlikely that new stations and services will become a non-issue. As the nation's geo-demographics constantly change, so must the rail network. In its recent strategy statement, BR envisages opening over 100 new stations and re-instating services on over 60 miles of track on the Regional Railway.

Table 1
Opening/Closure of Stations on Publicly Owned Passenger Railways in Britain

Includes Tyne and Wear Metro and Dockland Light Rail

	Open	Closed	Net Balance
1970-74	18	130	-112
1975-79	38	13	+25
1980-84	44	10	+34
1985-90	116	14	+102
TOTAL	**216**	**167**	**+49**

1.3 THE 'METHODOLOGY GAP'

British Rail have developed a reasonably sophisticated approach to modelling the demand for existing services that has been given the acronym, MOIRA [5]. This approach consists of an elasticity-type model based on a number of time-series studies that have developed elasticities with respect to fare, levels of service quality and GNP. An example of such a study is the 'Leeds model' developed by Owen and

Phillips [6].

However, such an approach is inapplicable to the case of new rail stations and services for at least two, closely related, reasons. Firstly, elasticity models are only applicable where changes are marginal. The introduction of a new rail service is clearly non-marginal. Secondly, elasticity models are applied incrementally around the base level of demand. A problem here is that for local rail services, assuming a reasonably fine zoning system, zones with no nearby rail station can have zero base demand. No matter how big the change in service, with an elasticity approach demand would still remain zero. Elasticity approaches might still apply for InterCity services, where the zones will be at a coarser level and there is always likely to be some positive level of demand. New stations on the InterCity network might be modelled by examining the elasticity of demand with respect to access conditions. This is the principal behind Parkway Access Models. Elasticity model approaches may also apply where the existing local rail network has comprehensive coverage. This may be true of parts of Network South East's operating area, for example in Kent.

However, for local rail services, particularly those operated by Regional Railways, there has been something of a 'methodology gap'. Fortunately, a number of different techniques have been developed in the mainstream of travel demand forecasting that may have relevant applications. These modelling approaches tend to be cross-sectional rather than time-series based, that is they examine a group of observations at a single period of time, rather than a single observation over a number of time periods. These approaches may be classified in terms of a number of dimensions, of which two are most relevant. The first is related to the specification of the unit of observation. A distinction is normally made between aggregate approaches based on zonal data, for example based on the definition of a station's catchment area(s), and disaggregate approaches, based on data at a household, or more usually, individual level. The second distinction is related to the type of behaviour being measured. Here the distinction is between the Revealed Preference (RP) approaches, based on observed behaviour, and Stated Preference (SP) approaches, based on hypothetical behaviour. These different demand forecasting approaches will be outlined in more detail in sections two and three.

Mention should be made here of two approaches that will not be investigated further. Firstly, there is a considerable literature on determining the optimal station spacing for rapid transit lines which was initiated by Vuchic [7]. This approach may be relevant to Light Rapid Transit systems and, possibly, for identifying new station sites in continuously built-up rail corridors. For example, an application of this approach carried out by Preston [1] on the Leeds-Bradford corridor indicated there may be scope for five intermediate stations (compared to the current two). Secondly, some studies have made use of historical extrapolation to estimate the usage of re-opened lines, taking into account population changes and different levels of service [8]. This approach has some broad parallels with the BR methodology for existing stations. It can not be used for brand new stations but has proved to be a surprisingly useful measure for station re-openings.

1.4 THE SCALE OF INVESTMENTS

A number of different types of new stations have been opened in Britain in the recent past. The vast majority serve residential areas and are largely unmanned (at least outside the Network South East area). There have been a number of stations that attract, rather than generate travel. These may serve factories, offices and education establishments, with the Cross City Line in Birmingham providing good examples with Longbridge, Five Ways and University stations respectively. Other stations may provide better access to central business areas (eg. Argyle Street in Glasgow), out-of-town shopping centres (eg. Gateshead Metro Centre, Meadowhall) and airports (eg. Stansted). These stations will require their own specialised forecasting approaches, although for small-scale developments estimating rail trips as a function of either proposed employment levels or retail floorspace may suffice. Similarly new stations on the InterCity network such as Bristol Parkway and Birmingham International require their own forecasting methodology, as discussed above.

The majority of the new stations opened in recent years are unmanned halts, serving residential areas. Their design is relatively basic and hence costs are correspondingly low. The capital costs of a typical West Yorkshire new station, based on two wooden platforms capable of accommodating four car trains, simple shelters, access ramps and lighting were around £100,000 at mid 1984 prices. Indeed these low costs were an impetus to the new station boom, although it does seem that the real costs of station construction have subsequently increased. The latest information available to us is that the standard West Yorkshire style new station can cost in excess of £200,000. This is reflected in the capital cost figures used in Table 2. Operating costs of maintaining and administering a new station were put at a notional £1,700. This ignores the additional fuel and braking costs of stopping a train, which for an hourly service, may come to an additional £1,700 or so [9]. The key assumption though is that the additional stop can be accommodated without any additional resources in terms of rolling stock and staff; in essence that there is some slack in the timetable.

Table 2 Demand and Catchment Area Population Required for a New Station to Break-Even (Notional 1990 prices)			
Mean Fare (pence)	New Station Costs	Daily Ons and Offs	Population within 800m
50	A B C	73 115 160	2300 3590 5020
100	A B C	37 58 80	1170 1800 2520
150	A B C	24 38 53	770 1200 1670

New Station Cost Assumptions:

A: Capital Costs £90k, Recurrent Costs £3k pa
B: Capital Costs £150k, Recurrent Costs £4k pa
C: Capital Costs £225k, Recurrent Costs £4k pa

Assumes all revenue net to the rail operator. Surveys for six West Yorkshire stations indicated that around 13% of revenue, on average, was abstracted from existing rail, and these figures therefore should be adjusted upwards. One survey of a new station located within 1km of an existing station indicated that up to 70% of revenue was abstracted from that station.

If this assumption holds then Table 2 shows that fairly low levels of demands will be sufficient to financially justify a new station. This table updates work we originally carried out for BR's Policy Unit [10, 2]. The basis for the calculations are Net Present Values based on a 30 year project life and an 8% interest rate [see the technical appendix at the end of this section]. For example, new station A with a mean fare of £1.50, which may be thought of as a single platform rural station, will require around 24 ons and offs per day. Using trip rates derived in West Yorkshire (see Section 2.2), this was estimated to require a population of less than 800. By contrast new station C, with a mean fare of only 50 pence, which may be thought of as a double platform, inner city station, requires around 160 ons and offs per day. This in turn might require a population of over 5,000 within 800 metres of the station.

These calculations assume that the additional stop does not deter existing travellers. The argument for this assumption is that passengers are unable to perceive time penalties as small as one or two minutes. However, when a number of new stations are being considered on the same line this assumption is unrealistic. There are likely to be some existing passengers at the margin who are likely to be put off travelling by rail. This factor is likely to further count against inner city sites where the trains are generally already well loaded and where the additional time penalty is most likely to cross the critical threshold. In addition, as the number of new stations that are opened increases the assumption of spare capacity becomes less likely as services are slowed down and the likelihood of overcrowding increases, and hence rolling stock requirements increase. Thus service levels and stopping patterns need to be considered simultaneously.

On their own new stations are relatively modest investments but it may be useful to consider three scales of investment:

(i) The lowest scale is the one-off unmanned halt on an existing rail service with capital costs under £0.5 million (in many cases substantially so).

(ii) The middle scale consists of packages of unmanned halts or an individual manned local station on existing rail services. The costs here may be in the range £0.5 to £10 million and in many cases they are at the lower end of the range.

(iii) The upper scale involves new stations on a new service. The costs may include upgrading a freight only rail line to passenger services, new rolling stock and in some cases new sections of track. The cost may range from £0.75 (the Walsall-Hednesford line) to over £12 million (the Ivanhoe line). These costs are still well below the costs of most Light Rapid Transit schemes (for example the first phase of the Manchester Metrolink is £90 million). An important threshold is £5 million because schemes with capital costs in excess of this are eligible for grants from central government under Section 56 of the 1968 Transport Act. However, any application requires a detailed assessment study to be undertaken that examines a range of options and considers non-user benefits (such as congestion relief, environmental improvements and developmental effects) as well as revenue and user benefits (see [11]). This in turn requires a detailed forecasting methodology capable of predicting not only the volume of rail traffic but also the extent to which this is diverted from other modes. This again argues in favour of a model structure incorporating an explicit mode choice model, rather than an elasticity type model.

Technical Appendix to Section One

The Net Present Value of a project may be defined as:

$$NPV = \sum_{n=0}^{N} \frac{B_n - C_n}{(1+r)^n} \qquad (1)$$

where

B_n = Benefits in year n. For a financial appraisal, this is net revenue to the rail operator.

C_n = Costs in year n. These may be defined as capital costs, K, in year 0 and recurrent costs, RC, in all subsequent years

r = Interest rate. The Government test discount rate is currently 8%

N = Project life. For rail this is usually assumed to be 30 years, although for wooden platform new stations this may be over-optimistic.

Assuming benefits, B, and recurrent costs, RC, are constant in each year n, equation 1 can be set to zero and rearranged to give the break-even revenue required:

$$B = \left[\frac{Kr}{1 - \frac{1}{(1+r)^N}} \right] + RC \qquad (2)$$

For the new station scenarios given in Table 2 the results for a 30 and 15 year project life are as follows:

New Station Costs	Annual Revenue Required (£)	
	15 year project life	30 year project life
A	13,515	10,994
B	21,524	17,324
C	30,287	23,986

This shows that halving the project life, increases the revenue required for financial break-even by about a quarter.

SECTION TWO

AGGREGATE APPROACHES TO DEMAND FORECASTING

2.1 PREVIOUS WORK

Aggregate methods are based on zonal data. They may be cross-sectional and/or time-series based. BR's initial demand forecasting approach was based on a cross-section of intercity flows and was given the acronym, MONICA (Model for Optimising the Network of Inter City Activities) [12]. However, in application it was found that the model failed to accurately predict the effects of changes in service levels and was superseded by the time-series based MOIRA approach discussed in section 1.3.

However, there have been few models of local rail demand, and those that have been developed tend to be time-series based and concentrate on commuting [13, 14]. We have, though, identified two aggregate approaches that are worthy of further development. Firstly, there are trip rate models (TRM) that estimate the usage of a rail station as a function of its catchment area population. Models of this type have been developed for long-distance rail travel by Rickard [15]. Secondly, there are what might be called direct demand models (DDM), that estimate rail flows as a function of the origin's population, the destination's attractiveness, the level of rail service and the degree of competition from other modes. Such models are often based on the gravity model $T_{ij} = f(O_iD_jC_{ij}^{-1})$ where T_{ij} = number of trips between i and j, O_i = population of origin i, D_j = population of destination j and C_{ij} = Cost of travel (or, as a proxy, distance) between i and j. The MONICA model was of this type, as was the model developed by White and Williams [16] for the Reading-Tonbridge line.

2.2 TRIP RATE MODELS (TRM)

Surveys of users of six new stations in West Yorkshire identified two main catchment areas: the 0-800m zone, accounting for 62% of users and with the vast majority walking, and the 800m-2km zone, accounting for 25% of users with the majority still walking. It is only from beyond 2km when the majority use mechanised access modes (see Table 3). It should be noted that the determination of station catchment areas is, in itself, worthy of specialist study (see, for example, [17]). It is a weakness of aggregate procedures that catchment areas (=zoning systems) have to be pre-defined before we can progress any further. There is considerable evidence that stations serving large towns and cities with high levels of rail service have much wider catchment areas than stations serving small towns, suburbs and rural areas with only moderate levels of service. The assumption of symmetrical catchments is also a heroic one. Rather than circular, catchment areas are likely to be elliptical with a considerable tail in the opposite direction to the main outward movement of rail traffic (especially if fare is distance related).

Table 3
Origin Distance by Access Mode (%)

	% of users	Of which				
		walk	bus	car driver	car pass.	other
0-800m	62	97	0	1	3	0
801m-2km	25	74	8	8	10	0
Over 2km	13	33	19	17	27	4
Source: [1]						

Table 4 Trip Rates for 11 New Stations (Daily ons and offs per thousand population - rounded)				
	0-800m	800m-2km	% from beyond 2km	Source
Fitzwilliam	17	0	20	[1]
Deighton	14	2	8	[1]
Crossflatts	20	6	20	[1]
Slaithwaite	24	6	21	[1]
Bramley	15	3	9	[1]
Saltaire	31	8	9	[1]
West Yorkshire - 6 stations	21	4	13	[1]
East Garforth	102	10	1	[18]
Frizinghall	29	1	3	[18]
Sandal	11	4	23	[18]
Langley Mill	10	3	43	[19]
South Wigston	30	2	21	[20]
Unweighted Mean	27.5	4.1	16.2	
Standard Deviation	24.6	2.9	11.3	

Given information on actual usage, simple trip rates can be easily developed as shown by Table 4. This table gives data for the first nine stations opened in West Yorkshire and two opened in the East Midlands. Overall, it is estimated that an average of around 29 rail trips per day per thousand population are made by people living within 800m of a station and 4 trips per day per thousand population by people living between 800m and 2km from a station. A further 16% of trips are made by people living beyond 2km. It should be noted that these figures refer to new stations only one or two years after opening and as a result may be underestimated. However, it is clear (from the standard deviations, for example) that there are massive variations in trip rates. The highest trip rates for people living within 800m is recorded at East Garforth, which may be typical of prime commuter belt, and the lowest trip rates are either for sites close to central areas (Sandal, Deighton, Bramley) or for free-standing, industrial towns (Langley Mill). The other main source of variation is the percentage of trips coming from beyond 2km. For stations close to a main centre, this figure will be between 0 and 10%. For stations on the edge of the built up area a more typical figure will be 20%. For the one free-standing town in our sample the figure is over 40%. This partially reflects the greater proportionate use of this station for long distance travel.

More sophisticated trip rate models might incorporate the socio-economic composition of the population, the level of rail service and that of competing modes. A model of this sort has been developed for Greater Manchester PTE and has been termed a 'trip end' model [21]. Examples of the types of model that were developed are given by Table 5. These models were calibrated with data for 36 stations on the Altrincham, Bury, Oldham and Rochdale lines using ordinary least squares multiple regression provided by the SAS (Statistical Analysis Systems) computer package. For both models, the dependent variable was the log of the number of boarding passengers at each station on a weekday. In addition to the population within 2 kilometres of a station, significant explanatory variables included the proportion of the population within social classes I and II (Professional and Managerial), the proportion in social class IIIM (Skilled Manual), rail frequency, rail fare per mile, bus frequency and car speed. Model 1 has a high R^2 but was affected by a number of statistical problems. In particular, the model is affected by simultaneity problems in that we are unable to assess the extent of cause and effect between demand and supply. For example, does a station have a high level of service because it has high demand or does it have high demand because it has a high level of service? The answer to this problem is to correctly specify a set of demand and supply equations and estimate them using Two Stage Least Squares. However, specifying the system of equations is not straightforward and is, in most cases, thwarted by lack of data. A more pragmatic approach may be to develop generalised cost measures in which variables that are likely to be affected by simultaneity (frequency, fare) are combined with those that are not (in-vehicle time). This is done in model 2 and may be justified in that the elasticities of rail fare and frequency come down from initial values of -1.01 and 1.22 to -0.66 and 0.52 respectively. Based on empirical evidence from elsewhere, it is the latter values that seem the more plausible (see also Section 4.2).

However, the main problem with trip rate models is that they fail to take into account the attractiveness of destinations and that, consequently, the specification of level of service variables are imprecise. For example, the rail and bus frequencies are based on services to central Manchester even though some trips are being made to non-central Manchester destinations. Somewhat surprisingly, when the dependent variable was split between trips to central and non-central Manchester, the models performed better (in terms of goodness of fit) for the non central Manchester trips. An important lesson from this Greater Manchester work was that a high R^2 is not, on its own, a reliable indicator for model selection.

Table 5 **Greater Manchester Trip End Models** (t-statistics in brackets)			
	Model 1		Model 2
Intercept	7.333 (9.899)	Intercept	2.260 (0.710)
POP	0.00005 (6.587)	LPOP	1.003 (4.720)
RSOC2	34.442 (3.962)	LRSOC2	1.030 (3.999)
RSOC3	-24.309 (-2.302)	LRSOC3	-0.579 (1.663)
FREQ	0.013 (6.755)	LGCRA	-0.609 (-1.839)
FDIST	-0.0139 (-5.141)	L(GCBU/GCRA)	0.134 (0.193)
BFREQ	-0.002 (-3.586)	L(GCCA/GCRA)	1.785 (2.439)
CSPEED	-4.069 (-3.697)		
R^2	0.877		0.764
$\bar{R}^2$	0.846		0.716
E_{freq}	1.22		0.52
E_{fare}	-1.01		-0.66
Variable definitions are given in the Appendix			
N.B. Model 1 is a semi-log model, in which (absolute) Elasticities vary in proportion to the value of the particular attribute, whilst Model 2 is a log linear (or double log) model in which elasticities are constant.			

2.3 DIRECT DEMAND MODELS

Instead of predicting the number of trips by rail k from origin i (T_{ik}), we define direct demand models as estimating the number of rail trips between origin i and destination j by mode k (T_{ijk}). An example of a model of this type was what we termed the Aggregate Simultaneous Model (ASM), as opposed to the conventional, four-stage aggregate sequential model used in many Land Use and Transportation Studies. This model was calibrated with data on 99 flows estimated from BR's 1981/82 Passenger Train Surveys for 39 small town, suburban and rural stations in West Yorkshire. Two preferred model forms were developed: a log linear and a semi-log model. These are represented by models 1 and 2 respectively in Table 6. The formulations were partly chosen because they reduced problems of multicollinearity (correlation between variables) and heteroskedasticity (non-constant variance of the error term) that in combination can bias the parameter values and their statistical significance. However, the models only have a moderate goodness of fit, almost half the variation is unexplained. In particular, the ASM underpredicted flows from long established commuter stations. In part, this may be because these commuter stations draw users from beyond 2 kilometres or have, over time, attracted people who, all other things being equal, have a greater than average preference for rail travel. If six outliers of this type were excluded the R^2 of model 1 increased to 0.66.

Based on comparison of the R^2 measure, the constant elasticity model was just preferred to the variable elasticity, semi-log model. However, recent simulation work by Fowkes and Wardman [22] shows that when there is a lack of variation in the data (as is likely to be the case with an aggregate model), a double log model may be erroneously preferred to a semi-log model. All in all, the evidence for constant elasticity models may not be as strong as it first appears.

Table 6 Regression Models of Rail Demand (t-statistics in brackets)						
Dependent variable: LFLOW						
Models	1		2		3	
Intercept	5.496	(3.025)	-1.468	(-0.790)	-3.580	(-2.231)
LOPOP	0.380	(2.617)	0.423	(2.868)	0.562	(3.230)
LOPOP2	0.164	(1.733)	0.147	(1.542)		
LRSOC	0.246	(2.034)	0.248	(2.047)		
LDRX	0.269	(6.678)	0.291	(6.507)		
LREMP					0.252	(4.051)
LGCRA	-1.239	(-4.307)				
GCRA			-0.007	(-3.971)		
LRS					0.574	(3.315)
LGCOTH	-1.341	(-2.269)	0.507	(1.721)		
LBS					-0.250	(-2.408)
IC					0.966	(4.634)
INTOPP					-1.247	(-8.077)
R^2	0.539		0.532		0.709	
$\bar{R}^2$	0.509		0.502		0.678	
The variables used in these models are defined in the Appendix						

Aside from some particular specification and measurement problems, the ASM is affected by problems common to cross sectional models. In particular, it lacks a dynamic structure (which is important when patronage growth over time is considered) and is afflicted by simultaneity problems. The model was also shown to lack temporal transferability. Models 1 and 2 were recalibrated with 1984 data (based on self-completion questionnaires) and, out of 14 parameter values, 5 were shown to have significantly changed their value, at the 5% significance level. Despite these problems, the ASM has been applied to around 80 sites in 12 different counties. It has become evident that its spatial transferability is limited and that it is relatively insensitive to service level changes.

A possible improvement might be to develop separate models for work and non-work journeys (or, alternatively, peak and off-peak trips). It was necessary to develop a non-work trip model for West Yorkshire, to be used in conjunction with the disaggregate models of work trips described in the next section. This model was calibrated for 64 flows based on 1984 data and is given as model 3 in Table 6.

2.4 OVERVIEW

In this section we have shown that simple aggregate models can easily be developed and applied to forecast the demand for new passenger rail services and stations. However, trip rate models, based solely on population, exhibit a large amount of variation and are only likely to be applicable if used to forecast demand in very similar circumstances to that in which they are calibrated. Direct demand models may be more transferable as they take into account a number of factors other than population. However, in the case of new stations and services, they have to be based on cross-sectional data and as a result are particularly prone to problems of simultaneity. Moreover, the aggregate models we have discussed have a fundamental problem in that we have to define the unit of aggregation (the catchment area of a station or service) before we commence our analysis. Partly because of this, disaggregate approaches have been developed in which definition of catchment areas is less vital. It is to these that we turn to in the next section.

Technical Appendix to Section Two: Definition of Variables

(A) 'Trip End Model'

L	=	As a prefix, denotes a logarithm has been taken
POP	=	Population within 2 kilometres of a station
RSOC2	=	Proportion of population within 2 kilometres of a station in social classes I and II
RSOC3	=	Proportion of population within 2 kilometres of a station in social
FREQ	=	Number of rail departures per day
FDIST	=	Mean Rail Fare divided by distance from central Manchester
BFREQ	=	Number of bus departures per day
CSPEED	=	Mean car speed for a journey to central Manchester
GCRA	=	Generalised Cost of Rail (see below but, in this case, excludes walk time)
GCBU	=	Generalised Cost of Bus
GCCA	=	Generalised Cost of Car

(B) 'Aggregate Simultaneous Model' - All Purposes

FLOW	=	Number of trips from i to j and j to i per average autumn weekday
OPOP	=	Population usually resident within a straight line distance of 800 metres of the station
OPOP2	=	Population usually resident within a straight line distance of 800 metres and 2 kilometres of the station
RSOC	=	Number of residents within social classes 1 and 2 within 800

metres of the station divided by OPOP

DRX	=	Number of work places within 800 metres of the destination station divided by the economically active population
GCOTH	=	Index of competition, expressed as:
		GCRA/(GCRA + GCBU + GCCA) (Model 1)
		GCBU + GCCA (Model 2)

where:

GCRA	=	Generalised cost of rail = 2 x (walk + wait time) + in-vehicle time + fare/VOT

where:

Walk	=	Access and egress time
Wait	=	Calculated as a function of headway = 3.0 + 0.185 service interval
Fare	=	Half Standard Return
VOT	=	Department of Transport value of behavioural non-working in-vehicle time
GCBU	=	Generalised cost of bus = 2 x (walk + wait time) + in-vehicle time + fare/VOT

where:

Walk	=	Calculated as rail walk time divided by the number of bus stop

		pairs on competing bus routes within 800 metres of a station
Wait	=	Calculated as a function of headway = 1.46 + 0.26 service interval
GCCA	=	Generalised cost of car = in-vehicle time + operating costs/VOT + parking charge/VOT

where:

Operating costs are taken as fuel costs only, assuming fuel consumption of 44km per gallon in urban conditions and 62km per gallon in rural conditions.

In-vehicle time based on link flow speeds of 46km per hour in urban conditions and 80kph in rural conditions.

(c) Aggregate Simultaneous Model - Non Work Trips

FLOW	Number of non work trips (excluding education) from i to j and j to i per average weekday
OPOP	As above
REMP	Retail employment within the central area shopping zone
RS	Rail service frequency during off peak periods (0930-1500 hours and 1800 hours and beyond)
BS	Bus service frequency during off peak periods
IC	Dummy variable, = 1 for stations serving medium sized towns, with services timetabled to connect with inter city services. Else = 0
INTOPP	Proxy variable to take into account the number of competing or intervening variables

SECTION THREE

DISAGGREGATE APPROACHES TO DEMAND FORECASTING

3.1 PREVIOUS WORK AND BASIC THEORY

When used to forecast the demand for new local rail stations and services, aggregate approaches have a number of weaknesses. They fail to establish the importance of factors that exhibit greater intra-zonal than inter-zonal variation. This is particularly true of walk and wait time which may be critical in the choice of public transport mode. They fail to take into account micro-level information on economic activity which will clearly affect travel demand. More generally, aggregate models lack a firm behavioural basis, although direct demand models can be shown to have a tentative link with utility theory [23].

These shortcomings may be overcome by making use of individual data on the times and costs of the mode actually used and at least one alternative (or preferably a full choice set of alternatives) in order to calibrate a mode choice model. Such disaggregate models are normally based on observations of actual behaviour, which is normally referred to as a Revealed Preference (RP) approach. A number of studies have used a disaggregate RP approach to evaluate new rail investments in the UK [24], the US [25] and the Netherlands [26].

An alternative disaggregate approach that has emerged over the past decade is that of Stated Preference (SP), which is a generic term that refers to a range of hypothetical questioning techniques [27]. The key difference, compared to RP approaches, is that SP approaches are based on hypothetical rather than actual behaviour. The earliest transport applications of the SP approach in the UK were developed by consultants SDG for BR [28] and the credibility of SP approaches, at least in determining relative valuations, was enhanced by the Department of Transport's Value of Time Study [29].

In application, as we shall see, there are some problems with the SP approach. A simpler approach to forecasting the demand at a new station is to ask the question "if a new station was opened at i with level of service Q how often, and for what journeys, would you use it?". This approach, which we have termed the Stated Intentions (SI) approach has been used in a number of studies to forecast usage of new stations, for example in Scotland and Somerset. However, such an approach is likely to lead to a gross overestimate of demand, unless adjusted [30].

In the rest of this section, we shall examine these three disaggregate approaches in more detail, but before doing this we shall briefly outline the behavioural basis for disaggregate models and outline the commonly used logit model.

Disaggregate models have their basis in random utility theory, where utility (U) is a measure of the satisfaction gained from consuming a particular good. Because transport is a derived demand (ie. we do not normally travel for travel's sake), we normally gain negative satisfaction from transport and hence we are really dealing with disutility. The concept of utility is closely linked with that of generalised cost (GC) with the two being linked, in the range of interest to us, by the formula $U = -\delta GC$, where δ = a scalar. Random utility theory (and common sense) tells us people will normally choose the good with the greatest utility or, more accurately in a transport context, the mode with the least disutility. For the binary situation this can be expressed as:

$$P_{i1} \quad = \quad \text{Prob}\ (RU_{i1} > RU_{i2}) \qquad (1)$$

where

P_{i1} = Probability of person i choosing mode 1

RU = Random Utility eg., assuming a linear additive function

$RU_{i1} = \Sigma_j \beta_{ij1} X_{ij1} + \varepsilon_{i1}$

where

X_{ij1} = the value of the jth relevant attribute (time, cost etc)

β_{ij1} = parameters to be estimated

ε_{i1} = an error term which introduces a stochastic (or probabilistic) element so as to take into account unobservable aspects and omitted factors.

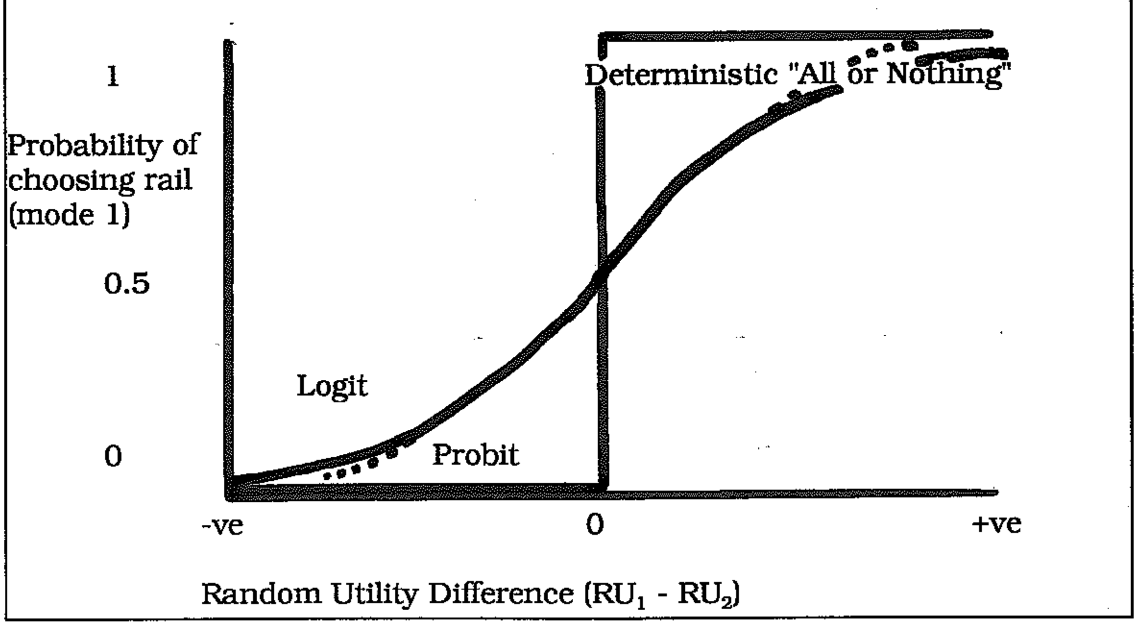
Different model forms may be developed depending on the assumed distribution of the error term. The most commonly used form is the reciprocal exponential distribution, which is a form of Weibull distribution. This may be represented as:

$$\text{Prob}\ (\varepsilon < K) = \exp\ (-\exp\ (-K)) \qquad (2)$$

where K = any constant value.

This distribution produces the S-shaped, ogive curve as shown by Figure 1. By comparison, adopting a deterministic approach, in which the error term is ignored, will result in an 'all or nothing' assignment to either mode 1 or mode 2. The distinction between probabilistic and deterministic approaches will be returned to later in this section.

Figure One: Comparison of Probit, Logit and Deterministic Curves



Assuming that the errors are identically and independently distributed (IID) we may derive the multinomial logit model (MNL) for any number of modes m as:

$$P_{i1} = \frac{\exp\,(U_{i1})}{\sum_m \exp\,(U_{im})}$$

(3)

For the binary choice between two modes this can be re-written and simplified as:

$$P_{i1} = \frac{\exp\,(U_{i1})}{\exp\,(U_{i1}) + \exp\,(U_{i2})} = \frac{1}{1 + \exp\,(U_{i2} - U_{i1})}$$

(4)

Equation 4 can be easily transformed to give:

$$Log_e\left(\frac{P_{i1}}{1 - P_{i1}}\right) = U_{i1} - U_{i2}$$

(5)

This is referred to as the Berkson-Theil transformation and has the advantage that it can be estimated by regression although it assumes that either the response of each individual i is not discrete (0 or 1) but consists of some series of probabilities (for example, a scale such as 0.9, 0.7, 0.5, 0.3, 0.1) or that individual discrete choices have been aggregated to form proportions. The former approach can be adopted within an SP experiment, whilst the latter approach forms the basis for the development of logit models with aggregate data, based on either RP or SP approaches.

3.2 DISAGGREGATE REVEALED PREFERENCE APPROACHES

Disaggregate RP models were developed by us with data from the 1981 West Yorkshire Corridor Study, which collected information on the journey to work as part of the study into the Value of Time mentioned earlier [29]. The model form chosen was the hierarchical logit (HL). This form was chosen because it overcomes the Independence of Irrelevant Alternatives (IIA) property which affects the more widely used multinominal logit model (MNL) outlined above. The main problem with the MNL stems from the IIA property which precludes the possibility of differential substitutability and complementarity. In other words, the probability of choosing any option in relation to any other option is unaffected by expansion or contraction of the choice set ie:

$$\frac{P_2}{P_1} = \exp\,(U_2 - U_1) = \textit{constant, with respect to additional modes} \tag{6}$$

It was hypothesised that rail users, all other things being equal, are proportionally more likely to be drawn from bus than car. This was confirmed by a generalised likelihood ratio test, a statistical test that indicated that, in this case, the IIA axiom does not hold and, therefore, an HL model structure was preferred to the MNL model.

HL models are based on a decision tree structure. Suppose we assume that the mode choice process is divided into two stages:

j = the choice between private and public transport (the upper nest)

k = the choice between public transport modes (the lower nest).

It should be stressed that we do not necessarily adopt this structure because we believed people choose modes like this; it is merely a device to overcome the undesirable properties of MNL.

The perceived utility to individual i of choosing mode type (j,k) may then be written:

$$U^i_{(j,k)} = U_j + U_k + U_{jk} + \varepsilon^i_j + \varepsilon^i_k + \varepsilon^i_{jk} \tag{7}$$

Assuming that the ε terms are IID for each individual and that var (ε_j) and var (ε_k) are zero, results in the MNL. If either var (ε_j) or var (ε_k) are not zero, then there will be correlation between the U^i_{jk} terms. For example, suppose var (ε_k) = 0 but var (ε_j) ≠ 0, then individuals with high values of U for bus will also have high U values for rail. To take this into account, and assuming no common measurable attributes amongst public transport modes (which will not be realistic in areas where rail and bus fares are identical), an HL model can be developed as follows.

$$P_{(j,k)} = \left[\frac{\exp\,(U_j + \phi\, U_j*)}{\sum_j \exp(U_j + \phi\, U_j*)}\right] \cdot \left[\frac{\exp\,(U_k)}{\sum_k \exp\,(U_k)}\right] \tag{8}$$

where

$$U_{j*} = \log\left(\sum_k \exp\,(U_k)\right) \tag{9}$$

and is known as the logsum or expected maximum utility (EMU). In our example, it represents the combined attractiveness of public transport.

HL models were estimated indirectly using the BLOGIT package [31] with the composite cost term (or expected maximum utility (EMU)) being calculated with FORTRAN programs. A bottom-up approach was adopted, with the lower nest (or split) estimated first, followed by the upper nest. It is acknowledged that direct estimation (or full information Maximum Likelihood) is preferable to indirect estimation [32] but the requisite software was not available. More recently, packages such as ALOGIT have become available which make direct estimation relatively straightforward.

At the calibration stage problems were encountered in including socio-economic variables. The preferred model was thus market segmented and consisted of an MNL model for non car owning households and an HL model for car owning households. The structure of this model is given by Table 7. A model of this form proved very data intensive, as it required information on modes used, times and costs disaggregated by car ownership, and sufficient data only existed to validate the model for five new stations and make predictions for a further three potential sites. A simpler formulation is provided by a single market HL model, as shown by Table 8. The spatial transferability of the HL/MNL model was tested by applying the model to a different data set. A likelihood ratio test showed that the model was not transferable but, in part, this was due to problems with the quality of the validation data set. It is not the purpose of this seminar to comment in detail on the models in Tables 7 and 8, but it should be noted that some perverse results were achieved, for example insignificant parameter values and high adjusted rho-squared measures. It should be noted here that the rho-squared measure in maximum likelihood estimation is not comparable to that of R^2 in regression analysis and that, for example, an adjusted rho-squared measure of between 0.2 and 0.4 can represent an excellent fit [57]. Such results may be attributed to the fact that, out of necessity, we were using an RP data set of only limited quality.

Table 7
Market Segmented HL and MNL Models

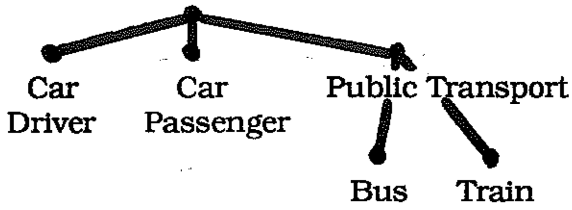
(A) Non Car Owners

	Parameter Value	(t-stat)
ASC-Pass.	-0.844	(-1.305)
ASC-Bus	0.427	(1.004)
Wait time	-0.090	(-2.630)
Walk time	-0.071	(-2.335)
IVT	-0.029	(-1.339)
Availability	-3.012	(-4.643)
Adjusted Rho Squared		0.500
Number of observations		173

<u>NOTES</u>

ASC	=	Alternative Specific Constant
IVT	=	In Vehicle Time
OVT	=	Out of Vehicle Time
EMU	=	Expected Maximum Utility

(B) Car Owners



	Parameter Value	(t-stat)
Upper Split		
ASC-Pass.	-0.339	(-0.596)
ASC-Driver	1.597	(2.789)
IVT	-0.064	(-3.178)
OVT	-0.059	(-1.481)
Total Cost	-0.013	(-4.176)
EMU	0.377	(4.996)
Adjusted Rho Squared		0.803
Number of Observations		721
Lower Split		
IVT-Train	-0.111	(-1.785)
IVT-Bus	-0.118	(-2.605)
Walk time	-0.191	(-3.998)
Wait time	-0.276	(-2.565)
Total Cost	-0.067	(-2.196)
Adjusted Rho Squared		0.574
Number of Observations		97

Table 8 Single Market HL Model					
	Parameter Value	(t-stat)		Parameter Value	(t-stat)
Lower split			*Upper split*		
Wait time	-0.132	(-3.025)	ASC-Driver	2.742	(5.867)
Walk time	-0.184	(-5.221)	ASC-Pass.	0.804	(1.962)
IVT-Bus	-0.092	(-3.024)	EMU	0.205	(2.763)
IVT-Train	-0.080	(-2.295)	OVT	-0.067	(-2.698)
Total cost	-0.044	(-2.490)	IVT	-0.011	(-0.743)
			Total Cost	-0.014	(-6.252)
Adjusted Rho Squared		0.466	Adjusted Rho Squared		0.779
Number of Observations		179	Number of Observations		907

A further example of an RP model is one that we developed in conjunction with consultants Transportation Planning Associates [33] in order to predict the demand for a new rail service to the towns of Brighouse and Elland in West Yorkshire. This was done by calibrating a model based on the travel behaviour of individuals living in the nearby towns of Mirfield and Sowerby Bridge and then applying this model to times and cost data collected in the Brighouse-Elland area. The details of this model are presented in Table 9. It is again based on an HL model in the belief that certain choices are not independent.

Table 9
A Revealed Preference Model to Predict the Demand for a New Rail Service to Brighouse and Elland

	Parameter values	t-statistic	Adjusted value
(A) Lower Nest - Choice of Access Mode for Rail			
ASC-Walk	1.355	1.55	2.302
ASC-Bus	0.441	0.59	0.035
ASC-Park 'n' Ride	1.274	1.44	0.329
OVT	-0.177	-3.18	V of OVT 5.36
IVT	-0.043	-0.62	V of IVT 1.30
Cost	-0.033	-1.80	
Rho-squared 0.04, Percent Correct 67, Observations 74			
(B) Middle Nest - Choice of Public Transport Mode			
ASC-Rail	0.915	2.07	-0.384
Walk	-0.034	-1.09	V of Walk 2.13
Wait-Rail	-0.074	-1.71	V of Wait 4.63
IVT	-0.043	-2.83	V of IVT 2.69
Cost	-0.016	-2.32	
Logsum	0.926	4.17	
Rho-squared 0.28, Percent Correct 67, Observations 147			
(C) Upper Nest Choice of Mode			
ASC-Driver	1.283	2.63	1.664
ASC-Passenger	0.339	0.73	0.318
IVT	-0.021	-1.54	V of IVT 2.33
Cost	-0.009	-3.64	
Logsum	0.266	2.23	
Rho-squared 0.17, Percent Correct 60, Observations 158			

Abbreviations: ASC = Alternative Specific Constant
IVT = In-Vehicle Time
OVT = Out-of-Vehicle Time (Walk and Wait Time)
V = Value in pence per minute

The Brighouse-Elland model was again calibrated by a bottom-up approach but this time involving three stages. The first stage (the lower nest) involved predicting the choice of access mode, given rail is the chosen main mode. The alternatives considered were walk, bus, park and ride and kiss and ride (with the latter being the base). The second stage (the middle nest) predicts the choice between bus and rail, given that public transport is the chosen main mode. The information from the lower nest is incorporated by the logsum variable, the parameter value of which should always be greater than 0 and less than or equal to 1. The third stage involves the choice of main mode, with the information from the middle and lower nest again being incorporated by a logsum variable, the parameter value of which should again be between 0 and 1, but should also be less than the value of the previous logsum parameter. These restrictions on the value that the logsum parameter can provide a useful in-built diagnostic test.

The data supported the hierarchical structure but also illustrated a number of problems with RP models. Although over 1100 interviews were undertaken, only a small number of observations (280) were used in the calibration stage due to non-relevant choices and missing information on times and costs. This is a similar breakdown to that of the 1981 West Yorkshire study, where 4598 interviews were undertaken of which only 850 were used in the final models. This reflects the data inefficiency of RP methods based on household interviews, particularly when dealing with a minor mode such as rail. To overcome this, use was made of choice based sampling, but this meant that the alternative specific constants in the model have to be adjusted to reflect the population's modal shares, rather than the sample's. The formula used to carry out this adjustment was as follows:

$$a_i = a_i' - \log_e (H_i'/H_i)$$

where

a_i	=	adjusted (unbiased) ASC for alternative i
a'_i	=	unadjusted (biased) ASC for alternative i
H'_i	=	proportion choosing alternative i in the sample
H_i	=	proportion choosing alternative i in the total population.

Partly as a result of the low number of observations, a large number of the parameter values were insignificant at the 5% level (9 out of 17), whilst there was some indication of correlation between time and cost variables. Overall goodness of fit was modest. This all reflects the statistical inefficiency of RP methods.

A problem with disaggregate models in forecasting arises because the individual choice estimates have to be expanded over the population of interest in order to obtain a reliable, unbiased forecast of group behaviour. The problem arises because, for non linear functions such as the logit model, a function of averages of variables is not the same as the average of this function. Hence, use of aggregate data with a model calibrated with disaggregate data will lead to systematic biases [34]. This has become known as the 'aggregation problem'. This can be solved quite easily if a random sample of individuals amongst the relevant target population can be obtained. However, such a 'sample enumeration' approach can be very costly.

A way of using aggregate data in a manner that purportedly reduces this problem is the incremental logit model [35]. This model has been extended so as to incorporate an HL structure and accommodate new modes [36, 37] and has been termed the

Extended Incremental Logit model (EIL). The main advantage of the EIL is that it reduces data requirements to existing modal shares and the differences between the utilities of new and existing public transport modes. An example of a form of the EIL is given in the Technical Appendix 3.1.

3.3 STATED PREFERENCE APPROACHES

Stated Preference (SP) experiments involve presenting respondents with hypothetical sets of attributes for a number of choices. In the experiments we have undertaken, a binary choice between the existing mode (either bus or car) and the proposed rail service is examined. The attributes normally considered are in-vehicle time, walk-time, frequency and cost. Respondents are presented with up to 18 sets of these attributes for both choices and are then asked to indicate their response in terms of a discrete choice (ie. they are asked whether they would choose rail or their existing mode). Other forms of response include rating, either semantic (eg. definitely use rail, probably use rail, no preference, probably use existing mode, definitely use existing mode) or numeric, and ranking. Discrete choice response is preferred because it most accurately parallels the actual decision to be made [58]. An early example of one of our designs is given in Technical Appendix 3.2. This was for a study examining a new service between Leicester and Burton-on-Trent (the Ivanhoe Line [38]). Other SP studies we have undertaken included that of a service between Nottingham and Worksop via Mansfield (the Robin Hood Line [39]) and between Blackburn and Hellifield (the Ribble Valley Line [40]).

SP methods tend to be used for two reasons. Firstly, RP methods may be impossible because a comparable local rail service does not exist. This was believed to be the case in the two major studies we undertook in the East Midlands. Secondly, SP has a number of advantages over RP. It can be more data efficient, as by asking a series of hypothetical questions several observations per individual can be collected. It also has advantages of statistical efficiency. For example, the survey can be designed so as to ensure orthogonality between key variables (ie. avoid correlation) and ensure variation in key attributes.

In our earliest designs we ensured orthogonality between the attributes by adopting fractional factorial designs but in subsequent work it became apparent that some correlation between cost and time attributes may be desirable [41]. The most important consideration in the design of SP experiments is the inclusion of an adequate spread of 'boundary values', ie. the attribute valuations for which respondents will be indifferent between two options. For example, if the only difference between two options was that the first had 10 minutes less journey time but cost 20p more than the second option, then the boundary value of time would be 2p/min. By seeking respondents choices between options containing a range of boundary values of time it is possible to infer the value of time of the respondents.

Usually there will be more than two attributes changing their levels between two options and so boundary values are only determined as a function of other variables. It is often beneficial to hold all but two attributes at a constant level between options so as to predetermine the boundary value between these two attributes. We call these 'fixed boundary values', and the inclusion of a range of these will sort each individual into an interval (or 'bin') according to their responses. We call this 'bin analysis' and an example is presented in Table 10a.

Table 10a An Illustration of Bin Analysis						
Option A		Option B		Boundary Value of Time	Respondent Choice	
Time	Cost	Time	Cost		Option A	Option B
15	50	30	35	1p/min	75	25
15	40	25	35	0.5p/min	90	10
20	50	25	40	2p/min	40	60
20	60	30	30	3p/min	15	85

Table 10b % of Values of Time in Stated Range		
	%	Cumulative %
Under 0.5p/min	10	10
0.5p/min - 1p/min	15	25
1p/min - 2p/min	35	60
2p/min - 3p/min	25	85
Over 3p/min	15	100

In Table 10a 100 respondents have chosen between 4 sets of 2 options. 90 of them are prepared to pay (at least) 0.5p/min to save time, 75 to pay 1p/min, 40 to pay 2p/min, and 15 to pay 3p/min. Table 10b shows a 'bin analysis' of these data.

From Table 10b we can deduce that the average value of time lies in the range 1p/min to 2p/min. By interpolation we could form a point estimate as:

$$1 + \left(\frac{50-25}{35}\right) = 1.71 \text{ p/min}$$

As can be seen, this is achieved without the 'black box' of disaggregate logit computer packages, and so carries considerable weight.

Our work has been based on self completion questionnaires, although it is acknowledged that in some respects interviews are better, particularly if performed with a lap-top computer so that adaptive designs can be considered. However, such methods are still at an early stage of development and we feel that, at present, self completion SP experiments are the most cost-effective in this particular choice context.

In our earliest work, which examined the case for a Leicester-Burton rail service, the SP survey was customised for existing bus and car travellers to central Leicester from the outer Leicester suburbs and the Ashby/Coalville area. Altogether, 1,254 individuals were contacted, of which 638 (51%) returned questionnaires. Each individual was presented with 16 sets of hypothetical times and costs for train and their existing mode and were asked to indicate which mode they would use. The models were calibrated by maximum likelihood, with the BLOGIT package again being used. The resultant models of mode choice are given by Table 11. Compared to the RP mode choice models that have been developed in this work, the SP models' parameter values tend to have greater statistical significance (although this is, in part, because there are repeat observations for each individual respondent), socio-economic variables can be explicitly included and, because of the orthogonal design, the problems of collinearity between times and cost which appear to have affected the RP models are avoided.

Table 11 SP Models of Mode Choice: Leicester-Burton Case Study				
Parameter	Bus-Train Model		Car-Train Model	
	Value	(t-statistic)	Value	(t-statistic)
ASC (Train)			-1.907	(8.89)
IVT	-0.086	(10.21)	-0.064	(16.96)
OVT_t	-0.067	(9.84)	-0.082	(5.69)
OVT_c			-0.040	(1.88)
COST	-0.056	(19.61)	-0.035	(17.35)
$FREQ_t$	+1.327	(15.73)	+1.452	(18.72)
$FREQ_b$	-0.863	(3.34)		
MALE	+0.359	(3.70)		
INCOME > £9,999			-0.151	(2.09)
AGE > 39			-0.135	(1.90)
LEISURE	-0.189	(1.88)	+0.592	(7.19)
LEIC SUBURBS	-1.022	(7.64)	-0.581	(7.08)
Adjusted Rho Squared	0.25		0.22	
No. of Observations	2549		4314	
Notes: OVT_t denotes OVT train, OVT_c denotes OVT car, $FREQ_t$ and $FREQ_b$ represent the number of trains and buses per hour				

Examples of later models we have developed are given by Table 12. Like the models in Table 11, they are based on binary logit. SP can be used to develop more complicated models in theory but in practice it is advisable to keep an experiment relatively simple. Table 12 shows that models can be developed based on very small numbers of individuals (only 29 in the case of the bus v train model), although we would normally aim for substantially larger sample sizes. Nonetheless, the t-statistics and the rho-squared measure suggest a relatively good fit. One feature of SP data is that it facilitates the examination of non-linearities. For example, in the car v train model the three levels of rail frequency are specified separately (this is sometimes referred to as piecewise estimation), whilst natural logs have been taken of walk and in-vehicle time so that the resultant values of time decrease as walk or in-vehicle time increases.

Table 12
Stated Preference Models Developed to Predict the Demand for a New Rail Service to Clitheroe

(A) Bus v Train Model (t-statistics in brackets)				
	Parameter value		Value in pence	
ASC-Bus	-0.732	(1.63)	-22.73	(1.58)
Bus Headway	-0.018	(1.76)	0.55	(1.93)
Total Time	-0.072	(5.79)	2.25	(5.36)
ASDV-Work/Education	1.063	(3.56)	33.00	(3.13)
Cost	-0.032	(8.95)		
Rho-squared 0.55, Percent Correct 81, Observations 507, Individuals 29				
(B) Car v Train Model (t-statistics in brackets)				
ASC-Car	1.008	(2.85)	61.07	(2.09)
FREQ30	0.366	(1.55)	22.19	(1.44)
FREQ20	0.874	(3.24)	52.94	(2.85)
FREQ15	0.961	(3.69)	58.22	(2.82)
Ln (Walk)	-1.323	(5.70)		
Ln (IVT)	-1.918	(7.16)		
Cost	-0.017	(6.29)		
Rho-squared 0.32, Percent Correct 70, Observations 892, Individuals 56				
Abbreviations: ASDV = Alternative Specific Dummy Variable FREQ30,20,15 = Rail frequency every 30,20,15 mins				

However, there is a problem with SP models that becomes apparent at the forecasting stage. The models are based on binary logit, the coefficients of which are estimated in units of residual deviation ie they are estimated as $\Omega\alpha$ where α is an unscaled parameter, Ω is a scalar calculated as $\pi/(\sqrt{3}\,\sigma)$ and σ is the standard deviation of the error differences between modes. A problem arises where σ is not the same as that which would apply to the actual choices being made. This is likely to be the case for SP experiments where uncertainties/difficulties respondents have with hypothetical choices are likely to be greater than those for actual choices. Thus, for comparable models, we believe that σ is likely to be larger with SP data than with RP data. This in turn will reduce the absolute size of parameter values and hence utilities. For example, in binary choice situations in which rail is the minor mode (ie. it has lower average utility than the other mode in the choice set), this will lead to overestimates of the probability of choosing rail. This example is likely to be typical of many situations in which a new station or service is being considered and is an example of what has been termed the scale factor problem [42]. Suggested solutions based on re-scaling with RP data or by pivoting around known elasticities or known parameter values are inappropriate in this instance as RP data can not exist for a new mode and neither will reliable, local, parameter/elasticity estimates.

However, there are two methods by which forecasts can be derived:

(i) The **deterministic** method assigns an individual to the mode with the highest utility, given the estimated parameters and the costs and times which would prevail for train and bus/car in the situation to be forecast. This is best done with models developed for as small as possible sub-groups of the sample.

(ii) The **probabilistic** method calculates the probability of choosing train for each individual given the estimated utility differences for the situation to be forecast. Aggregate shares are simply the weighted sum of individual shares.

The two methods give different results. In binary choice, because of the shape of the logit function (see Figure One), if rail is the minor mode (ie. a share of less than 0.5, which is the case in most actual situations) the probabilistic forecast will be greater than the deterministic given our belief that σ is too high in SP experiments. Where rail is the major mode, the reverse will be true. The deterministic method has an advantage in that, because the scale factor applies equally to all coefficients and hence does not affect relative utilities, the scale factor problem is avoided. The disadvantage is that the deterministic method, by definition, does not include the stochastic component of random utility (ie. the error term), and so does not permit occasional choices of non optimal modes as would occur in practice due to special factors affecting individuals. Given that we believe rail to be a minor mode, the probabilistic forecasts are likely to overstate rail's market share and the deterministic forecasts understate it, it may be then assumed that these two forecasts bound the actual value. Therefore, an average of these two forecasts may provide a reasonable approximation of the true value. This point is represented empirically by Table 13.

Table 13
SP Estimates of Rail Shares for the Leicester to Burton Corridor

	Bus Users	Car Users	All Users
Probabilistic Forecast	0.142	0.162	0.155
Deterministic Forecast	0.119	0.089	0.100
Mean	0.131	0.126	0.128

Recent empirical work by Mark Wardman [43] indicates that the residual deviation from an SP model may be around 20% greater than that in a comparable RP model and the problems stemming from the scale factor problem may not be too severe. However, there is some conflicting evidence and there is no general agreement at the present time. Where possible, it may be worth combining RP and SP approaches to produce hybrid preference models. The approach to this would be as follows. Firstly, the utility weights are calculated for each alternative $_n$ from SP studies and combined with the attribute levels faced in practice, to produce utility terms U^{sp}_n. These are then rescaled with RP data on actual choices, as follows:

$$P_1 = \frac{\exp(\beta_0 + \beta_1 U_1^{sp})}{\sum_n \exp(\beta_0 + \beta_1 U_n^{sp})}$$

(11)

Wardman's work, admittedly in a non-rail context, produced parameter estimates (and t-statistics in brackets) for β_0 of 0.39 (4.69) and for β_1 of 1.18 (18.21).

Another way of combining RP and SP approaches has been explored in a recent study we have been involved in with consultants, Transportation Planning Associates, that examined Transpennine rail services. Here, an RP model was used to estimate parameter values of 'conventional' variables such as IVT, OVT, Cost, Frequency and Interchange, whilst an SP model was used to estimate the effects of 'softer' variables such as delay, overcrowding and different forms of rolling stock

3.4 STATED INTENTIONS APPROACHES

The conventional application of SP models is to apply them with information on the origin/destination of existing trips and aggregate, engineering times and costs. An example is the Walsall-Hednesford rail study [44]. A number of problems emerge here. The use of a disaggregate model with aggregate data will lead to biases (which might be reduced by using the incremental logit), whilst the engineering times and costs will be greatly affected by measurement error. Moreover, in many areas detailed information on current travel by car and bus does not exist and is very expensive to collect. An alternative that has been developed by the Institute for Transport Studies, in conjunction with Local Authorities, is to carry out a self-completion survey of the area where a new service is to be introduced in order to collect information on existing travel patterns as well as allowing respondents to state their intention of using the new service [45]. However, such SI data, unless adjusted, is prone to a number of systematic biases, which are likely to lead to gross overestimates of demand. These biases include:

(i) Self selectivity bias. In a self completion survey, rail users are more likely to return the survey form than non users. To adjust for this bias Heggie and Papoulias [46] propose that non respondents should be treated as non users of the new facility.

(ii) Non commitment bias. Respondents are not committed to behave in the way they have responded. This may be exacerbated by misperceptions. When respondents come to actually use the service they may find the timings inconvenient, the trains overcrowded or unreliable.

(iii) Policy response bias. Respondents may answer strategically in order to achieve the desired policy response (eg. get the new station opened).

Thus work by Couture and Dooley [30] showed that in the case of a new transit system in Danville, Illinois such a simplistic approach resulted in a ratio of intended to actual users of three to one. A study of South Wigston station (Leicestershire) indicated that assuming non respondents are non users reduces the bias but predicted usage was still between 38% and 73% higher than actual usage [47].

As a result, SP surveys are undertaken to assess the extent of these biases. For example, the SP survey of the Leicester-Burton rail service followed an SI survey in which 29,873 households were contacted, with 4,820 returned, representing a response rate of 16%. The socio-economic characteristics of this sample were compared with those of the population, as given by the 1981 Census, in order to ensure representativeness.

Table 14
Response Rate to Stated Intentions/Preference Surveys

		Questionnaires		Response Rate (%)	SI Over-estimate (%)
		Distributed	Returned		
Leicester-Burton	SI	29873	4820	16	29
	SP	1254	638	51	
Nottingham-Worksop	SI	58430	10214	17	54
	SP	2241	1132	51	
Leicester-Loughborough	SI	6313	1794	28	65
Clitheroe	SI	8500	555	7	90
	SP	262	139	53	
TOTAL	SI	103116	17383	17	49
	SP	3757	1909	51	

Table 14 shows that we have now applied this approach in four major studies; the three studies ([38] to [40]) mentioned at the beginning of section 3.3 and a fourth, a study of improved rail services between Leicester and Loughborough [48]. This fourth study was carried out as an extension to the Leicester-Burton study and as a result made use of the SP model developed in that study.

Table 14 shows that a typical response rate to the SI survey is 17%, although this can be exceeded in areas of high socio-economic status where the proposed rail service is perceived to be highly relevant (eg. the villages between Leicester and Loughborough). The response rate to the follow-up SP survey is much higher, being consistently above 50%, although this is from respondents who have indicated their willingness to take further part in the survey. Response rates can be boosted by offering prizes and sending out reminders but may also artificially stimulate interest in the new service and thus bias results.

On average, it is estimated that SI forecasts of rail usage are greater than SP forecasts by around 50% if non respondents are assumed to be non users. There is, however, considerable variation with car users particularly likely to overstate their demand. These findings on the accuracy of the SI approach are within the range found by Hockenhull, but recent work at Steeton and Silsden station (in West Yorkshire) suggests that the difference between SI and SP forecasts may be less acute [49]. However, this reflects a different set of circumstances. At the time of the South Wigston survey, no decision had been made as to whether a new station should be opened whilst at the time of the Steeton survey, the station was already under construction. The incentive to bias survey responses was therefore much greater in the former case than the latter. The SI/SP approach requires validation but the South

Wigston and Steeton studies do indicate that it can provide reasonably accurate forecasts if applied carefully.

3.5 OVERVIEW

We have shown in this section that a number of disaggregate approaches to forecasting the demand for new passenger rail services and stations. Although only different ends of a continuous spectrum, it has been shown that disaggregate approaches have a number of theoretical advantages over aggregate approaches. In particular, they are able to assess the effect of variables which are vital to the choice of public transport mode, such as walk and wait time, that exhibit little inter-zonal variation. It should, though, be noted that the disaggregate approaches, as developed, do have their limitations. In particular, they are based on logit models which have fixed coefficients and therefore can not take into account taste variation [59]. In theory, more mathematically advanced model forms such as multinomial probit can overcome this problem but, in practice, a more sensible approach might be to develop logit models that are segmented, for example, by income [29]. However, the main problems with disaggregate approaches emerge at the applications stage. Our forecasts are required at the aggregate level of a new service or a new station. If we can afford to collect information on a random sample of individuals in our population of interest (or, better still, such information already exists) then this is not a problem. However, in practice this is not often possible and we have to make some use of aggregate data in producing forecasts.

We have also shown that there are two main disaggregate approaches. RP approaches have the advantage of being firmly rooted in actual choice behaviour and are not affected by the 'scale factor' problem. However it should be noted that in RP models there is likely to be measurement error in the independent variables, due to mis-reporting of times and costs. Moreover, they have disadvantages of data and statistical inefficiency when compared to SP approaches. SP is particularly suited to examining the effect of new choice situations and of variables that do not contain much variation in current situations (eg. type of rolling stock on a particular service). However, an SP experiment needs to be designed very carefully, particularly so as to contain relevant boundary values, whilst in application care needs to be taken to ensure that non-traders are correctly represented. In forecasting with SP a particular problem emerges, that has been termed the scale-factor problem, which stems from the fact that there may be measurement error in the dependent variable ie. we are observing hypothetical rather than actual behaviour. However, there are a number of pragmatic ways around this problem. Furthermore, as with all disaggregate approaches, there may be practical difficulties in applying SP. A possible solution, which also allows generated trips to be considered, is to carry out an SI survey and then to design an SP experiment that may correct the biases inherent in such an approach.

Overall, the relative advantages of SP and RP approaches seem fairly balanced, and if resources are not a constraint it may be sensible to develop approaches that are a combination of the two. Of course, in most situations, resources are a constraint and in the next section, we shall go on to determine how to choose between RP and SP approaches.

Technical Appendix to Section Three:

3.1 The Extended Incremental Logit (EIL) Model

For the single market HL model given by Table 8, the EIL can be written as

$$P'_{PT} = \frac{P_{PT}\,[\,\exp(U'_{NT} - U_{XT}) + \exp(U'_{XT} - U_{XT})\,]^{\phi}}{P_{PT}\,[\,\exp(U'_{NT} - U_{XT}) + \exp(U'_{XT} - U_{XT})\,]^{\phi} + [1 - P_{PT}]} \qquad (1)$$

where

P'_{PT} (P_{PT}) =	Proportion choosing Public Transport in the after (before) situation
U' (U) =	utility measure in the after (before) situation
XT =	old Public Transport mode (bus)
NT =	new Public Transport mode (rail)
ϕ =	EMU (Logsum) parameter.

From Table 8

U_{XT} =	-0.132 * Wait Time -0.184 * Walk Time -0.092 * IVT - 0.044 * Cost
U'_{NT} =	-0.132 * Wait Time -0.184 * Walk Time -0.080 * IVT -0.044 * Cost
ϕ =	0.205

The lower split shares would then be

$$P'_{NT} = \frac{\exp(U'_{NT} - U_{XT})}{\exp(U'_{NT} - U_{XT}) + \exp(U'_{XT} - U_{XT})} \cdot P'_{PT} \qquad (2)$$

and

$$P'_{XT} = \frac{\exp\,(U'_{XT} - U_{XT})}{\exp\,(U'_{NT} - U_{XT}) + \exp\,(U'_{XT} - U_{XT})}\;.\;P'_{PT}$$

(3)

As, in most cases, we would assume no change in the utility of the existing Public Transport mode, exp ($U^{\vee}_{XT}$ - U_{XT}) simplifies to 1.

For completeness, and assuming no change in private transport utilities, private transport's share (denoted by subscript M) in the after situation may be defined as:

$$P'_{M} = \frac{P_{M}}{P_{PT}\,[\exp\,(U'_{NT} - U_{XT}) + \exp\,(U'_{XT} - U_{XT})\,]^{\phi} + [1 - P_{PT}]}$$

(4)

Alternatively, this can be written as:

$$P'_{M} = P_{M}\;\frac{1 - P'_{PT}}{1 - P_{PT}} \;=\; 1 - P'_{PT}$$

(5)

3.2 Example of a Stated Preference Questionnaire

In this final section we would like you to consider again your journey to Leicester but now you would also have the opportunity to travel by train. We would like to know how you would react if travel by bus and by train to Leicester was as described by the 16 situations listed on the following 2 pages.

In comparing the two methods of travel, you must assume that everything else besides the costs and times presented would be the same as for the journey you actually made, for example, you would still want to be at your final destination at the same time.

Train and Bus are described in terms of the following factors:-

(a) IN-VEHICLE TIME. This is the time, in minutes, actually spent on the train or bus.

(b) OUT-OF-VEHICLE TIME. This consists of the time, in minutes, spent getting to or from the bus or train and the time spent waiting.

(c) FARE. This is how much you would have to pay, in pence, for a single journey. Do NOT adjust these fares in order to take into account any travel cards etc. you may possess or other reductions you would be eligible for.

(d) THE NUMBER OF TRAINS AND BUSES PER HOUR (FREQUENCY). Buses would arrive in Leicester at the same times as at present. Trains may depart for Leicester, Mondays to Saturdays, every half hour, every hour and once every two hours, arriving at Leicester at the following times:-

Every half hour	Every hour	Once every two hours
6.45 am	6.45 am	6.45 am
7.15 am	7.45 am	8.45 am
7.45 am	8.45 am	10.45 am
8.15 am		12.45 pm
8.45 am	and then at 45 minutes past the hour	2.45 pm
		4.45 pm
and then at 15 and 45 minutes past the hour		6.45 pm
		8.45 pm
until	until	
	6.45 pm	
8.45 pm	7.45 pm	
9.15 pm	8.45 pm	

In each case the last train back from Leicester would be at 9.15 pm.

In the EXAMPLE below, if your choice would be to travel by bus then you would tick the box associated with bus as shown.

	In-vehicle time	Out-of-vehicle time	Fare	Frequency	Choice
Train	20 mins	15 mins	65 pence	1 train every 2 hours	[ ]
Bus	20 mins	5 mins	45 pence	As Now	[✓]

Now please consider the 16 different situations presented below and in each indicate which means of travel you would use. IT DOES NOT MATTER IF THE COSTS AND TIMES WE HAVE OFFERED YOU ARE VERY DIFFERENT FROM THOSE YOU WOULD NORMALLY FACE.

	In-vehicle time	Out-of-vehicle time	Fare	Frequency	Choice
Train	15 mins	10 mins	55 pence	1 train every 30 mins	[ ]
Bus	15 mins	10 mins	55 pence	As Now	[ ]
Train	15 mins	5 mins	45 pence	1 train every hour	[ ]
Bus	15 mins	10 mins	65 pence	As Now	[ ]
Train	20 mins	20 mins	65 pence	1 train every hour	[ ]
Bus	20 mins	10 mins	50 pence	As Now	[ ]
Train	20 mins	20 mins	70 pence	1 train every 2 hours	[ ]
Bus	20 mins	10 mins	40 pence	As Now	[ ]
Train	15 mins	20 mins	55 pence	1 train every hour	[ ]
Bus	20 mins	10 mins	55 pence	As Now	[ ]
Train	15 mins	20 mins	45 pence	1 train every 2 hours	[ ]
Bus	20 mins	10 mins	65 pence	As Now	[ ]
Train	20 mins	5 mins	65 pence	1 train every 30 mins	[ ]
Bus	25 mins	10 mins	50 pence	As Now	[ ]
Train	20 mins	10 mins	70 pence	1 train every hour	[ ]
Bus	25 mins	10 mins	40 pence	As Now	[ ]

Please turn over

	In-vehicle time	Out-of-vehicle time	Fare	Frequency	Choice
Train	15 mins	5 mins	55 pence	1 train every 2 hours	[ ]
Bus	25 mins	10 mins	55 pence	As Now	[ ]

Train	15 mins	10 mins	45 pence	1 train every hour	[ ]
Bus	25 mins	10 mins	65 pence	As Now	[ ]

Train	15 mins	20 mins	65 pence	1 train every hour	[ ]
Bus	25 mins	10 mins	50 pence	As Now	[ ]

Train	15 mins	20 mins	70 pence	1 train every 30 mins	[ ]
Bus	25 mins	10 mins	40 pence	As Now	[ ]

Train	15 mins	20 mins	55 pence	1 train every hour	[ ]
Bus	30 mins	10 mins	55 pence	As Now	[ ]

Train	15 mins	20 mins	45 pence	1 train every 30 mins	[ ]
Bus	30 mins	10 mins	65 pence	As Now	[ ]

Train	20 mins	10 mins	65 pence	1 train every 2 hours	[ ]
Bus	35 mins	10 mins	50 pence	As Now	[ ]

Train	20 mins	5 mins	70 pence	1 train every hour	[ ]
Bus	35 mins	10 mins	40 pence	As Now	[ ]

If you have any comments to make about this questionnaire, please write them in the space provided below.

THANK YOU FOR COMPLETING THIS QUESTIONNAIRE. WHEN YOU HAVE FINISHED PLEASE FOLD, PLACE IN THE ENVELOPE PROVIDED AND RETURN BY FREEPOST. NO STAMP IS REQUIRED.

SECTION FOUR

CHOOSING THE APPROPRIATE MODEL

4.1 INTRODUCTION

In this section we shall compare the different model forecasting approaches that have been developed. This will be done at three levels. Firstly, we shall compare some of the outputs of the different modelling approaches. Secondly, we shall assess the accuracy of the different forecasting approaches in terms of assessing demand. Thirdly, we shall assess the accuracy of the different forecasting approaches in terms of providing financial and social evaluation of new rail stations and services. Following this analysis, we shall suggest the most appropriate demand forecasting procedures for different forms of investment. This work will draw on a recent article in the Journal of Transport Economics and Policy [50] and two chapters to be published in forthcoming books [51, 52].

4.2 ASSESSING SPECIFIC MODEL OUTPUTS

Two specific outputs of our demand forecasting approaches can provide useful plausibility checks. These are:

(i) The value of time. This is the ratio of the rate of change of utility (or generalised cost) with respect to time to the rate of change of utility with respect to cost. Algebraically this may be written as:

$$VOT = \frac{(\delta U/\delta T)}{(\delta U/\delta C)} \tag{1}$$

For the typical, linear, additive utility function U = a + bT + cC, VOT is simply the ratio of the time parameter value to the cost parameter value b/c, although for non linear functions the mathematics becomes more complex.

(ii) Rail's elasticity of demand with respect to price. This is the ratio of the proportionate change in demand to the proportionate change in price:

$$Ep = \left[\frac{\Delta Q/Q}{\Delta P/P}\right] \tag{2}$$

Assuming infinitely small changes in P (and hence Q) and rearranging we obtain the point elasticity formula:

$$Ep = \frac{\delta Q}{\delta P} \cdot \frac{P}{Q} \tag{3}$$

For a simple model:

$$\begin{gathered} Q = aP^{b} \text{ or} \\ \log_e Q = \log_e a + b \log_e P \\ Ep = b \end{gathered} \tag{4}$$

This is a constant elasticity model. For the semi log model:

$$\begin{gathered} Q = a \exp (bP) \text{ or} \\ \log_e Q = \log_e a + bP \\ Ep = bP \end{gathered} \tag{5}$$

For the MNL model:

$$Ep = (1-Pr)\ \beta P \tag{6}$$

Where

Pr = probability of choosing rail

P = rail price

ß = rail price parameter value.

This needs to be calculated for each individual and a weighted average (based on Pr) calculated.

For the HL the estimation of **Ep** is more complicated, but the formula is given in some texts [53], [54].

Table 15 compares the results of the different modelling approaches in seven studies carried out by ITS with respect to these two outputs. It should be evident that we are not comparing like with like but, nonetheless, some interesting results emerge. We have not been able to estimate values of time from the aggregate models, because correlation between time and cost leads to implausible and statistically insignificant results. When developing generalised cost measures to be used in these aggregate models we need to 'import' values from other studies. The five disaggregate studies show a uniformly low value of time (mean 2.2 pence per minute), although there is some indication of higher values for work trips. These values of rail time are for the choice between bus and train. For the choice between car and train, the values are slightly higher (by about 35% for the three SP studies).

The results in terms of rail's demand elasticity with respect to price are much less consistent. The lowest (absolute) results are achieved by the two disaggregate RP studies undertaken in West Yorkshire, with a mean fare elasticity of -0.3. However, in the first study, undertaken in 1981, only work trips were examined and there is considerable evidence that these trips are less elastic than non work trips [55]. The second study was undertaken at a time of low rail fares, particularly in the off-peak and there is evidence that demand is less elastic at low fares than high fares [22]. In both cases, generated travel was not considered which will deflate the absolute level of the elasticities.

Table 15
Comparison of Rail Fare Elasticities and Values of Rail In-Vehicle Time
(pence per minute, mid 1990 prices)

Area	Type of Model	Value of Time	Fare Elasticity
West Yorkshire: 39 stations, 1981	Aggregate: Direct Demand	N/A	-0.83
Greater Manchester: 33 stations	Aggregate: Trip End	N/A	-0.66
West Yorkshire: 3 corridors, 1981	Disaggregate: RP (work only)	3.0	-0.34
West Yorkshire: 2 corridors, 1990	Disaggregate: RP	2.8	-0.26
Leicestershire	Disaggregate: SP	1.9	-1.51
Nottinghamshire	Disaggregate: SP	1.1 to 1.9	-1.99
Lancashire	Disaggregate: SP	2.3	-0.70
N/A = Not Applicable			

By contrast, very high rail price elasticities were achieved by the two SP studies carried out in the East Midlands, with a mean of -1.75. However, these were arc elasticities based on a 10% increase in rail fares in a situation where rail was already presumed to be 10% more expensive than bus. Because of the scale factor problem, point elasticities were likely to be biased but, unfortunately, in such a way that, if rectified, they would produce even higher absolute values. Furthermore, like the RP models, generated trips were not considered. However, unlike the RP models, all respondents to the SP survey currently travelled by an alternative mode to rail and it seems that the effects of habit and inertia were not properly represented. In particular, it was believed that our surveys under-represented non traders ie people who would not switch modes at any (reasonable) price. In part, this may be because in the SP experiments we present such variation in times and costs that people feel duty bound to trade but in practice such wide variations are unlikely to occur and they will be non traders. We attempted to rectify this in our SP survey at Clitheroe, with some apparent success, as a price elasticity of around -0.7 was produced when non traders were taken into account, compared to -1.3 when non traders were excluded. These results were more in line with those achieved in Greater Manchester and West Yorkshire by aggregate constant elasticity models, with the mean of our three most plausible elasticity results being -0.73 (compared to a mean of -0.90 for all seven results).

4.3 ASSESSING MODEL ACCURACY IN FORECASTING DEMAND

The accuracy of four different RP forecasting methods (both aggregate and disaggregate) were tested for six new stations in West Yorkshire.

(i) The West Yorkshire TRM, as given by Table 4. This is given by column A.

(ii) The ASM as given by model 1, Table 6. This is given by column B.

(iii) The HL/MNL model (Table 7), aggregated by SE. This method produces forecast for work trips only. Non work trips are estimated by model 3, Table 6. This is given by column C.

(iv) The HL model (Table 8), aggregated by EIL. Non work trips are again estimated by model 3, Table 6. This is given by column D.

Table 16 shows that the TRM produces a forecast that is, on average, within 42% of initial usage, with a RMSE of 71 trips. It is, however, only a very simplistic approach and is only presented here as a counter point to the more sophisticated approaches that have been developed. Of the three remaining approaches the most accurate, at least initially, is the HL/MNL model, which gives predictions, on average, around 34% of initial usage. It was estimated that the aggregate non work model contributed 75% of this forecasting error. By contrast, the HL model gives predictions within 54% of initial usage, with a RMSE of around 97 trips. This approach is only slightly more accurate than the ASM which gave predictions some 63% above initial usage, with a RMSE of around 108 trips.

Table 16 Forecasted Weekday Usage at New Stations (Initial Usage Indexed as 1.0)						
			Aggregate		Disaggregate or hybrid	
			A	B	C	D
	2nd year usage	3rd year usage	TRM	ASM	MNL/ HL with SE	HL with EIL
Fitzwilliam	1.56	1.75	1.39	1.31	-	1.84
Deighton	1.98	1.91	1.76	2.72	1.28	1.98
Crossflatts	1.52	1.63	0.80	2.32	1.48	2.03
Slaithwaite	0.73	1.11	0.67	1.22	1.05	0.92
Bramley	0.89	0.86	1.47	1.35	1.71	1.75
Saltaire	1.25	1.48	0.58	1.49	0.99	1.11
RMSE:						
Initial usage			71.3	108.3	78.6	96.9
Second year usage				73.5	93.9	85.8
Third year usage				64.9	105.8	93.6
AD:						
Initial usage			0.422	0.630	0.343	0.540
Second year usage				0.377	0.371	0.312
Third year usage				0.259	0.370	0.316

RMSE (Root Mean Square Error) = $\sqrt{\Sigma (F-A)^2/n}$

where F = Forecast new station daily usage (ons plus offs)
A = Actual new station daily usage
n = Number of observations

AD (Absolute Deviation) = $\Sigma|F-A|/\Sigma A$

With the exception of the TRM (which was based on first year usage), the models examined in Table 16 are forms of equilibrium models. From count data, it is apparent that new station usage has been growing in absolute terms. However, this is against a background of increasing rail usage in West Yorkshire, as between 1982 and 1986 demand at 38 existing local stations increased by 48%. In Table 16, second and third year usage figures at six new stations are expressed in relation to the overall increase in demand for rail services as a whole. It can be seen that, with the exception of one station, over the first three years demand has grown at a faster rate than that of the network as a whole. Initially, this trend was extrapolated over five years, with the result that demand in year 5 was estimated to be 75% greater than that in year 1. However, later work suggests that real growth at new stations only occurs in the first three years, with usage in year 3 being 35% higher than that in year 1 [18]. Table 16 shows that if these dynamics are taken into account the accuracy of the three equilibrium models, at least as measured by the AD, is broadly comparable in year 2, but by year 3 the ASM appears to be the most accurate, with the forecast being, on average, within 26% of actual usage. The comparable figures for the MNL/HL and the HL models are 37% and 32% respectively. The ASM's better performance over time is possibly due to its ability to incorporate generated trips, particularly for work journeys.

In the study of the new rail service between Leicester and Burton-on-Trent it was possible to compare aggregate RP techniques with disaggregate SI/SP approaches. However, it is not possible to compare the accuracy of these different services as the rail service has not yet opened. The approaches compared were:

(i) The ASM, again based on model 1, Table 6, but adjusted in the light of findings at South Wigston where it was found the ASM underpredicted demand by 58%.

(ii) The TRM for South Wigston, as given by Table 4.

(iii) The results of the SI survey, assuming that non respondents are non users.

(iv) The results of the SI survey, amended in the light of the SP experiment. This was done by using the SP models in Table 11 with reported time and cost data to predict individuals' mode choice. This was then compared with what individuals said they would do in the SI survey.

Table 17
Comparison of Forecasting Methods for a New Rail Service between Leicester and Burton on Trent
(Indexed)

ASM	TRM		SI survey adjusted by SP		
	S. Wigston	SI Survey	DF	PF	Mean
1.00	1.49	3.07	1.86	2.88	2.38

DF = Deterministic Forecast, PF = Probabilistic Forecast

The methods are compared in Table 17. It can be seen that the lowest demand forecasts are provided by the ASM. In part, this reflects problems with transferability, particularly with respect to the measure of attractiveness of destinations. It may also reflect that a model calibrated for existing rail services may not be appropriate for a new service. The main problem is that the model was calibrated for stations serving small towns, suburbs and rural areas. This is reflected by the fact that catchment areas are specified as being highly localised. In reality, catchment area size will vary from site to site rather than be fixed. The assumption of localised catchment areas is appropriate for new stations on existing services as all medium/large communities can be expected to already have stations. However, new stations on new services may well serve medium to large freestanding towns. Experience in validating the ASM in West Yorkshire suggests that the model will underpredict usage from such sites.

Compared to the ASM, the South Wigston TRM predicts usage of the service to be 49% higher. As expected, the SI survey indicated that usage would be high, being almost three times the level predicted by the ASM. However, the SP models did suggest that demand would be lower. Based on the mean of the probabilistic and deterministic forecasts, usage from the SP models was estimated as being between 61% and 94%

of that given by the SI survey. If this pattern is repeated for all 18 intermediate stations on the line rather than just the 6 sites that were included in the SP survey, then usage is estimated as being more than double that forecast by the ASM.

In Table 18, in order to assess the accuracy of our disaggregate approaches, we have converted the four main studies of new services we have undertaken into trip rates, based on the catchment area 0 to 2 kilometres (and beyond in some instances). The bottom of the right hand column shows that we forecast a mean rate of 24 daily rail trips per thousand population, with a standard deviation of over 6. This is similar to the mean trip rate estimated for four schemes that have already gone ahead, where the mean trip rate is 20 per thousand population and the standard deviation is again 6 plus (although there may be still scope for growth over time for some of these schemes). Given the extent of systematic biases, we were concerned that our SI/SP approach may be still over-estimating demand but the evidence in Table 18 indicates that this may not necessarily be the case. Indeed, our highest forecast trip rates are provided by the RP predictions for Brighouse-Elland.

Table 18 Daily Trip Rates per Thousand Population (0-2km approximately)			
	New stations/ services already opened		New stations/ services yet to be opened
West Yorkshire - 9 new stations	19.4	Nottingham - Worksop	18.6
Walsall - Hednesford	12.3	Moira - Barrow-u-Soar	28.7
Edinburgh - Bathgate	29.9	Clitheroe	16.9
Aberdare	18.8	Brighouse/Elland	32.3
Mean	20.1	Mean	24.1
Standard Deviation	6.3	Standard Deviation	6.5
Source: [56]			

In considering comprehensive new services, additional trips of 1,000 per day appears to be an important threshold. On average, Table 18 suggests that a catchment area population of up to 50,000 would be required to sustain such a level of usage. This gives a crude indication of the size of community (or communities) that might be able to sustain a new service.

We are unable to estimate precisely the relative accuracy of the different forecasting approaches, the evidence presented in Tables 4, 15 and 18 give some broad indications. Based on twice the standard deviation of the sample mean, Table 19 shows the rounded confidence limits (approximately at the 95% level) that might be attached to each of the methods we have developed.

Table 19 **Confidence Limits for Each of the Forecasting Methods Developed**		
	Initial usage	'Equilibrium' year usage
TRM	±35%	±50%
Trip End		±30%
ASM	±50%	±20% *
MNL/HL with SE	±30%	±30% *
HL with EIL	±45%	±25% *
SI/SP		±30%

* Third year usage

In Figure Two, we represent these results graphically. Excluding the results from the TRM (which are affected by a degree of circularity in that the model was calibrated on a sub-set of the stations it was applied to), there does appear to be a trade-off between accuracy and cost, at least for forecasting first year demand. Cost here is based, very crudely, on the amount of research time we spent in developing each type of model. The more expensive modelling approaches do seem to give the most accurate forecasts, although it is difficult to put an exact cost to each modelling approach. It should be noted that the MNL/HL and HL approaches are not completely disaggregate, a direct demand model was used to forecast non-work trips. The MNL/HL approach was more accurate when just forecasting work trips. Comparable confidence intervals in this instance were around ± 15%.

In the case of third year (= equilibrium level) usage there appears to be a U-shaped relationship between accuracy and cost. Initially, as cost increases, so does accuracy, culminating in the ASM giving an accuracy of around ± 20%. However, as cost increases further, accuracy decreases slightly to be only between ± 30%. This may be because the MNL/HL and HL approaches can not take into account 'generated' work journeys (in fact, more likely to be relocations of home and/or workplace).

Figure Three gives a more theoretical representation. As model complexity increases (and this may be expected to be closely paralleled by costs), specification error is likely to decrease as more explanatory variables are taken into account. However, measurement error may be expected to increase as the models' data input requirements increase. Thus total error will at first decrease with complexity, but can then increase, resulting in a U-shaped curve. Given the very broad confidence levels at which we are working, we would be unable to identify a specific point at which the optimal level of accuracy was reached. What we might be able to detect is a broad range at which the accuracy of the different methods, in terms of forecasting patronage, is similar. In other words, we might expect our U-shaped curve to have a flat bottom. In normal circumstances, we would choose the least costly approach. However, this assumes that we are only interested in forecasting demand but in the next sub-section we go on to show that this may not be the case.

Figure Two: Graphical Representation of the Accuracy/Cost Trade-Off

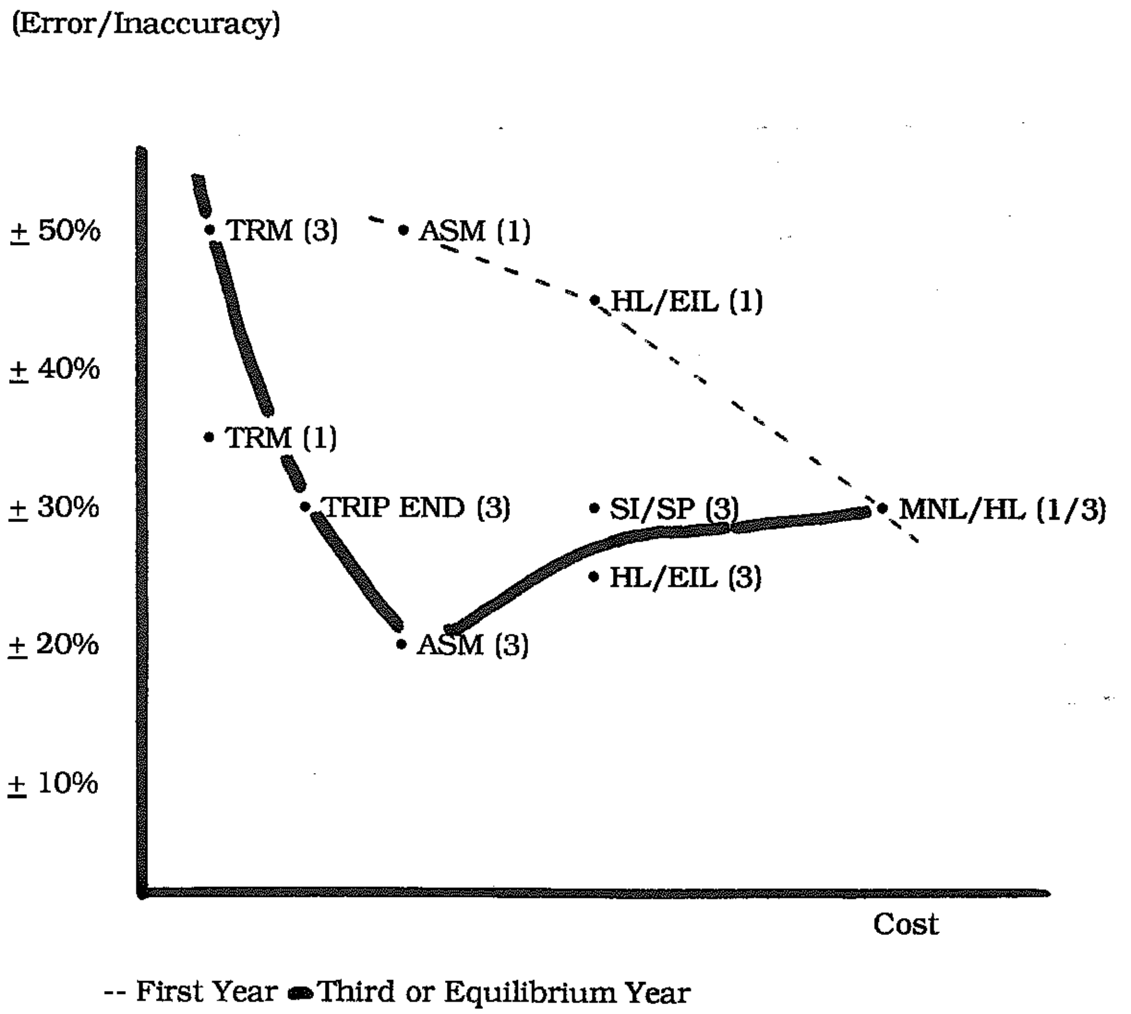
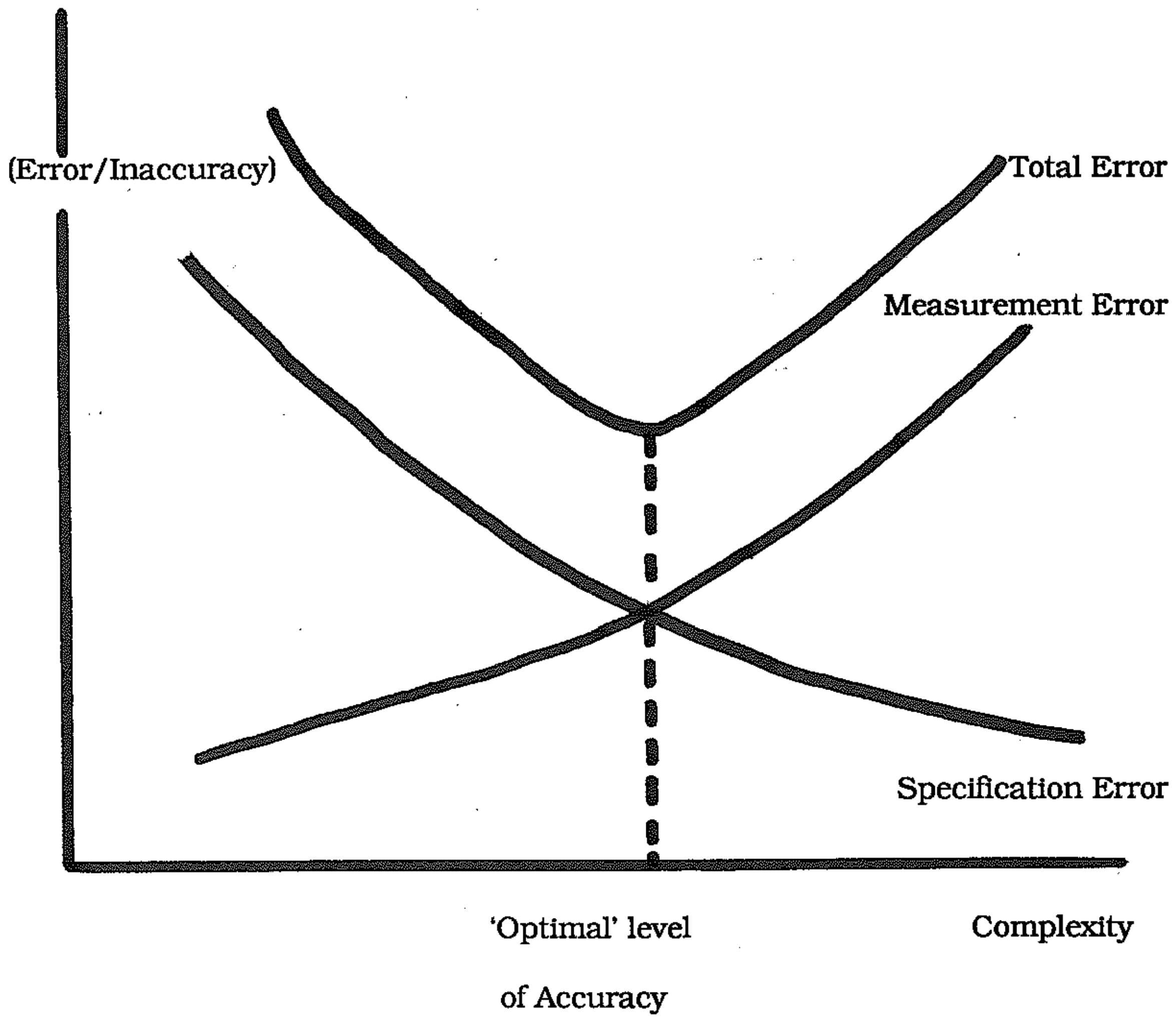


Figure Three: Theoretical Representation of the Accuracy/Cost Trade-Off



4.4 ASSESSING MODEL ACCURACY IN EVALUATING DEMAND

Throughout most of this work we have implicitly assumed that the likely level of usage of a new station or service is the key determinant in deciding whether such new schemes should go ahead. That, in practice, this is not likely to be the case is illustrated by Table 20.

Table 20
Ranking of Six New Stations in West Yorkshire based on Various Criteria

	Demand (Base)	Gross Revenue	Financial Appraisal - Rail only	Financial Appraisal - Rail and Bus	Social Cost-Benefit Analysis
Fitzwilliam	6	5	5	3	1
Deighton	5	4	4	2	2
Crossflatts	4	1	2	1	4
Slaithwaite	3	6	6	4	3
Bramley	2	3	1	6	6
Saltaire	1	2	3	5	5
Mean Difference from Base	-	1.67	1.67	3.0	2.67
Note: 1 = best 6 = worst					

This Table shows that the ranking of the first six new stations to be opened in West Yorkshire changes depending on the criterion on which they are assessed. The first column ranks stations in terms of daily ons and offs after the first year of opening. The second column ranks stations in terms of gross revenue. The differences may be considered similar to those of comparing passengers with passenger miles, given that the rail fare scale has a distance-related element. In the third comparison, a financial appraisal is undertaken in which it is assumed that the PTE only has direct responsibility for rail services (the current position). An NPV was calculated based on net rail revenue, capital and recurrent costs. There are only slight changes in rankings compared to the gross revenue figures. However, in the fourth comparison, it is assumed that the PTE has direct responsibility for both bus and rail services (the pre 1985 Transport Act) position. Rather than net rail revenue, only net public transport revenue is considered. It can be seen that the rankings of the stations changes dramatically. Moreover, in general it appeared that the NPVs in the third column were greater than those in the fourth, suggesting that, somewhat perversely, deregulation may have further encouraged development of local rail services. Lastly, in the fifth column a social cost-benefit analysis was undertaken. In addition to net public transport revenue, benefits included user benefits, in terms of time and cost savings to new station users (although often offset by time penalties suffered by existing users), and non-user benefits, in terms of congestion relief and accident reductions. It can be seen that the rankings do not change too drastically from that of the financial appraisal of column 4. However, in general (but not always), the absolute value of the NPV tends to increase, strengthening the case for new stations. For example, for the six new stations as a whole, moving from a financial appraisal to the rail and bus operator to a social cost-benefit analysis increased the NPV from £28k (at 1986 prices) to £179k. By contrast, a financial appraisal that only includes the rail operator gave an NPV of £1597k [11].

In terms of the models' performances with respect to these additional dimensions, the following comments can be made. The TRM can only give an estimate of total usage, but it can not tell you where people are travelling to and hence can not give estimates of gross revenue. The ASM does tell you what the main destinations are and hence can estimate gross revenue but it does not tell you where patronage is coming from (ie whether it is abstracted or generated) and hence can not give estimates of net revenue or user benefit. Thus, for either financial appraisal or social cost-benefit analysis, disaggregate approaches are required. Even then, if they are applied in aggregate, for example using the EIL, estimation of user benefit is more problematical, although still achievable. A major weakness of the disaggregate approaches, as developed, is that they focus solely on mode choice. In principle, there is no reason why disaggregate trip generation models can not be developed. In practice, this has proved difficult to achieve. However, in the study of a new rail service for Brighouse and Elland [33], we were able to develop an aggregate trip generation model which took the following form (t-statistics in brackets):

$$\%GEN = \underset{(1.900)}{6.882} + \underset{(1.612)}{0.071}\ \Delta GCOST + \underset{(4.014)}{18.233}\ SAT \quad R^2\ 0.67 \quad \bar{R}^2\ 0.61$$

where % GEN = percentage of total new station usage that is generated

ΔGCOST = reduction in mean generalised cost as a result of introducing the new rail service

SAT = dummy variable for Saturdays.

This model was calibrated for 14 observations for stations in South and West Yorkshire. This model indicates that on a weekday a minimum of 7% of rail traffic is generated, with this figure increasing to 25% on a Saturday. The percentage of generated travel is then estimated to increase by one percentage point for each 14 pence increase in the difference between the generalised cost of travel by the previous mode and the generalised cost of travel by rail.

4.5 CONCLUDING REMARKS

Given Britain's rapidly changing demography, there will always be a case for some new rail stations and services (and, indeed, in some instances station closures and service withdrawals). A starting point should be a systematic review of new stations and service potential. An example is illustrated by Figure Four. The starting point is to take the existing passenger rail network in a specific area such as West Yorkshire. One might also wish to add freight only lines such as the Brighouse/ Elland, Spen Valley (South) and Featherstone lines (as well as the Roses Link line), and former track alignments in which right of way has been preserved such as Spen Valley (North), the Scholes and South Garforth spurs. In our initial work in the mid 1980s these were not considered viable policy options; changing socio-politics may be as important as changing geo-demographics. Potential new station sites were identified by excluding those section of track:

(1) Which are 1 mile (1.6km) within an existing station on the same line. This is based on our finding that the majority of new local station demand comes from within 800 metres.

(2) Which are affected by engineering constraints such as tunnels, deep embankments etc.

(3) Which are affected by capacity constraints. In the mid-1980s sites to the immediate east of Leeds City Station were excluded. Today, sites to the west of City Station and on the East Coast Main line close to Leeds City Station might also be excluded (eg. Armley and Beeston).

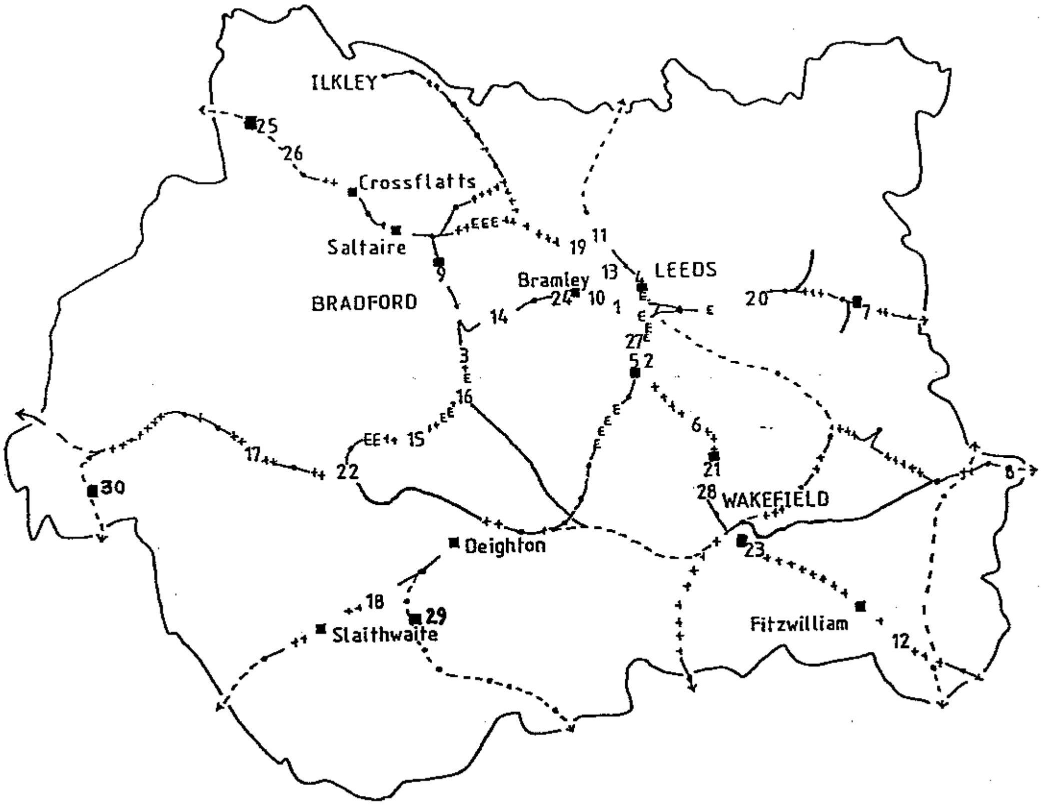
(4) Which serve non-built up areas. Initially, this was based on visual inspection of OS maps. Subsequently, based on Table 2, a minimum population of 800

within 800 metres was stipulated. Two sites (East Ardsley and Luddendenfoot), failed this test. Geo-demographic information systems may be particularly useful in performing this task.

(5) Exclude those sections of track not supported by Section 20 or likely to have support withdrawn. This was relaxed in two instances (west of Keighley and east of Knottingley). Subsequently, it has been relaxed in two further cases, the Huddersfield-Sheffield line and south of Todmorden.

In our initial work 28 sites were evaluated, although retrospectively this ought to have been 24. However, given changes in rail policy an additional 19 sites might have been considered. Of the 28 sites initially considered, our work recommended, on the basis of social cost-benefit, 10 sites to be developed. Subsequently, West Yorkshire PTE have opened 9 sites. However, only 3 of these were on our list of 10.

Figure Four



KEY

- • existing station
- ▮ new station opened 1982-84
- section within 1 mile of existing station
- --- section not financially supported by the PTE, or support likely to be withdrawn
- +++ section alongside non built up area
- EEE section affected by engineering constraints
- — proposed passenger service on new track or freight line

Potential stations:

1. Armley 2. Beeston 3. Bowling 4. Burley 5. Cottingley
6. East Ardsley 7. East Garforth 8. East Knottingley 9. Frizinghall
10. Gamble Hill 11. Hawksworth 12. Hemsworth 13. Kirkstall
14. Laisterdyke 15. Lightcliffe 16. Low Moor 17. Luddendenfoot
18. Milnsbridge 19. Newlay 20. Osmondthorpe 21. Outwood
22. Salter Hebble 23. Sandal 24. Stanningley 25. Steeton 26. Utley
27. Wortley 28. Wrenthorpe 29. Berry Brow 30. Walsden

Once the number of new stations to be investigated further has been identified, it is then necessary to decide what demand forecasting approach to apply. For the three levels of investment identified in section 1.4 we would suggest the following:

(i) For one-off new stations, forecasting might be based on a trip rate model, preferably locally calibrated. If there is no suitable existing local station then either transfer a trip rate or direct demand model from elsewhere and/or undertake a Stated Intentions survey, but checking the possible bias by using either an existing RP or SP mode choice model.

(ii) For packages of new stations, develop a direct demand model for existing local stations and apply to predict the usage of potential new stations. For the 'best' sites, develop an SP mode choice model and apply in conjunction with existing origin/destination information to determine the extent of mode switching. This is an approach we are currently developing for Lancashire County Council. Where a network of local rail stations does not exist, reliance would have to be put on SP or 'imported' RP approaches.

(iii) For major new services, requiring Section 56 grant, disaggregate approaches are required. Where possible these should be based on RP models, although supplemented by SP data to improve data and statistical efficiency. In many cases where rail represents a new service to the area or incorporates radically new features, it will be necessary to rely solely on SP data. Ideally, the resultant model would be applied with disaggregate time and cost information (the 'sample enumeration' approach) but more usually use will be made of aggregate engineering or Stated Intentions data. It is important to ensure that the modelling approach adequately deals with generated trips. Where possible, some checks with RP data should be made even if this only involves comparisons at a very broad level [56].

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ACKNOWLEDGEMENT

The research into new stations and services has been a team effort. The work was initiated by Chris Nash and the principal researcher has been John Preston. The work started as an SERC research studentship and has continued with an ESRC grant and over a dozen research contracts. A number of people have worked on these projects including Tony Fowkes, Mark Wardman, Ken Mason, Eileen Hill and Dave Aldridge. In addition, Masters students Glyn Hockenhull, Andy Clarke, Alan Peakall and David Taylor provided useful work in their dissertations.