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Railway Station Choice Modelling: A Review of Methods and Evidence

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Since the first railway station choice studies of the 1970s, a substantial body of research on the topic has been completed, primarily in North America, the UK and the Netherlands. With many countries seeing sustained growth in rail passenger numbers, which is forecast to continue, station choice models have an important role to play in assessing proposals for new stations or service changes. This paper reviews the modelling approaches adopted, the factors found to influence station choice, and the application of models to real-world demand forecasting scenarios. A consensus has formed around using the closed-form multinomial logit and nested logit models, with limited use of more advanced simulation-based models, and the direction effects of a range of factors have been consistently reported. However, there are questions over the validity of applying non-spatial discrete choice models to a context where spatial correlation will be present, in particular with regard to the models' ability to adequately represent the abstraction behaviours resulting from competition between stations. Furthermore, there has been limited progress towards developing a methodology to integrate a station choice element into the aggregate models typically used to forecast passenger demand for new stations.

Keywords: railway station choice; demand forecasting

1. Introduction

The continued and substantial growth in passenger rail travel in many countries (Amadeus, 2013) means that rail service planning remains an important issue for transport planners and policy-makers. In order to predict the full impacts of opening or closing railway stations, or substantially modifying services, it is necessary to understand the mechanisms behind passengers' station choice decisions. The extent to which station and service changes lead to passengers switching from one station to another can have a crucial impact on the business case for these changes. It is not sufficient to simply forecast the number of passengers who would use a new station or service, as traffic abstracted from another station will usually contribute much less additional revenue to the operator (and generate lower levels of societal benefits) than traffic newly generated or abstracted from a competing transport mode. In order to make a significant contribution to the wider transport planning process, station choice models therefore need the ability to forecast the impacts on travel demand of changes to stations and service patterns, and not be limited to identifying how a range of factors influence choice and explain current travel behaviour.

The need to understand and predict station choice decisions has resulted in a substantial body of research on this topic, but there has been little progress towards synthesising the results to establish a consensus on the most appropriate modelling method. This paper aims to fill this gap by conducting a comprehensive review of previous research, comparing methods used and factors included in the models. It also considers how station choice models have been incorporated into more general passenger demand forecasting methods, as well as identifying priorities for future research aimed at developing a transferable and integrated approach which can be used to inform planning decisions in a range of contexts.

2. A Brief History of Station Choice Modelling

The earliest station choice research dates back to the mid-1970s in North America. Liou and Talvitie (1974) modelled access mode and station choice on the Illinois Central Railroad using a sequential multinomial logit approach which pre-dated the formal definition of the nested logit (NL) model, and Desfor (1975) used binary probit to explore choice between station pairs on a commuter line into Philadelphia.

No further work has been found until Harata & Ohta (1986) modelled main travel mode, access mode and station choice before and after the opening of a new station near Tokyo. This appears to be the first study to implement the NL model, which was adopted in several subsequent joint access mode and station choice studies (Davidson & Yang, 1999; Debrezion, Pels, & Rietveld, 2009; Fan, Miller, & Badoe, 1993; Givoni & Rietveld, 2014), while the multinomial logit (MNL) model has been used to model station choice alone (Adcock, 1997; Blainey & Evens, 2011; Debrezion, Pels, & Rietveld, 2007a; Kastrenakes, 1988; Mahmoud, Eng, & Shalaby, 2014).

Lythgoe and Wardman (2002) extended a direct-demand model for parkway stations to include a station choice element using NL and later enhanced this using cross-nested logit (Lythgoe, Wardman, & Toner, 2004). More recently a latent segmentation approach has been used to model access mode and station choice (Chakour & Eluru, 2014), and station choice under parking search time uncertainty has been modelled using mixed logit (ML) (Chen et al., 2015).

In addition to academic research, models have been developed for use in central or local government transport models and as part of specific rail development proposals. Examples in the UK include: a binary logit model for West Coast Main Line track access assessment (MVA Consultancy, 2011); an MNL model to assess the demand for HS2 (Atkins Limited, 2011); and incorporating a station choice element into regional transport models (Fox, 2005; Fox, Daly, Patruni & Milthorpe, 2011). A summary of prior station choice research is given in Table 1.

3. Application of Discrete Choice Models

The station choice studies above share a common approach: they utilise discrete choice models based on random utility theory. In these models an individual is assumed to choose the one alternative, from a group of alternatives known as the choice set, that maximises their utility. The researcher attempts to measure utility by identifying attributes of the alternatives and/or the individual. That part of utility that the researcher cannot measure, the unobserved utility, is treated as a random component. The utility that an individual derives from an alternative can be expressed using the following formula:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

where U_{ni} is the utility for individual n of alternative *i*, V_{ni} is the utility measured by the researcher, and ε_{ni} is unobserved utility. In practice *V*, which is known as representative utility, will be a function (usually linear additive in form) consisting of the selected attributes and their respective parameters. The parameters, if unknown, are obtained statistically, for example by maximum likelihood estimation. As part of utility is unobserved it is not possible to say for certain what alternative an individual will choose, it is not deterministic. Instead, the *probability* of an alternative being chosen is calculated.

3.1 Binomial and Multinomial Logit

The simplest discrete choice model, used when there are only two alternatives, is binomial logit. It was applied in a British study carried out for the Office of Rail Regulation to assess applications made by open access operators to provide 'secondary' stations with new direct services to major destinations such as London, potentially competing with 'primary' stations already offering direct services. Pairs of primary and secondary stations were identified and binomial logit models used to forecast the proportion of passengers choosing each station under different fare structures (MVA Consultancy, 2011).

However, most station choice studies have used larger choice sets, with many applying the MNL model which is suitable for any number of alternatives. The earliest was Kastrenakes (1988) who developed a model for New Jersey Transit that forecast the proportion of travellers from each minor civil division using each station in that division's observed choice set. The most ambitious study in terms of dataset size, with some 230,000 trip observations from the UK mainline network and London Underground, sought to develop a station choice model to incorporate into the UK rail industry demand model, MOIRA, although no progress beyond this preliminary work has been publicly reported (Adcock, 1997). In the Netherlands, Debrezion et al. (2007a) developed three models based on different approaches to defining the utility function (see Section 4.2); and in Canada the station choice of park and ride commuters taking cross-regional trips in the Greater Toronto and Hamilton area was investigated, with separate models calibrated for three market segments (Mahmoud et al., 2014).

The key assumptions that underlie the MNL model are that the unobserved components of utility of the alternatives are independent of each other and have an identical (Gumbel) distribution (IIGD). As a consequence, it exhibits the independence from irrelevant alternatives (IIA) property which means that the ratio of probabilities for any two alternatives, and therefore the odds of choosing one alternative over another, remain the same irrespective of other alternatives or their attributes (Train, 2009). This results in proportional substitution behaviour where, for example, the addition of a new alternative to a choice set will reduce the probabilities of all the existing alternatives by the same percentage. This is a key weakness of MNL models, as such behaviour is unlikely to be exhibited in reality, where new alternatives are more likely to abstract users from alternatives which are similar to them.

3.2 Nested Logit

The NL model relaxes these assumptions by grouping together alternatives that are a-priori thought to have unobserved factors of utility that are correlated, into sets known as nests. The theoretical basis of the model is that each pair of alternatives in a nest has the same correlation of unobserved factors, but there is no correlation between pairs of alternatives in different nests. Each nest exhibits IIA, but IIA is relaxed between nests (Train, 2009). The NL model can be thought of as two modelling steps[1]. At the upper level, the model predicts the marginal probability of an individual choosing a particular nest, and at the lower level the model predicts the probability of choosing an alternative within a nest, conditional on that nest being chosen.

Station choice studies have predominantly chosen a two-level model with access mode at the upper level and station choice at the lower level (Davidson & Yang, 1999; Debrezion et al., 2009; Fan et al., 1993; Givoni & Rietveld, 2014). Models with station choice at the upper level have either not been consistent with random utility theory (Debrezion, Pels, & Rietveld, 2007b; Fan et al., 1993) or collapsed to the standard MNL model (Wardman & Whelan, 1999). Nesting by access mode results in improved models compared with MNL, presumably as correlations between unobserved factors common to each mode can be accounted for, resulting in better fitting models and less biased coefficients. This is confirmed by studies which have reported inclusive value (IV) parameters[2] that lie between 0 and 1, indicating that correlation exists and the nest structure is consistent with RUM. As shown in Table 2, the correlations are in the moderate to low range.

It should be noted that the NL model does not impose any behavioural assumptions about the decision order, it is merely a mathematical construct to relax assumptions in a specific manner (see, for example, Hensher, Rose, and Greene (2005); Koppelman and Bhat (2006); Preston (1991)). It is not uncommon for researchers to misunderstand this. For example, Chakour and Eluru (2014) state that the NL model "imposes a hierarchy that is very hard to validate in the dataset" and seek to overcome this by developing a latent segmentation model where there are assumed to be two decision sequences (or segments) - either station choice first or access mode choice first - and observations are split between the segments using a binary logit model. The implicit assumption is that individuals make a choice, based on utility maximization, of the order in which they are going to make a choice of access mode and station choice. The authors describe this as "behaviourally representative", but do not present any evidence that this reflects actual behaviour. They adopted a model that considered whether household residence is decided before or after choice of workplace (Waddell et al., 2007). It is clearer in this instance that an individual may weigh-up the utility arising from the order in which these two decisions are made, whereas in the station choice context individuals might be expected to consider choice of station and access mode simultaneously (and indeed to treat them as a single choice decision).

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[1] Assuming a two-level NL.

[2] The IV parameter represents the degree to which unobserved factors are correlated and alternatives in a nest are substitutes for one another.

3.3 The Spatial Choice Problem

Consider a scenario where there is a choice between three stations as shown in Figure 1(a), where the probability of an individual from origin O choosing one of two nearby stations A or B is 0.4 and of choosing more distant station C is 0.2. Assuming that A and B are near perfect substitutes for each other, if B was closed the probability of choosing A would be expected to increase to 0.8, with the probability of choosing C unchanged, as shown in Figure 1(b). However, an MNL model would allocate station B's probability proportionately between stations A and C resulting in the probability of choosing C rising from 0.2 to 0.33, as shown in Figure 1(c). In this example, the unobserved utilities of A and B are highly correlated due to their location in space; they exhibit spatial autocorrelation (SAC). If an NL model was constructed to limit the impact of IIA, a spatially-based grouping might be considered, with A and B in one nest and C in another, as shown in Figure 2.

With the exception of Lythgoe et al. (2004) who developed a cross-nested logit model to allow the number of journeys abstracted from competing stations, expressed as a proportion of predicted new journeys, to vary depending on the proximity of a station to its competitors, the issue of SAC has been ignored in the station choice literature. The previous studies using NL have placed the same stations in each access mode nest. Rather than creating distinctive groupings of alternatives, this creates multiple groupings of the same alternatives, and if proportional substitution is an issue for one nest it is likely to be an issue for all nests. The inability of the models, as applied, to deal with inappropriate substitution behaviour suggests that an alternative approach might be warranted, especially when the ability to predict abstraction from existing stations is required.

While the NL model has been applied to spatial choice problems in a variety of research fields, it requires the researcher to divide continuous space into discrete clusters of space, which is difficult to do in a manner that is justifiable and not arbitrary, particularly if the model is to be transferred to a different area from the one on which it was calibrated. An alternative approach that has been applied in other research fields is to include an accessibility term within the MNL model. This term is a measure of the accessibility of an alternative to all other alternatives within a choice set and can take a variety of forms. It is often a Hansen-type measure, where the distance between alternatives is weighted by a size-based attraction variable (e.g. population). As the term includes information from other alternatives the IIA property no longer holds and the model is able to capture competition (or agglomeration) effects. Examples include the competing destinations model (CDM) proposed by Fotheringham (see Pellegrini & Fotheringham (2002) for a review), and recent work by Ho and Hensher (2016) who used accessibility terms to account for spatial competition in workplace choice models. Other researchers have created new GEV models using McFadden's generator function (Train, 2009). One example is the Generalised Spatially Correlated Logit (GSCL) model developed by Sener, Pendyala, and Bhat (2011), in which the degree of spatial correlation is represented by a function of a vector of attributes that defines the spatial relationship between all pairs of alternatives.

3.4 More Complex Models

Alternative discrete choice models are available that, by making different assumptions about the distribution of unobserved utility, can represent any pattern of substitution and, unlike MNL and NL, account for random variation in taste. However, this increased flexibility comes at a cost. The models are more complex to implement and interpret and the choice probabilities usually have to be approximated by simulation. Examples include the probit model, which assumes unobserved utility follows a multivariate normal distribution, and the ML model, where unobserved utility is represented by two components – one that is assumed to be IIGD and another that can follow any specified distribution. There has been only limited application of these models in station choice modelling.

Desfor (1975) used a probit model but made the simplifying assumption that commuters only considered the two lowest cost stations for the census block where they resided, based on a non-stochastic trip cost function consisting of distance, fare and parking cost. This allowed binary probit models to be estimated for the pair of lowest cost stations for each census block, with the difference in trip cost the only explanatory variable. While the models were reported to correctly predict the choices made by 88% of commuters, only those who chose one of the two highest utility stations could be included in the validation. This is likely to have enhanced model performance as the 20% of cases removed were arguably the more difficult ones to predict, and their exclusion limits the model's usefulness for forecasting, as it is impossible to make an a-priori assessment of which travellers will choose one of the two lowest cost stations.

Chen et al. (2014) proposed a framework for modelling station choice of park and ride passengers under conditions of uncertainty, where the utility function is based on Prospect Theory (Kahneman & Tversky, 1979). They suggest that as well as assessing the factors (outcomes) of each alternative, an individual considers the likelihood of these outcomes occurring, and their choice will depend on their attitude to risk. This framework was used to develop an ML model to estimate station choice under parking search time uncertainty (Chen et al., 2015). In a comparator MNL model parameters for variation in parking search time and availability of parking bays were found to be significant at the 1% level. However, in the ML model where these were treated as random parameters they were not significant and apparently not random. The ML model did indicate that survey respondents were risk averse to variation in parking search time, and this model had a lower AIC than the MNL model, but its validity is questionable.

3.5 Model Validation and Testing

The performance of discrete choice models is often assessed using a likelihood ratio index, usually adjusted McFadden's ($adjR^2$) which penalises for the number of predictor variables. It is, however, only valid to compare models on the basis of their $adjR^2$ if they have been estimated using identical samples and the same set of alternatives (Train, 2009). Another commonly used measure of model performance, adopted in several station choice studies (Blainey & Evens, 2011; Desfor, 1975; Fan et al., 1993; Harata & Ohta, 1986; Liou & Talvitie, 1974; Mahmoud et al., 2014) is predictive accuracy. For each individual, the alternative with the highest probability is compared with the choice actually made. Across all individuals, the percentage where these match is called the 'percent correctly predicted', and might be used to compare model performance. However, this approach is fundamentally flawed as the researcher cannot say which alternative an individual will choose, as the true utility of each alternative is unknown. By definition, the choice with the highest probability will not always be chosen, it is just more likely to be chosen (Train, 2009). A better measure is to compare the number of times an alternative was chosen with the sum of the predicted probabilities for that alternative across the sample, and then derive a performance measure for the whole model (Hensher, Rose, and Greene, 2015). This approach enables the predictive performance of models estimated on different samples to be compared.

Validating a predictive model against the sample used to calibrate it can lead to optimistic performance estimates. Additional validation can include testing the model on similar but independent data, for example by splitting the data into two parts and using one to develop the model and the other (the hold-out sample) to measure its performance, or by using advanced techniques such as cross-validation or bootstrapping (Steyerberg et al., 2001). The validation and testing methods used in station choice research are summarised in Table 3, and it is apparent how little testing has been carried out. The two earliest studies tested models against data from a new location (Liou & Talvitie, 1974) and an additional survey (Desfor, 1975), and the 'percent correctly predicted' measure suggested they performed well. Lythgoe and Wardman (2002, 2004) estimated demand for two new parkway stations, and found that the model substantially under-predicted demand.

3.6 Conclusions

A consensus has formed around using closed-form models to predict station choice, with MNL used to model station choice alone and NL used to model combined access mode and station choice. A significant weakness of these models is their inability to account for spatial correlation between stations (unless a suitable nested structured is defined) or to allow patterns of substitution that adequately represent competition between stations. Solutions applied in other fields, such as including an accessibility term or applying a specialist GEV model, should be explored in the station choice context. Researchers are beginning to apply more complex models but these have not yet been used to account for individual taste variation or to represent specific substitution patterns, despite this flexibility being their key benefit. Before developing ever more complex explanatory models it is important that the predictive performance of the simpler approaches is more rigorously assessed using measures consistent with probabilistic choice models. When more complex models are developed, it is essential that their predictive performance is compared with simpler models so that an informed assessment of the trade-off between complexity and performance can be made.

4. Measuring Representative Utility

The factors that influence observed utility can be grouped into attributes of the alternatives and characteristics of the decision makers (Ortúzar & Willumsen, 2011). In terms of station choice, the attributes of the alternatives can be split into those relating to accessibility and those relating to railway service (Givoni & Rietveld, 2007). Choices also depend upon the prejudices and tastes of individuals, and it may be possible to represent some of these by introducing socioeconomic variables (Ortúzar & Willumsen, 2011). The interplay of the factor types is illustrated in Figure 3.

4.1 Accessibility Attributes

4.1.1 Access and Egress

A common variable included in previous research is access distance from trip origin to departure station, with increasing distance expected to have a negative effect on choice. Most studies have used a straight line measure (Adcock, 1997; Debrezion et al., 2007b, 2009; Desfor, 1975; Mahmoud et al., 2014), which is unlikely to reflect the true distance travelled. This can be improved by measuring distance via the road network (Blainey & Evens, 2011; Fan et al., 1993; Givoni & Rietveld, 2014). Distance is normally included as a continuous variable, although Debrezion et al. (2007a) entered a series of distance bands as dummy variables, allowing a coefficient to be estimated for each band. The coefficient was positive for all bands, but higher for lower distances, declining smoothly as distance increased.

An alternative is estimated travel time or in-vehicle time for the access trip, which again is expected to have a negative effect. This may simply be distance converted into time (Kastrenakes, 1988), or a more accurate reflection of journey time by access mode, for example public transport (Debrezion et al., 2009; Givoni & Rietveld, 2014) or car (Fox, 2005). Travel time is intuitively more appropriate, as the time taken to get to a station is likely to be more important than the distance travelled (which may be unknown).

Previous studies using the MNL model typically estimate a single parameter for access distance or time. This represents an average effect on utility across all access modes. In the case of NL models, a separate access parameter is usually specified for each access mode nest (Debrezion et al., 2009; Givoni & Rietveld, 2014). MNL models might be improved if separate dummy variables representing each access mode interacted with access distance or time were defined.

In some studies, factors relating to the access journey are incorporated into a composite measure of generalised cost or generalised journey time (GJT) (Lythgoe & Wardman, 2004; MVA Consultancy, 2011), and less common variables include the cost of the access journey, such as car cost or bus fare (Fox, 2005; Liou & Talvitie, 1974; Wardman & Whelan, 1999), and public transport frequency (Debrezion et al., 2009; Wardman & Whelan, 1999).

Little attention has been given to the egress journey, although Adcock (1997) considered the entire trip from ultimate origin to final destination, with access and egress distance included as factors. He found that passengers were willing to accept longer access journeys than egress journeys, perhaps due to the availability of a car or better knowledge of public transport at the "home" end.

Kastrenakes (1988) used a variable to indicate whether a station was considered to be the local station to the residents choosing it. Interestingly, this was not correlated with access time and Kastrenakes suggests it could be capturing "intangibles" such as a greater awareness of services and parking within a passenger's home town. The aggregate nature of the study could be masking correlation at the individual level, although similar "nearest station used" variables have improved disaggregate models (Adcock, 1997; Fan et al., 1993).

4.1.2 Facilities

Car parking is the dominant station facility attribute considered in prior studies, and has taken several forms, such as presence of a car park (Debrezion et al., 2007a, 2009; Liou & Talvitie, 1974), number of parking spaces (Blainey & Evens, 2011; Chakour & Eluru, 2014; Fan et al., 1993; Fox, 2005; Mahmoud et al., 2014), availability of spaces (Kastrenakes, 1988), and parking cost (Desfor, 1975; Kastrenakes, 1988; Mahmoud et al., 2014; MVA Consultancy, 2011). In most cases the presence of a car park and number of parking spaces has a positive effect, although there have been conflicting results and counter-intuitive coefficient signs in some cases, possibly due to endogeneity issues. A positive coefficient for parking fee and a negative coefficient for availability, whilst counter-intuitive, may indicate that a station is very popular (Kastrenakes, 1988), and a positive coefficient for parking spaces may not indicate that more spaces attract passengers but that more passengers lead operators to provide more spaces (Chakour & Eluru, 2014).

4.1.3 Land-use

Only Chakour and Eluru (2014) have considered the effect of land-use. They identified six characteristics of Montreal traffic analysis zones using principal component analysis, such as high density/high walkability, commercial, or government/institutional. The variables were found to be inelastic, with a 15% uplift resulting in a change in mode share and station choice of less than 1%, leading them to conclude that access mode and station choice “do not react to land-use changes.” However, research in related areas suggests that land-use may play an important role in station choice. For example, Cervero et al. (1995) found that residential density and land-use mix influence how passengers access stations and the size of access catchments.

4.2 Railway Service Attributes

Attributes used to represent railway service quality include measures of train frequency, such as trains per hour, per day or at peak periods (Blainey & Evens, 2011; Debrezion et al., 2007a; Fan et al., 1993; Kastrenakes, 1988); rail journey time (Fox, 2005; Givoni & Rietveld, 2014; Harata & Ohta, 1986; Liou & Talvitie, 1974); journey distance (Blainey & Evens, 2011); fare (Adcock, 1997; Fox, 2005; Harata & Ohta, 1986); and number of transfers (Fox, 2005; Harata & Ohta, 1986). In some cases a single measure of GJT, derived from several railway service attributes, has been used (Kastrenakes, 1988; Adcock, 1997; Lythgoe & Wardman, 2004; MVA Consultancy, 2011; Atkins, 2011). The aforementioned measures have the intuitively expected effect on utility in all studies, with the exception of Blainey and Evens (2011), where a positive coefficient for journey distance was obtained for South Wales. Distance may not be a good proxy for time, as a longer route could be faster depending on the line running speed, stopping patterns and whether the service is direct, and this may have resulted in a misspecified model.

To explore the effect of train frequency on utility, Debrezion et al. (2007b) used two alternative utility function forms. A cross-effect function, where access distance categorical dummy variables were cross multiplied with frequency of service, revealed that the positive effect of frequency on utility is greater for passengers living closer to a station; while a translog function showed that utility declines smoothly as access distance increases for all frequency levels, but with a flatter curve for stations with higher service frequency, indicating that a station's catchment is larger when frequency is higher.

An alternative approach to individual rail service attributes was developed by Debrezion et al. (2009), primarily because they used aggregate data and did not have individual trip information. They combined three determinants of rail service quality - waiting time; transfer time; and in-vehicle time - into a single Rail Service Quality Index (RSQI). Coefficients estimated using a doubly-constrained flow model[3] based on ticket data for stations in the Netherlands were used to calculate multiple RSQIs for each departure station, one for each destination station. These were aggregated to obtain an overall RSQI for each station that was entered into the model and found to have a significant and positive effect on station choice.

4.3 Socioeconomic Attributes

Some studies have included socioeconomic attributes, mostly relating to age (Chakour & Eluru, 2014; Fan et al., 1993; Fox, 2005), sex (Chakour & Eluru, 2014; Fan et al., 1993; Fox, 2005), income (Fan et al., 1993; Liou & Talvitie, 1974) and car ownership (Chakour & Eluru, 2014; Debrezion et al., 2009; Fox, 2005). Research shows that a passenger's propensity to use a station other than their nearest increases as the number of cars per household increases, with the effect most marked in moving from a one to two car household (Adcock, 1997). This suggests that car ownership may influence station choice.

4.4 Conclusions

The direction effect of a range of access and rail service factors has been consistently reported. The evidence indicates that station utility decreases as the access journey becomes further or longer, as the rail leg journey time increases, when the journey involves more transfers or has a higher fare, and when service frequency is reduced. Establishing the effect of station facilities, such as car parking, is more problematic, potentially due to endogeneity issues. While a number of important explanatory variables have been established there is still potential to identify new ones. For example, researchers have paid scant attention to the impact of land-use factors, and spatially detailed land-use datasets, such as the Ordnance Survey's 'Points of Interest' data in Britain, are an untapped resource. There may also be gains in predictive performance with improved measurement of the variables that have greatest explanatory power, such as access journey and rail service factors. This could be through better measurement of access journey time by mode using route planning software, incorporating road speed information that could identify congestion prone stations, or better alignment of survey trip data with train sched-

[3] A "flow model" is a spatial interaction model that estimates passenger flows between all origin-destination station pairs based on attributes of the origin, destination, and their separation.

ule information so that the service available to each individual is better represented.

5. Data Considerations

5.1 Data Sources

The data required for station choice modelling is usually obtained from revealed preference (RP) origin-destination passenger surveys carried out at stations or onboard trains. Wardman and Whelan (1999) combined data from an RP and stated preference (SP) survey, and Chen et al. (2015) solely used SP data. The surveys may be at the national level, for example Blainey and Evens (2011) and MVA Consultancy (2011) used data from the National Rail Travel Survey carried out in Britain during 2004-2005, or at the local or regional level, such as the survey of commuter rail lines carried out by New Jersey transit (Kastrenakes, 1988). An alternative approach was adopted by Desfor (1975) who collected licence plate numbers from cars that were parked or dropping off passengers and used the registered addresses of the vehicle owners as a proxy for trip origin.

The models developed to assess demand for stations on the planned high speed rail line between London and the West Midlands in the UK (HS2) were not based on any observed station choice data. Rather than calibrating a model to estimate parameters, GJTs were calculated using established elasticities from an existing multi-modal model of travel in Britain and the (dis)utility of each alternative was entered into MNL probability equations (Atkins Limited, 2011). This approach is fairly simplistic as it assumes that GJT (which excluded fare) is the only factor impacting station choice and it uses standard elasticities.

The approach adopted by Lythgoe and Wardman (2002, 2004) does not require data on ultimate trip origins or destinations as the dependent variable is not observed station choice but the number of rail trips on particular flows derived from ticket sales data.

Table 1 includes information on the survey size and data type used in station choice studies.

5.2 Disaggregate vs. Aggregate

Discrete choice models are often thought of as disaggregate-only models which are estimated using data at the individual level. However, the dependent variable can also be the observed share of each alternative at some unit of aggregation, and this approach has been adopted in some studies. For example, Debrezion et al. (2007a) used the observed proportion of the three most frequently chosen stations at postcode area level as the dependent variable in an MNL model, and Debrezion et al. (2009) estimated an NL model with the proportion of joint access mode and station choice for each postcode area as the dependent variable. However, there are consequences of aggregating data prior to model estimation: it is statistically inefficient as data from a large number of individual observations is grouped into a relatively small number of zone-based observations; the model cannot account for intrazonal variability (for example, station access distance is the same for an entire zone); and there is the potential for statistical bias (for example, caused by the issues of 'ecological fallacy' (Ortúzar, 1980) and the 'modifiable area unit problem' (MAUP) (Openshaw, 1984)).

5.3 Defining Choice Sets

A choice set must meet three conditions to be consistent with the discrete choice framework. First, the alternatives must be mutually exclusive; second, the number of alternatives must be finite; and third, the choice set should include all possible alternatives (Train, 2009). A passenger can only depart from and arrive at a single railway station, and there are clearly a finite number of stations in any choice set, so the first two requirements are met. The third is more problematic, as the researcher usually only knows what choice was ultimately made (unless data is from an SP survey). The choice set will depend on the stations which are feasibly available based on a passenger's origin and destination, but will also vary on an individual basis, influenced by sociodemographic characteristics, level of knowledge, attitudes and perceptions (Basar & Bhat, 2004). The choice set might also be constrained in certain circumstances. For example, if an individual can only walk to a station, then there must be a cut-off distance at which a station is no longer considered feasible. A feature of logit models is that an alternative can never have a probability of zero, and if an alternative has no realistic prospect of being chosen it can be excluded from the choice set (Train, 2009). However, setting a threshold is fraught with difficulties, and often a fuzzy concept. How, for example, can the appropriate cut-off distance for walk access to a station be set, when it will surely vary on an individual basis?

Castro, Martinez, and Munizaga (2009) highlight the potential for "serious problems" with model predictions if the choice set is poorly specified and argue that while in some circumstances it might be plausible to exogenously define feasible alternatives, for example in the case of travel mode choice, in other situations, such as when modelling spatial alternatives, it becomes very complex or arbitrary. A potential solution is to use a probability-based approach, for example the two-stage MNL model developed by Basar and Bhat (2004) to study airport choice, where the probability of an alternative being in an individual's choice set is modelled first.

The methods used in prior research to define choice sets can be split into three groups, based on distance, observed choice, and catchments. In the distance-based method each individual has their own choice set determined by the closest *x* stations to their origin, with the aim of maximising the number of observed choices accounted for, while keeping the number of alternatives to a reasonable number (Blainey & Evens, 2011; Fan et al., 1993; Mahmoud et al., 2014). In the observed choice method, the choice set is defined at the area level, for example the stations chosen by passengers living in a particular locality (Kastrenakes, 1988) or the most frequently chosen stations in a postcode area (Debrezion et al., 2009). The catchment-based method assigns a catchment of a certain radius to each station, and this determines whether an alternative is within either an individual or area-based choice set (Adcock, 1997; Lythgoe & Wardman, 2004). Unusually, Adcock (1997) used alternative rail legs from trip origin to destination as the choices, rather than stations, reflecting that the entire door-to-door trip was modelled. Chakour and Eluru (2014) defined individual-level choice sets using a ratio based on the concept of the maximum distance passengers are willing to travel relative to their nearest station.

5.4 Conclusions

While aggregate data has been used to model station choice, this has been dictated by limitations of available data, rather than modelling needs. The preferred option for future research is individual trip data where the ultimate origin (and destination if required) is at a spatial resolution sufficient for the variability in explanatory factors between decision makers to be revealed. For example, in the UK the unit postcode area boundary is probably the maximum spatial unit of address aggregation appropriate[4]. A definitive mechanism for defining choice sets has not been established, and the methods adopted have been fairly simplistic and not evidence-based. It is not clear, for example, what the implications are of seeking to maximise the number of observed choices that are accounted for, when this may add alternatives to the choice set that would never realistically be considered. Research is needed to evaluate the different methods for generating choice sets for station choice models, including an assessment of their impact on predictive performance.

6. Station Choice Models in Station Demand Forecasting

While from a transport planning point of view it might be expected that a key aim of station choice modelling would be to predict the impact of changes to station and service provision, few of the studies discussed in this paper have addressed this issue, instead focussing on developing models to better understand the factors that influence station choice. There are several examples of local applications, for example Harata and Ohta (1986) used their model to estimate aggregate passenger flows at their study station, and Kastrenakes (1988) examined the effect of introducing a hypothetical commuter line by using predicted station shares to weight variables in a mode choice model. However, there has been limited progress toward integrating a station choice element into the aggregate models, such as trip end and flow models, that are typically used to predict demand for new stations or services. This is a concern given that trip end models were used to forecast demand for around two-thirds of recently opened stations/lines in the UK (where information was available) while four-stage type models were rarely adopted (Steer Davies Gleave, 2010).

Trip end and flow models require a station catchment to be defined, which serves as the unit of aggregation for relevant data such as population. Two methods are commonly used: a buffer around a station, such as the 0.8km and 2km radial catchments proposed by Preston & Aldridge (1991); or dividing the population into zones and allocating each zone to its nearest station, for example Blainey (2010) assigned census output areas based on road travel time. Both methods produce deterministic catchments, where a particular trip origin falls within the catchment of a single station, and stations are implicitly assumed to not compete with one another. Research has shown that in reality station catchments are far more complex than these simplistic catchment definitions allow (for example, see Blainey & Evens (2011)), suggesting that the aggregate models might be improved by defining

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[4] The unit postcode typically represents around 15 addresses.

probabilistic catchments using a station choice model. Wardman and Whelan (1999) explored this by attempting to incorporate probabilistic station catchments into a direct demand model by apportioning population to one of five competing stations for each postal sector. However, due to time and computer resource constraints they had to use a subset of the data, which resulted in the model failing to converge. This approach does not appear to have been revisited since, despite the substantial advances in computational capability. In an alternative approach, developed by Lythgoe and Wardman (2002, 2004), station choice is an intrinsic component of a flow model, with a station's generation potential represented by the population within 40km allocated to a grid of zones, as formulated below:

$$V_{aij} = n \times P_a \times \Pr(rail_{aij}) \tag{5}$$

where V_{aij} is the (unknown) number of trips from zone *a* to destination *j* via station *i*, *n* is the unknown average number of decisions to travel (by any mode or not at all) in one year, and P_a is the population of zone *a*. $Pr(rail_{aij})$, the probability of an individual in zone *a* choosing to travel to destination *j* using station *i*, is obtained from an NL model with a choice between rail and no rail at the upper level and choice of station at the lower level (Lythgoe and Wardman 2002, 2004). However, the methodology is limited to forecasting demand for inter-urban journeys in excess of 80km, although this was subsequently reduced to 40km (Lythgoe et al., 2004).

There are a few examples of a limited station choice element being introduced into regional strategic (four-stage type) models. Fox (2005) developed a park-and-ride station choice model, where station choice is modelled for car access mode only, that was incorporated into the Policy Responsive Integrated Strategy Model (PRISM), a disaggregate demand model for the West Midlands region of the UK. A similar model was later developed for the Sydney Strategic Travel Model (STM) (Fox et al., 2011).

6.1 Conclusions

The lack of integration with demand forecasting is a significant limitation of previous research, and the absence of a choice-modelling methodology which can adequately capture patterns of abstraction and competition between railway stations may have contributed to the limited accuracy of recent demand forecasts for new stations in the UK (for example, see: Smith (2011); Steer Davies Gleave (2010)). Given that trip end models are the predominant model type used to forecast demand for new stations, future research should seek to improve these models by incorporating probabilistic catchments derived from station choice models.

7. Discussion

The station choice models reviewed in this paper appear to do a reasonable job of explaining observed station choice behaviour, but it is less clear how well they can predict station choice in real-world scenarios, or how they can be used to improve industry standard rail demand forecasting methods, such as those in the UK Passenger Demand Forecasting Handbook (Association of Train Operating Companies

(ATOC), 2013). Station choice models have usually been treated as stand-alone entities, but in practice they need to be linked into general travel demand models in order to reliably assess the impacts of transport schemes. Only the work of Lythgoe and Wardman (2002, 2004) has really focussed on developing models for forecasting applications, but this was limited to a specific context (parkway stations) and forecasting performance was not particularly good.

The lack of real-world validation makes it difficult to determine whether the more complex models that have been proposed in recent research, for example ML, are justified in terms of producing better performing models. From the point of view of practitioners, this lack of attention to validation is a key weakness of previous research, because the usefulness of these models in practice is predicated upon the extent to which they can accurately predict travel behaviour following the opening of a new station. This problem is exacerbated by a failure to demonstrate (or often even investigate) the spatial or temporal transferability of station choice models, making it impossible to apply them beyond the local context in which they were developed. The effects of explanatory variables have tended to be viewed as specific to the local context in which models are calibrated, rather than local manifestations of more general traits of travel behaviour, but similarities in these effects in different settings suggests that there are more general phenomena at work.

In order to advance the field of station choice modelling beyond its current ability to explain observed travel behaviour in particular circumstances, to a situation where it can provide a meaningful contribution to predicting future travel patterns, further research is needed to develop a station choice model that can be used to define probability-based station catchments within models that forecast the effect of new stations or substantially changed services on demand. Ideally, such a model should be readily transferable, and not limited to modelling station choice in specific local contexts. Collecting sufficient data and calibrating a robust model on a case-by-case basis is expensive and time consuming, and this could be avoided if a single generalised model with wide applicability was developed. This requirement for a generalised choice model is of course not unique to station choice modelling, but there are also some more specific shortcomings of previous research that could be addressed by such a model. In particular, it should recognise that stations are located in space and do not exist in isolation from one another, and be able to represent the effect of a new station, or significant service change at a station, on demand at nearby stations. By adopting a model specification that allows a flexible or more complex substitution pattern and making use of the increasingly wide range of open source data on travel behaviour and transport service provision, it should be possible to develop a modelling framework that can provide planners with a robust evidence base for decision making on railway capacity provision and allocation. The continued temporal transferability of this framework would, of course, rely upon it being regularly updated to account for ongoing changes in modes used for station access and egress, such as ride-sharing services (in the short-term) and autonomous vehicles (in the longer term), but this update process would be more likely to occur if choice models were fully integrated into wider demand modelling methodologies rather than treated as stand-alone entities.

This review has shown that there has been a tendency in the past for research in this field to repeatedly cover the same ground, by seeking more sophisticated ways to explain choice behaviour in a particular local context, even though the improvements in explanatory power given by more complex methods are often very limited. There seems relatively little to be gained by continuing along this trajectory and simply continuing to attempt to explain local choice behaviours in new contexts, when such explanatory models have very limited potential for forecasting. While there are undoubtedly still aspects of station choice behaviour which are poorly understood and modelled, at present it appears that there is more to be gained through the development of a generalised station choice modelling framework which allows the findings from previous research to be used to assist in the development of transport schemes. This should be a priority for future research, to ensure that the substantial body of evidence on this topic can be fully exploited by transport practitioners and therefore generate benefits for society.

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Author	Country	Focus of study	Main Statistical Approach	Data type	Survey size
Liou and Talvitie (1974)	USA	AM/SC	MNL	Disaggregate	3,694
Desfor (1975)	USA	SC	Probit	Disaggregate	150
Harata and Ohta (1986)	Japan	AM/SC	NL	Disaggregate	1,358
Kastrenakes (1988)	USA	SC	MNL	Aggregate	26,000
Fan et al. (1993)	Canada	AM/SC	NL	Disaggregate	1,824
Adcock (1997)	UK	SC	MNL	Disaggregate	230,000
Wardman and Whelan (1999)	UK	AM/SC	NL	Disaggregate	32,525
Davidson and Yang (1999)	USA	AM/SC	NL	Disaggregate	11,000
Lythgoe and Wardman (2004)	UK	SC	NL	Aggregate	n/a
Lythgoe et al. (2004)	UK	SC	Cross-nested logit	Aggregate	n/a
Fox (2005)	UK	SC (PnR)	NL	Disaggregate	8,508
Debrezion et al. (2007a)	Netherlands	SC	MNL	Aggregate	unknown
Debrezion et al. (2009)	Netherlands	AM/SC	NL	Aggregate	unknown
Blainey and Evens (2011)	UK	SC	MNL	Disaggregate	113,518
Atkins Limited (2011)	UK	SC	MNL	n/a	n/a
Fox et al. (2011)	Australia	SC (PnR)	NL	Disaggregate	unknown
MVA Consultancy (2011)	UK	SC	Binary logit	Disaggregate	3,957
Chakour and Eluru (2014)	Canada	AM/SC	Latent segmentation	Disaggregate	3,902
Chen et al. (2014)	Australia	SC	ML	Disaggregate	n/a
Givoni and Rietveld (2014)	Netherlands	AM/SC	NL	Disaggregate	8,491
Mahmoud et al. (2014)	Canada	SC	MNL	Disaggregate	2,297
Chen et al. (2015)	Australia	SC	ML	Disaggregate	600

SC = station choice

AM = access mode

PnR = Park and ride

KnR = Kiss and ride

Table. 1: Summary of station choice research

Paper	IV Parameter	Correlation	Notes
Harata and Ohta (1986)	0.641	0.359	*before* new station
Harata and Ohta (1986)	0.740	0.260	*after* new station
Fan et al. (1993)	0.414	0.586	
Debrezion et al. (2009)	0.614	0.386	
Givoni and Rietveld (2014)	0.546	0.454	

Table. 2: Reported IV parameters and calculated correlation for NL models

Author(s)	Validation		Testing	
	Fit (adjR^2 unless stated)	Predictive accuracy (%)	Method	Predictive accuracy (%)
Liou and Talvitie (1974)		SC: 79-82; MC: 92	Data from other railroads	SC: 96-98 MC: 86
Desfor (1975)		PnR: 91; KnR: 88	Additional survey	PnR: 87; KnR: 90
Harata and Ohta (1986)		SC: 88-90; MC: 85-89		
Kastrenakes (1988)	0.325			
Fan et al. (1993)	0.904 (SC); 0.656 (MC); 0.614 (subway)	92.3 (SC); 78.6 (MC); 67.9 (subway)		
Wardman and Whelan (1999)	0.0837 (with respect to constants)			
Lythgoe and Wardman (2002, 2004)	0.532		Demand forecast for new parkway stations. Warwick flows to London under-forecast by 28%.	
Lythgoe et al. (2004)	0.611			
Debrezion et al. (2007a)	0.377 (linear); 0.274 (cross-effect); 0.410 (translog)			
Debrezion et al. (2009)	0.251			
Blainey and Evens (2011)	0.795 (NE); 0.632 (Wales)	83 (NE); 72.3 (Wales)		
Chakour and Eluru (2014)	BIC (11288.90)		Hold-out sample (no results)	
Mahmoud et al. (2014)	0.53 (rail & subway); 0.24 (rail); 0.32 (subway)	76.42 (rail & subway); 75.23 (rail); 79.18 (subway)		
Chen et al. (2015)	AIC (MNL: 1873.6; ML: 1644.2)			

SC = station choice
MC = mode choice
PnR = Park and ride
KnR = Kiss and ride
BIC = Bayesian Information Criterion
AIC = Akaike Information Criterion
NE = North East England

Table. 3: Validation and testing of station choice models

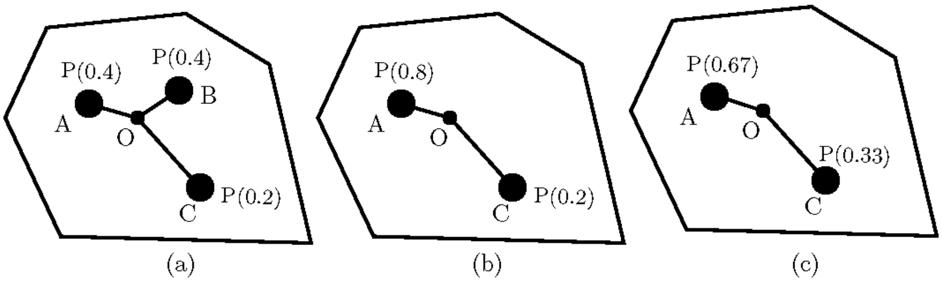

Figure 1. IIA substitution behaviour

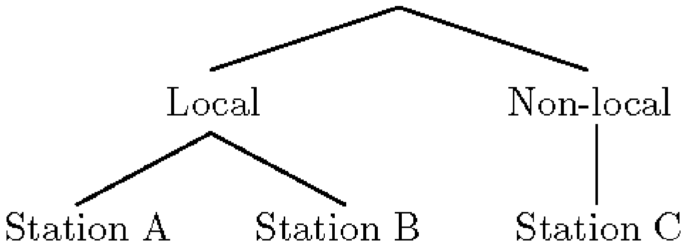

Figure 2. Nesting stations to address IIA.

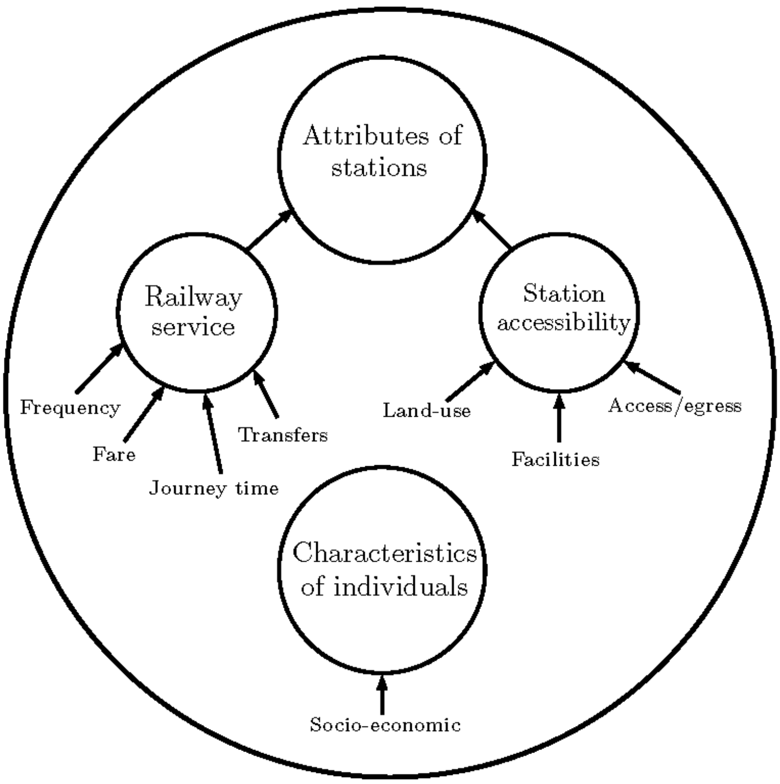

Figure 3. Factors that influence station choice.