Department for Transport

SUPPLEMENTARY GUIDANCE

NTEM Sub-Models

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Transport Analysis Guidance (TAG)

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This TAG Unit is part of the section **SUPPLEMENTARY GUIDANCE**

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This Unit

This supplementary guidance gives a detailed background to the principles and mechanisms of the National Car Ownership Model (NATCOP) and the National Trip End Model (NTEM). These models contribute to generating trip end forecasts known as the NTEM data set that users may access freely through use of the TEMPRO software.

Not covered in this guidance is the “Scenario Generator”, which is a demographic forecaster that inputs into the car ownership and trip end models. Further information on this can be obtained from the DfT web site.

1 The National Car Ownership Model

1.1 Summary

1.1.1 The National Car Ownership Model (NATCOP) calculates the probability of households owning 0, 1, 2 and 3 or more cars for a given forecast year. This information is important in transport modelling since household car ownership fundamentally affects the demand for travel of persons within each household. This is used in transport models to segment travellers into more detailed user classes in order to more accurately model travel behaviour and mode shift responses. Output from NATCOP is also fed into the National Trip End Model (NTEM) as part of the TEMPRO system. This affects the number and purpose of trips within that model when applied to trip rates by person type.

1.1.2 The model assesses a household’s decision to own zero, one, two or three or more vehicles by way of three binary logit models[1]. This assessment is determined by a combination of:

- Demography (household structure, age, etc);
- Income and the national economic background;
- Type of area; and
- Other car-related factors (i.e. license holding, rates of company car ownership, etc).

1.1.3 The demographic data in the TEMPRO system is derived via the Scenario Generator and is fed directly into NATCOP by means of a target file. Other input assumptions such as income (growth) and GDP are taken from standard data sources used by the Department. Figure 1 below shows the basic process involved in the generation of car ownership forecasts.

[1] Gaudry, M., Dagenais, M., 1979. The Dogit Model Transportation Research – Part B 13 (2), p105-112

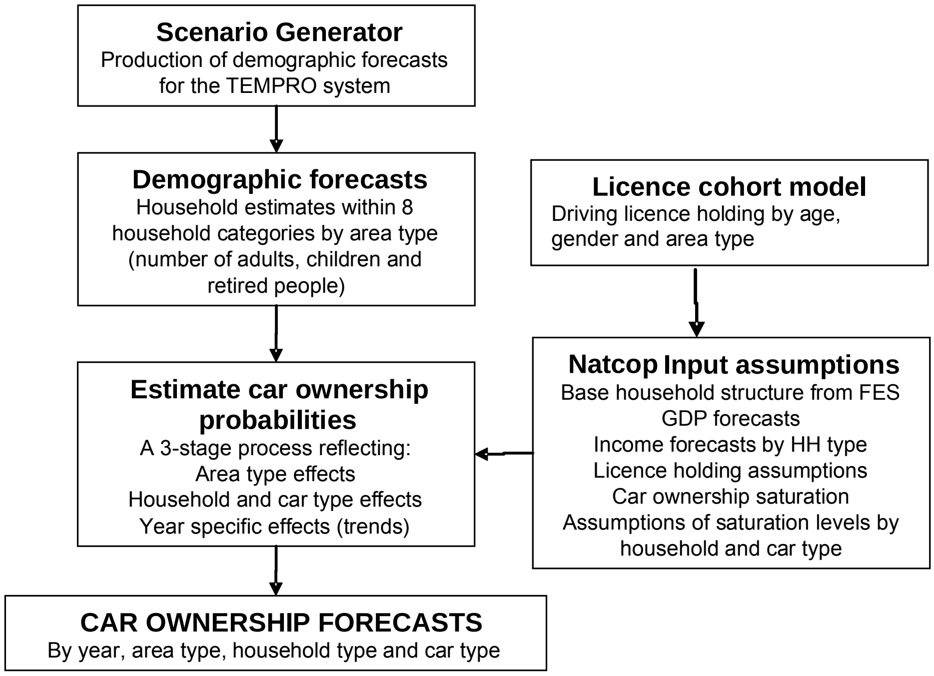

Figure 1 Generation of car ownership forecasts

1.1.4 The model outputs the following information, all at the NTEM zone level:

- Households with 0, 1, 2 and 3+ cars;
- Households by number of adults and number of cars owned; and
- Adults and children in households by number of adults and cars owned.

1.2 Model Structure

1.2.1 The car ownership set of models[2] use information on household income, household-type (defined by the age structure and number of residents of residents) and area-type (loosely defined by population density) to derive a probability that a given household will decide to own:

- One or more vehicles (P_{1+});
- Two or more vehicles conditional on ownership of one or more vehicles ($P_{2+|1+}$); and
- Three or more vehicles conditional on ownership of two or more vehicles ($P_{3+|2+}$).

1.2.2 These three models are estimated using data from Family Expenditure Survey (now the Expenditure and Food Survey) and National Travel Survey and relate the number of cars owned to the utility of ownership, which in turn is related to the socio-economic characteristics of the household, its geographical location, purchase and use-costs and license holding.

1.2.3 The mathematical specifications of the models are shown below:

$$P_{1+} = \frac{S_{1ah}}{\left[1 + \exp\left(-U_{1+}\right)\right]} \qquad (1)$$

2 The methodology is discussed in Whelan, G., 2006. Modelling car ownership in Great Britain from Transport Research Part A 41 p205-219

$$P_{2+|1+} = \frac{S_{2ah}}{\left[1+\exp\left(-U_{2+|1+}\right)\right]} \qquad (2)$$

$$P_{3+|2+} = \frac{S_{3ah}}{\left[1+\exp\left(-U_{3+|2+}\right)\right]} \qquad (3)$$

1.2.4 S is the saturation level by area (a) and household type (h). U is the utility of ownership and specified as follows:

$$U_{1+} = ASC_1 + b_1LPA_n + (c_1 + c_{h1}D_h + c_{a1}D_a)Y + d_1E + e_1O + f_1R + h_1LPA_h + k_1LPA_{n99} + l_1PD \qquad (4)$$

$$U_{2+|1+} = ASC_2 + b_2LPA_n + (c_2 + c_{h2}D_h + c_{a2}D_a)Y + d_2E + e_2O + f_2R + g_{21}CC_1 + h_2LPA_h + l_2PD \qquad (5)$$

$$U_{2+|1+} = ASC_3 + b_3LPA_n + (c_3 + c_{h3}D_h + c_{a3}D_a)Y + d_3E + e_3O + f_3R + g_{31}CC_1 + g_{32}CC_2 + l_3PD \qquad (6)$$

where:

LPA_h is the number of driving licenses per adult at the household level
LPA_n is the national number of licenses per adult (all years)
LPA_{n99} is the national number of licences per adult from 1999 onwards only
Y is household income
D_h is a vector of household type dummy variables
D_a is a vector of area type dummy variables
E is the number of adults employed
O is an index of purchase costs
R is an index of vehicle use costs
CC1 is a dummy variable if there is one company car in the household
CC2 is a dummy variable if there are two company cars in the household
ASC is a vector of alternative specific constants
PD is population density
b, c, d, e, f,g, h, k and l are parameter vectors to be estimated

1.2.5 The categories used in the car ownership model are household types and area types, as follows:

Household Type 1	One adult, not retired
Household Type 2	One adult, retired
Household Type 3	One adult, with children
Household Type 4	Two adults, retired
Household Type 5	Two adults, no children
Household Type 6	Two adults, with children
Household Type 7	Three adults, no children
Household Type 8	Three adults, with children
Area Type 1	Inner London
Area Type 2	Outer London
Area Type 3	Metropolitan Districts
Area Type 4	Population density (PD) greater than ten people per hectare Area Type 5 PD greater than two but less than or equal to ten people per hectare
Area Type 6	PD less than or equal to two people per hectare

1.2.6 The main inputs into the car ownership model are average household income growth which takes into account the predicted increase in GDP, factors which represent increase in licence holding and a purchasing cost index which represent the predicted cost of owning a car over time.

Table 1 Estimated Model Coefficients

	Model 1 (P1+)		Model 2 (P2+1+)		Model (p3+2+)	
	Coeff	**t-ratio**	**Coeff**	**t-ratio**	**Coeff**	**t-ratio**
ASC	-2.5917	-30.3	-7.1377	-56.4	-2.918	-11.9
income (base)	0.1014	10.6	0.0077	2.6		
income, HH type 2	0.0005	0.1				
income, HH type 3	-0.0282	-12.7				
income, HH type 4	0.0577	23.4	0.0083	2.8		
income, HH type 5	0.0158	7.7	0.0103	3.6		
income, HH type 6	0.0101	5.2	0.0061	2.2		
income, HH type 7	-0.0175	-8.4	0.0227	7.7	0.0321	25.3
income, HH type 8	-0.0214	-9.5	0.0125	4.3	0.0207	21.2
income, area type 2	-0.0016	-0.2				
income, area type 3	-0.0255	-2.7	0.0174	8.1		
income, area type 4	-0.0186	-2	0.0125	9.1		
income, area type 5	0.0038	0.4	0.019	13.2	0.0022	3.9
income, area type 6	0.0206	2.1	0.0227	15.2	0.0037	5.5
income, London area type	-0.0162	-1.6	0.0254	7.5		
Income, area type missing	-0.0073	-0.8	0.0271	16.5	0.0013	2.7
CC1			2.0266	23.2	0.3029	5.9
CC2					1.3698	9.6
number of workers in the household	0.4041	29.5	0.403	35.1	0.3929	20.2
purchase cost index	-0.0075		-0.0008		-0.0065	
running cost index	-0.0001		-0.0005		-0.0119	
Licences per adult (household level)	2.7656	44.7	2.2306	23.8		
Licences per adult (GB all years)	1.2592	10.9	5.4421	40.4	2.7842	8.3
Licences per adult (GB 1999+)	-0.1087	-2.7				
population density (2002-2014)	-0.0075	-8.3	-0.0059	-6.1	-0.0122	-7.2

1.3 Methodology

Introduction

1.3.1 The objective of this section is to detail both the methodology and practical application of prototypical sample enumeration techniques to forecasting car ownership at NTEM zone level using the NATCOP car ownership models.

1.3.2 The choice models discussed in Section 1.2 show the probability that a given household will own a given number of cars. It is the aim of this section to describe the way in which these models can be applied to generate forecasts of aggregate demand and market share.

Description of the Method

1.3.3 The way unbiased forecasts are generated from a choice model is by employing a technique known as sample enumeration. This approach rests on the assumption that the sample (usually the sample on which the model is calibrated) is representative of the population and that the forecast demand for each alternative can be estimated as

$$Q(i) = \sum_{n=1}^{Ns} w_n . P(i \mid X_n) \tag{7}$$

1.3.4 Where $P(i \mid X_n)$ is the probability that household *n* chooses alternative *i* given the set of attributes affecting choice X_n , Ns is the number of household in the sample, and w_n is a weight or expansion factor attached to household n in order to make its sum representative of the population. If the sample is representative, the weight for each observation is simply equal to the number of households in the population divided by the number of households in the sample ($N_T|N_s$).

1.3.5 If the sample is not representative of the population, perhaps because the model is being used to forecast in a different geographical area or in a time period some time into the future, then the base sample needs to be adjusted so that it can be considered to be representative. A solution proposed by Daly and Gunn (1985) involves adjusting the weights shown in equation 7 so that the new weighted base sample has the same aggregate characteristics as those published by planning authorities. The problem here is that we need to find a balance between generating a new sample that is consistent with a typical population (i.e. the base sample), while also achieving consistency with such aggregate statistics as are available.

1.3.6 Rather than re-weight each household in the sample individually, households are grouped into a number of pre-defined categories (c) that cover the main dimensions of the sample e.g. household size, numbers of adults, number of children and the age of the household head. The new frequencies of household in each category (ϕ_c) are determined my minimising equation 8 with respect to ϕ_c.

$$Y = \sum_t k_t \left(z_t - \sum_c \phi_c x_{tc} \right)^2 + \sum_c (\phi_c - f_c)^2 \tag{8}$$

where:

t is a vector of target variables shown to represent the aggregate characteristics of a given target area in a given time period

k_t is the weight attached to the importance of meeting target t;

z_t is target statistic t divided by the total number of households in the target area;

x_{tc} is the average amount of target variable t for a household in category c, hence $\sum_c \phi_c x_{tc}$ is the predicted total value per household of statistic t;

f_c is the frequency of household category c in the base sample.

Note that all terms of U are on a per-household basis.

1.3.7 The first term in U represents the error in not meeting the target marginal totals for each variable z, while the second term represents the divergence from the current distribution of households over the categories. The weights k are introduced so that differential importance can be given to meeting each of the different targets or that the balance between consistency with targets and consistency with base population can be adjusted. Setting large values of k would cause the optimisation to find a distribution of households that matched the target totals very well at the expense of substantial departures from the original distribution. The weights in equation 7 are then determined for each category:

$$Wc = \frac{N_t}{N_c} . \phi_c \qquad (9)$$

where:

N_t is the number of households in the target area

N_c is the number of households in category c in the base sample

1.3.8 The advantage of the method described is that a close fit to the ‘targets’ is obtained quickly and reliably with minimal departure from the original distribution. A further advantage is the flexibility available to shift the balance between meeting the targets and maintaining the original proportions. It might seem useful, for example, to keep the original proportions in a base year and to give more weight to the targets for a forecast year: this would be achieved by giving higher values to k_t for the forecast year than for the base year. Similarly, more important targets can be given more weight if required.

1.4 Forecasting method

Basis of the procedure

1.4.1 The objective of disaggregate modelling as applied to travel demand forecasting is to explain the choices made by individual decision-makers. This approach has proved very successful as a basis for the development of models and through the technique of sample enumeration, disaggregate models have also been used successfully for short-term forecasting. However, because straightforward applications of sample enumeration do not take account of the changing nature of the population (e.g. the general “greying” of the population), longer-term forecasting is not possible. To fill this gap, the technique of prototypical sample enumeration has been developed.

Disaggregate Models and Sample Enumeration

1.4.2 A key characteristic of disaggregate modelling is the statistical approach that it inherently takes to the analysis of data. This approach recognises that it is not possible to predict correctly how each individual (or household) in a population will behave, but this does not prevent information being obtained on the variables that influence – rather than determine – behaviour. The model for each individual is then formulated as

$$\Pr \{ c_i = k \mid K_i, S_i \} = p_k(K_i, S_i) \qquad (10)$$

1.4.3 given the probability that the choice c_i of individual i, whose characteristics are S_i, will be alternative k from the choice set K_i (which has availability and characteristics specific to individual i). It is a primary objective of the modelling then to specify how the alternatives in K are described and which characteristics S are relevant. A further important task in the modelling is to determine the form of p and estimate the values of unknown parameters that appear in it.

1.4.4 In order to make useful forecasts, a means must be found to aggregate, to derive from a model predicting the behaviour of individuals a forecast of the behaviour of an entire population. An important point is that it is not correct simply to set K and S to the average population values and apply equation (10) as if the entire population behaved like a mass of identical average individuals: this overstates the response to changes, an effect known as aggregation bias which has long been recognised (e.g. Daly, 1976, Gunn, 1984). Similarly, the model (10) cannot be used directly to calculate elasticities, again this leads to an overstatement of responsiveness.

1.4.5 A technique that does not have this disadvantage is sample enumeration. Essentially, sample enumeration simply applies the model (1) to each member of a sample in turn. Then, if the sample is representative, the sum of the forecasts for each individual is the unbiased forecast for the whole population. Formally, the expected demand Q_k for an alternative k is given by

$$Q_k = \Sigma_i \, w_i \, . \, p_k(K_i, S_i) \qquad (11)$$

where w_i is the expansion factor or weight attached to individual i in the sample in order to make its sum representative of the population. Very often, the sample used for forecasting is the same sample used for model estimation, while the weights w are determined by the sampling process used.

1.4.6 The advantages of sample enumeration using the basic equation (11) are its simplicity and convenience. The forecasts are unbiased. It is important to note that the procedure of sample enumeration is entirely independent of the form of the model that is used for forecasting: logit, linear, whatever model is used can be applied in this way.

1.4.7 The primary disadvantage of sample enumeration is that a representative sample may not be available, perhaps because the model is being transferred in time or space. In particular this will always be true when a forecast is required over any considerable period, so that a base-year sample can no longer be considered representative.

1.4.8 The conclusion is that the advantages of sample enumeration are substantial in some circumstances and therefore that it would be advantageous to be able to apply the technique more widely. A means was therefore required for generating representative samples for circumstances different in space or time from those for which real samples are available.

Prototypical Sampling

1.4.9 The most obvious way to produce samples representative of future conditions is to generate an artificial population which has, as far as is known, the characteristics of the future population. However, the forecasts that are generally available – e.g. from planning authorities – typically refer to aggregate statistics such as age-sex population distribution, rather than the composition of individual households. A method is therefore required for generating a sample of households that is internally consistent, i.e. that it ‘looks like’ a typical population, while also achieving consistency with such aggregate statistics as are available.

1.4.10 The objective of the method is thus to use an existing household sample to produce a sample that is or will be representative of one or more target areas. The key method used for adjusting the samples is the adjustment of the expansion weights present on the survey records (the FES does not include expansion weights all households are weighted by the total population divided by the sample size). The following section discusses the possible ways in which these weights can be adjusted.

Optimisation

1.4.11 There are two sets of procedures that have been used in practice to produce prototypical samples: Iterative Proportional Fitting (IPF) and Quadratic Optimisation. Both methods rely on the availability of a detailed sample of households that is not directly representative of a specific target area or year. The detailed sample may refer to another area (larger, smaller or elsewhere), another year or both. The objective of the procedure is to create samples that are representative of target areas, given data for those target areas that is much less detailed in character.

1.4.12 The construction of prototypical samples by the quadratic optimisation method (‘QUAD’) rests on the recognition that the data for the target area and the base sample may be inconsistent. That is, the method balances the need to meet the target area marginal totals against the wish to retain the detailed relationships between the frequencies of different household types indicated by the base sample. Weights can be given to the relative divergences: in this sense QUAD is a generalisation of the IPF method, which gives exact matches to the marginal totals but sacrifices faithfulness to the original detailed sample.

1.4.13 A further difference between most applications of QUAD and the IPF method explained by Beckman et al. is that QUAD constructs its detailed samples by weighting or re-weighting the records of the base sample, rather than by drawing from the base sample with fixed probabilities. This difference has the minor advantage that the rounding errors found in IPF are eliminated, but its more important advantage is that it avoids the additional step of drawing the sample. The output is thus a sample whose size is predetermined and independent of the target area; the fit to the target area is achieved by the weighting.

1.4.14 Re-weighting is applied to all of the households in each of a series of categories, pre-defined to cover the main dimensions of interest for the prediction of travel behaviour. The categories are defined with respect to variables such as household size, numbers of adults, number of workers and the age of the household head.

1.4.15 QUAD is called quadratic optimisation because it can be specified in the form of optimisation with respect to the new frequencies ϕ_c of households of each category c of a quadratic function for each target area, i.e. (following Daly and Gunn, 1985),

$$\phi = \text{argmin}\ (\ Q\ ),\ Q = \Sigma_t\ w_t\ .\ (z_t - \Sigma_c\ \phi_c\ .\ x_{tc})^2 + \Sigma_c\ (\phi_c - f_c)^2 \qquad (12)$$

and

w_t is the weight attached to the importance of meeting target t;

z_t is the value per household of target statistic t in the current area;

x_{tc} is the average amount of target variable t for a household in category c;

hence $(\Sigma_c\ \phi_c.x_{tc})$ is the predicted total of statistic t;

f_c is the frequency of household category c in the base sample.

1.4.16 The first term in Q clearly represents the error in not meeting the target marginal totals for each variable z, while the second term represents the divergence from the current distribution of households over the categories. The weights w are introduced so that differential importance can be given to meeting each of the different targets or that the balance between consistency with targets and consistency with base population can be adjusted. In fact, in most applications it has been found satisfactory to set all the w's to 1. Setting large values of w would cause QUAD to find a distribution of households that matched the target totals very well at the expense of substantial departures from the original distribution, i.e. a solution like that given by IPF.

1.4.17 Note that all terms of Q are on a per-household basis.

1.4.18 The simple form of Q makes it in principle easy to optimise. Given any starting value of ϕ, the global minimum of Q is always at the value ϕ^* given by

$$\phi^* = \phi - Q'(\phi)\ .\ Q''(\phi)^{-1} \qquad (13)$$

where Q' and Q'' are the first and second derivatives respectively of Q with respect to ϕ, i.e. Newton's calculation, which converges directly for a function which is exactly quadratic such as Q. The calculation is particularly easy if the starting value is taken at $\phi = 0$.

1.4.19 However, reality requires that constraints be imposed on the values of ϕ, e.g. that $\phi \geq 0$, and there is no guarantee that Newton's calculation will give such a result. The procedure that can be used in this case is then an iterative calculation, in four steps as follows.

Specify minimum values ϕ_{min} for ϕ and set $\phi_0 = \phi_{min}$ and i = 0.

Perform Newton's calculation as in equation (4) above deriving
$\phi_{i+1} = \phi_i - Q'(\phi_i).Q''(\phi_i)^{-1}$.

Check whether all free values of $\phi_i \geq \phi_{min}$ and that $Q' \geq 0$ for all constrained values of ϕ; if so, terminate.

Otherwise adjust any ϕ values that are less than ϕ_{min} to ϕ_{min}; free any ϕ values which are constrained and for which $Q' < 0$; set i = i+1 and repeat from Step 2.

1.4.20 This algorithm can be proved to converge to the overall optimum in a finite number of steps, because the set of constraints $\phi \geq \phi_{min}$ form a convex set while the function Q is concave. Each iteration of the algorithm gives a reduction in the value of Q. This theoretical result is however of limited value, because the number of steps might be quite large. If the number of categories is of the order of 50, as is commonly the case, the maximum number of steps could theoretically be 2^{50}, approximately 10^{15}. In practice, the number of steps turns out to be very limited: typically convergence is achieved in 5 or 6 iterations.

1.4.21 The values ϕ_{min} can in principle be chosen to be any (non-negative) limits that seem sensible, such as 10% of the frequency of each household category in the base sample. Their function is to prevent unusual, perhaps erroneous, target data from generating an impossible – or nearly impossible – future population distribution.

2 The National Trip End Model

2.1 Summary

2.1.1 The National Trip End Model (NTEM) produces estimates of person travel by all modes (including walk and cycle) for each zone in Great Britain, of which there 7,700. The model outputs trip productions and trip attractions in each zone (collectively known as trip-ends), which may be separated by mode, journey purpose, household car ownership category and time period.

2.1.2 The model produces a picture of the distribution of trip-ends based on land use and demographic forecasts that are produced through the TEMPRO system, namely the Scenario Generator and the National Car Ownership model (NATCOP). In principle the model bases the propensity to travel by different modes and for different purposes by the type of people that live in any particular area. As a final step, trip productions and attractions are reconciled over spatial units known as balancing areas. This ensures that the number of trip productions and attractions are equal across these areas. Refer to Figure 2 for a diagram of how the model works.

2.1.3 Trip end outputs from NTEM are used extensively in transport models. These allow the derivation of future year trip matrices, based on the forecast growth in trip-ends at suitable levels of disaggregation. Growth in trip-ends may also be used in scheme appraisals where no formal model exists by being a representation of traffic growth when combined with the National Road Traffic Forecasts (NRTF).

2.1.4 The NTEM uses base tables of trip rates, mode split and time period profiles derived from 1988-2012 NTS data. This is applied to forecast year population and employment levels in order to produce the trip-ends. Research has shown that trip rates are decreasing over time, however the underlying cause is not fully understood. Trip Rates in NTEM fall in line with observed NTS data and are then hold constant at 2016 levels to reflect the uncertainty in future trip rates.

2.2 Notation

2.2.1 It is useful to define a set of notation, which is used for the specification of all components of the trip-end model and software. The notation is as follows:

P_i^{psmd}	trip productions in ward i, by trip purpose p, traveller type s, mode m and time/day d
W_i^{pmd}	trip attraction weights in ward i, by trip purpose p, mode m and time/day d
A_i^{pmd}	trip attractions in ward i, by trip purpose p, mode m and time/day d
X_i^s, X_i^e, X_i^k	land use indicators s, e and k, in ward i

α^{per} weekly trip attraction rates for trip purpose p, and land use employment/population indicator e and area type r

$\hat{\alpha}^{pmkr}$ trip attraction factors for trip purpose p, mode m, and land use modal indicator k and area type r

β^{psr} weekly trip production rates for trip purpose p, traveller type s, and area type r

$\gamma^{pm|p'm'}$ weekly NHB trip production rates for trip purpose p and mode m, associated with HB trip purpose p' and mode m'

$\rho^{md|psr}$ proportion of trips by mode m and time d, given trip purpose p, traveller type s, and area type r.

O_i^{pmd} trip origins in ward i, by trip purpose p, mode m and time/day d

D_i^{pmd} trip destinations in ward i, by trip purpose p, mode m and time/day d

$\phi^{p_r d_r|sp_o d_o}$ Set of factors which identify the likelihood of a return trip being by purpose p_r at time d_r, for each outward trip by purpose p_o at time d_o by traveller type s. These are used to get from productions and attractions to origins and destinations

Each ward i in GB, is defined as the set of frozen 1991 Census wards and is uniquely identified by a ward_id code as used by the Office for National Statistics (ONS).

In addition each district I, within GB is located within a balancing area B, thus i $\in$ I $\in$ B. It is also useful to consider the sets of dimensions being modelled as follows:

H the set of home-based trip purposes p being modelled

N the set of non home-based trip purposes p being modelled

P the set of trip purposes p being modelled, {P} = {H} + {N}

S the set of traveller types s being modelled

D the set of time periods / days d being modelled

M the set of modes m being modelled

2.3 Model Structure

2.3.1 Figure B1 shows the stages of the calculations within the trip-end model. The calculations at each stage are relatively simple, although the quantity of data to be processed is reasonably large.

2.3.2 The first stage of the process is the estimation of trip productions as outlined at the top left of the diagram. The productions then need to be split into the modelled time periods, and by mode of travel. This is followed by the estimation of trip attraction weights as shown at the top right of the diagram, which will themselves then be split by time period and mode. In order to obtain an equal number of trip productions and attractions by a given purpose and mode at any one time, the number of attractions need to be calculated using a balancing procedure. The following sections outline the calculations involved at each stage.

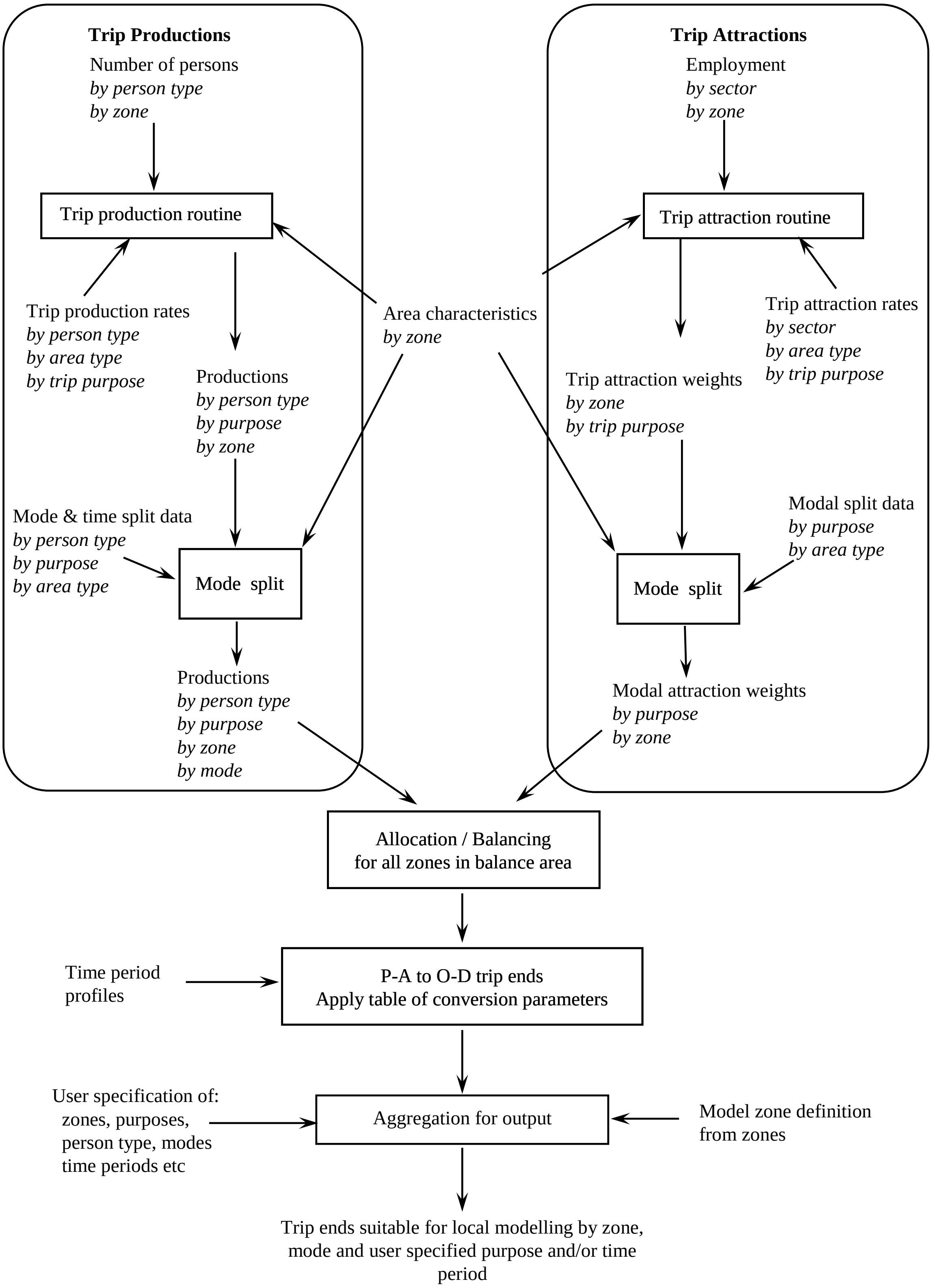

Figure 2 Model framework for trip-end forecasts

Estimation of trip productions by ward

2.3.3 Two sets of trip productions need to be estimated for each ward in GB: home-based (HB) and non home-based (NHB). These two types of trip productions are actually generated using different data and are covered separately below

HB trip productions

2.3.4 HB trip productions are segmented by:

trip purpose - 8 categories, $p \in H$; and

traveller type - categories distinguishing person and household characteristics, $s \in S$.

2.3.5 This is achieved quite simply by applying a set of trip production parameters for each purpose p, traveller type s, and area type r, derived from the NTS to a set of demographic data segmented by traveller type and the area type of each ward i.

2.3.6 Hence for each purpose and each person type, calculate:

$$P_i^{ps} = \beta^{psr} X_i^s \qquad (1)$$

where ward i lies in area type r and X_i^s is the number of persons of traveller type s in ward i and $p \in H$. The output from this stage is a set of weekly HB trip productions for each ward by purpose and traveller type.

NHB trip productions

2.3.7 NHB trip productions are less straightforward to estimate as they are associated with a variety of activities and the purpose definition applied to a NHB trip that is associated with the attraction. The NHB trip productions in a ward i, has therefore to be directly related to the total **HB** trip attractions to that ward. Ideally it would be related to all trip attractions. However doing so would make the procedure iterative in nature which would ideally be avoided given the scale of the model. Following this approach should not significantly reduce the quality of the results obtained.

2.3.8 The modal dimension is included here, to take account that NHB car driver trip productions are largely generated by HB attractions that previously arrived by that same mode.

2.3.9 Thus the NHB trip productions are estimated as:

$$P_i^{pm} = \sum_{p'm'} \gamma^{pm|p'm'} A_i^{p'm'} \text{ where } p \in N, p' \in H \text{ and } m, m' \in M \qquad (2)$$

2.3.10 This stage of the estimation process cannot therefore be completed, until the HB trip attractions have been calculated.

Segment trip productions by time period and mode

2.3.11 Having obtained estimates of trip productions for each purpose, ward and traveller type, these need to be segmented into time periods and modes. Since the modal split of trips by a given purpose was found to vary by time of day, a set of factors to split by mode and time were required based on NTS data.

2.3.12 Time periods represent both times of day, and days of the week. Since in the case of HB trip productions, approximately two trips are created (one from home and later one back to home), the time associated with a production has been defined as the time associated with first journey, ie the trip from the production end to the attraction end. This means that the number of HB trip productions in the evening peak is the number of journeys starting from home at this time and not those returning from work, school etc. For NHB trips only one journey occurs for each production and attraction, so the time period is a more straightforward concept.

2.3.13 The segmentation into time periods is based on a set of proportions derived from NTS. Thus:

$$P_i^{psmd} = \rho^{md|psr} P_i^{ps} \text{ where } p \in H \text{ for home-based trip productions} \qquad (3a)$$

$$P_i^{pmd} = \rho^{d|pmr} P_i^{pm} \text{ where } p \in N \text{ for non home-based trip productions} \qquad (3b)$$

where the sum over all modes *m* and time periods *d* gives the complete set of trip productions, so

$$\sum_{md} \rho^{md|psr} = 1 \text{ if } p \in H \text{, or } \sum_{md} \rho^{d|pmr} = 1 \text{ if } p \in N \qquad (4)$$

Trip attraction weights

2.3.14 Using a similar approach to the estimation of HB trip productions, trip attraction weights need to be estimated for each of the trip purposes being modelled for both HB and NHB trip attractions. For this stage there is no attraction data by traveller type, and possibly only limited information on the area type in which the ward is located (eg for Central London). However there is more information in the form of land use indicators *e* and *k*, attracting trips by purpose and mode to a given ward *i* in a region of type *r*. These attractors are used in one of two ways.

2.3.15 Firstly a set of *zonal weights* is defined for the purpose of *dividing the total trips* within the balancing area *among the different wards*. This function for estimating attraction weights takes the form shown in equation (5).

$$W_i^p = \sum_e \alpha^{per} X_i^e \qquad (5)$$

2.3.16 The land use indicators *e* applicable to each trip purpose *p* vary, and consist of a combination of data on the employment / population in the ward.

2.3.17 A second set of **modal weights** is defined for the purpose of **dividing the trips within a ward by mode**. This function for estimating attraction weights takes the form shown in equation (6). This is equivalent to the logit model form with the variables transformed.

$$\hat{W}_i^{pm} = \prod_k X_i^{k^{\hat{\alpha}^{pmkr}}} \Big/ \sum_m \left(\prod_k X_i^{k^{\hat{\alpha}^{pmkr}}} \right) \qquad (6)$$

2.3.18 The land use indicators *k* applicable to each mode *m* vary, and consist of a combination of data on the observed modal split pattern from the SWS 1991 Census tables for journeys to work, the ward's proximity to key transport nodes such as rail stations, density of employment etc.

Definition of the time period of a trip

2.3.19 The time of day / day of week split is that associated with the outward journey of a home-based production and attraction. In order that matrices for transport modelling can be generated at later stages in the forecasting framework, the definition of the time period associated with both the production and the attraction must be the same. The number of productions and attractions should then be in balance for each particular purpose *p*, mode *m* and time *d* combination. Thus long trips which start in one time period and end in another must only be associated with one, either the start time or the end time, or possibly the mid time. Analysis showed that when considering time periods of 3 hours or more, as in this study, it makes little difference whether the journey start or end time is used. As the timing of journeys is often determined by the required arrival time, this was adopted as the more appropriate variable to use.

2.4 Balancing process to obtain trip attractions

2.4.1 The data available for estimating trip productions is more comprehensive and reliable than for trip attractions. Thus the estimates of trip productions are expected to be fairly accurate, based on the data available. For trip attractions however, the patterns can be predicted using land use indicators but the attraction rates are less robust. The method being used therefore relies on the trip productions to provide the quantity of trip attractions by time period, and uses the trip attraction weights to allocate these trip-ends to wards by mode. As already mentioned the number of trip productions should equal the number of trip attractions for a given "Balancing Area" in each time period. A set of Balancing Areas has been defined using Census journey to work data. This is listed in appendix E. There are currently 50 Balancing Areas within GB which for now will be used for all purposes. The calculation of trip attractions will therefore be carried out for each Balancing Area *B* in turn as shown in equation (7).

$$A_i^{pmd} = \left[\sum\nolimits_{i \in B^p, s \in S} P_i^{psmd}\right] \cdot \frac{W_i^p \hat{W}_i^{pm} G_B^{m|pd}}{\sum\nolimits_{i \in B^p} W_i^p \hat{W}_i^{pm'} G_B^{m'|pd}} \text{ where } i \in B \qquad (7)$$

2.4.2 Here the form of equation (7) was devised to meet the following requirements:

a) within the Balancing Area the total trip attractions for each mode *m* will match the previously calculated modal trip productions, for every combination of purpose *p* and time period *d;*

b) between each ward the number of trips attracted will be in proportion to the zonal weights; and

c) within each ward the number of trips attracted will be in proportion to the modal weights.

2.4.3 To meet the requirement (a) above the modal adjustment factor is updated iteratively in each iteration *n* as:

$$G_{B0}^{m|pd} = 1$$

$$G_{Bn+1}^{m|pd} = G_{Bn}^{m|pd}\left[\sum\nolimits_{i \in B, s \in S} P_i^{psmd} \Big/ \sum\nolimits_{i \in B} A_i^{pmd}\right] \qquad (8)$$

Conversion to origins and destinations

2.4.4 Having obtained estimates of productions and attractions, it is useful to be able to provide estimates of actual trip origins and destinations. For NHB trips, the number of origins is the same as the productions and the destinations are the same as the attractions.

$$O_i^{pmd} = P_i^{pmd} \text{ and } D_i^{pmd} = A_i^{pmd} \qquad (9)$$

2.4.5 For home based (HB) trips the conversion is not so simple. For every trip from home, there will be another back home. From analysis of the NTS data it appears that the mode used for trips from home and back to home are highly likely to be the same. However, there is no reason for the trip purpose to be the same. For example a trip from home to work, may be followed by a trip from work to the shops and then from the shops back home. In terms of productions and attractions this would be recorded as a HBW production and attraction, and a NHB shopping production and attraction. However in terms of origins and destinations, this would be a HBW origin and destination, a NHB shopping origin and destination and a HB shopping origin and destination. Table B1 below shows the average number of P-A and O-D trip-ends by car driver mode in Great Britain in 1991 on a weekday.

Table 1 Numbers of P A and O D trip ends in Great Britain by car driver mode (thousands)

	Production	Attraction	Origin	Destination
Home Based trips	27,379	27,379	54,674	54,674
Non Home Based trips	7,937	7,937	7,937	7,937

2.4.6 This conversion of P-A trips to O-D trip-ends is further complicated by the time period in which the journeys take place. The time period associated with the trip productions and attractions is the time period of the outward journey. It is not possible to determine the time of the return HB journey directly from the time period of the productions or attractions. The return journey will occur either during the same time period or a later period in the same day. For the purposes of this project, it has been assumed that all travellers return home before the AM peak the following day.

2.4.7 Although the relationship between P-A and O-D trip-ends is likely to vary by traveller type, this dimension has not been incorporated within the model specification. Including such a dimension would have significantly increased both the resource and running time requirements of the trip-end model requiring many additional intermediate model results to be stored, without leading to a significantly improved model.

2.4.8 Using subscripts *o* and *r* to denote outward (ie from home) and return (ie to home) trips respectively, the number of origins and destinations by purpose *p*, mode *m* and time *d* associated with each ward are:

$$O_i^{pmd} = O_{io}^{pmd} + O_{ir}^{pmd} \text{ and } D_i^{pmd} = D_{io}^{pmd} + D_{ir}^{pmd} \qquad (10)$$

2.4.9 In the same manner as for NHB trips, the trip-ends for the outward journey can be directly associated with the productions and attractions of the same purpose, mode and time.

$$O_i^{pmd} = P_i^{pmd} \text{ and } D_i^{pmd} = A_i^{pmd} \qquad (11)$$

2.4.10 For the return trips the origins will be associated with attractions (e.g. Work, shopping); while the destinations are associated with the productions (Home). Thus:

$$O_{ir}^{pmd} = f\left(A_i^{PmD}\right) \text{ and } D_{ir}^{pmd} = f\left(P_i^{PmD}\right) \qquad (12)$$

where *f* is a simple function.

2.4.11 In practice, using the NTS database, a set of probabilities $\phi^{p_r d_r | p_o d_o}$ can be calculated which identify the likelihood of a traveller making a return trip being by purpose p_r at time d_r, for each outward trip by purpose p_o at time d_o.

2.4.12 Thus:

$$O_{ir}^{pmd} = f\left(A_i^{PmD}\right) = \sum_{p_o d_o} \phi^{p_r d_r | p_o d_o} A_i^{p_o m d_o} = \sum_{p_o d_o} \phi^{p_r d_r | p_o d_o} D_{io}^{p_o m d_o} \qquad (13)$$

where $\sum_{p_r d_r} \phi^{p_r d_r | p_o d_o} = 1$ (13a)

and

$$D_{ir}^{pmd} = f\left(P_i^{PmD}\right) = \sum_{p_o d_o} \phi^{p_r d_r | p_o d_o} P_i^{p_o m d_o} = \sum_{p_o d_o} \phi^{p_r d_r | p_o d_o} O_{io}^{p_o m d_o} \qquad (14)$$

where $\sum_{p_r d_r} \phi^{p_r d_r | p_o d_o} = 1$ (14a)

2.4.13 It should be noted that following this approach does not necessarily result, for a given purpose, in two origins and two destinations being created for each production and attraction. Similarly the number of trip origins for a given purpose will not necessarily be twice the number of trip productions for the same purpose.

2.4.14 However, the equation (14a) does ensure overall consistency in residence (e.g. production) zones which is what is required. Summing both sides of the equation (14) over the set of return purposes and time periods, p_r, d_r, shows that the right hand side, which is the total origins from a zone, equals the total destinations to that zone. A similar consistency condition is achieved at the attraction zone end by the equation (13a).

2.4.15 The return factors in formulae (13) and (14) were applied equally to every mode, since there did not appear to be major differences between the outward and return modal shares, once all trips have been summed together.

2.5 Definitions of segmentation

2.5.1 A summary of the categories within the model is provided here for reference.

Trip purpose

P1 HB Work
P2 HB Employers Business (EB)
P3 HB Education
P4 HB Shopping
P5 HB Personal Business (PB)
P6 HB Recreation / Social
P7 HB Visiting friends & relatives (for HB trips only)
P8 HB Holiday / Day trip
P11 NHB Work
P12 NHB Employers Business (EB)
P13 NHB Education
P14 NHB Shopping
P15 NHB Personal Business (PB)
P16 NHB Recreation / Social
P18 NHB Holiday / Day trip

Time of day / day of week

D1 Weekday AM peak period (0700 - 0959)
D2 Weekday Inter peak period (1000 - 1559)
D3 Weekday PM peak period (1600 - 1859)
D4 Weekday Early or Late (0000 - 0659) and (1900 - 2359)
D5 Saturdays (all times of day)
D6 Sundays (all times of day)

Mode

M1 Walk
M2 Cycle
M3 Car driver
M4 Car passenger
M5 Bus
M6 Rail (including underground)

Area type

2.5.2 Area types have been defined to be as consistent as possible with those proposed for NRTF, while making the best use of the NTS data (definitions).

A1 Inner London
A2 Outer London
A3 Metropolitan areas
A4 Urban Big (> 250k)
A5 Urban Large (100k to 250k)
A6 Urban Medium (25k to 100k)
A7 Urban Small
A8 Rural

Zonal attraction weights

E01 All Jobs
E02 Households

E03 Primary & Secondary schools
E04 Higher Education
E05 Adult education
E06 Hotels, camp sites etc
E07 Retail trade
E08 Health / Medical
E09 Services (business, other, postal/courier) & equipment rental
E10 Industry, construction and transport
E11 Restaurants and bars
E12 Recreation and sport
E13 Agriculture and fishing
E14 Business
E15 Holiday accommodation and second residences

Traveller type

2.5.3 Traveller types are defined as a combination of person type and household type. The person types being distinguished are:

Children (0 to 15)

males in full time employment (16 to 74)

males in part time employment (16 to 74)

male students (16 to 74)

male not employed / students (16 to 74) - Unemployed plus other Inactive

male 75+

females in full time employment (16 to 74)

females in part time employment (16 to 74)

female students (16 to 74)

female not employed / students (16 to 74) - Unemployed plus other Inactive

female 75+

While the household types to be distinguished are based on the number of adults and car availability:

1 adult households with no car

1 adult households with one or more cars

2 adult households with no car

2 adult households with one car

2 adult households with two or more cars

3+ adult households with no car

3+ adult households with one car

3+ adult households with two or more cars

3 Document Provenance

In November 2014, this document was updated with current information about the Department's Car Ownership Modelling Methodology.

In July 2016, this document was updated to reflect changes in the update to TEMPRO 7.