Application of Disaggregate Techniques to Calibrate a Trip Distribution and Modal-Split Model

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A trip distribution and modal-split model for use in a transportation planning study for Tilburg, Netherlands (170 000 population), was developed by using disaggregate models. The procedures adopted were based on the functional similarity of multinomial logit and Wilson's entropy maximizing model. A model system with four modes and six market segments was developed by using readily available software. Although it was impossible to develop a simultaneous trip distribution and modal-choice model, a satisfactory sequential model system, in which the mode choice utility functions were used as generalized prices in the distribution model, was obtained. This paper describes the basic philosophy of the approach, some of the problems encountered, and some of the results.

This paper describes a recent application of disaggregate modeling techniques in the development of a distribution and modal-split model system for use in an urban transportation planning study being undertaken in Tilburg, Netherlands. This study covers three municipalities in southern Netherlands with a total population of about 170 000. Tilburg is a town that developed in the last century and has a very good road system; it is also well served by an extensive bus network, although only some 2 percent of intraurban trips are made by bus. The first phase of the study began in 1972 when 4500 home interviews (9 percent sample) were conducted (3).

BASIC MODELING PHILOSOPHY

The most widely used disaggregate travel demand model is the logit model, which, in its multinomial form, can be written

$$\text{Prob}(a:A_t) = \frac{\exp U_a(X_a, S_t)}{\sum_{a=1}^{A_t} \exp U_a(X_a, S_t)} \quad (1)$$

where

$\text{Prob}(a:A_t)$ = probability of individual t choosing alternative a out of A_t, the full set of alternatives available to him, and
$U_a(X_a, S_t)$ = utility of alternative a to individual t (usually regarded as a function of the variables that characterize alternative a, denoted by X_a, and the socioeconomic variables that describe individual t, denoted by S_t, and described as the utility function).

A description of the derivation of logit and its main characteristics can be found in the literature (5, 9, 11). As usually applied in mode choice studies, logit is of similar functional form to the modal-split model that can be derived from Wilson's entropy maximizing model (12). This model, used widely in the United Kingdom, can be written

$$\frac{T_{ijm}}{\sum_{m=1}^{M} T_{ijm}} = \frac{\exp \beta C_{ijm}}{\sum_{m=1}^{M} \exp \beta C_{ijm}} \quad (2)$$

where

T_{ijm} = number of trips from i to j by mode m,
C_{ijm} = generalized cost of traveling from i to j by mode m, including any relevant modal constant or handicap, and
β = constant.

Wilson's modal-split model is a submodel of a simultaneous trip distribution and modal-split model that can be written

$$T_{ijmn} = a_{in} P_{in} b_j A_j f_n(C_{ijm}) \quad (3)$$

where

T_{ijmn} = number of trips from zone i to zone j by mode m made by person type n,
P_{in} = number of trip productions in zone i by person type n,
A_j = number of trip attractions in zone j,
$f_n(C_{ijm})$ = function for a specific person type of the generalized cost of travel from zone i to zone j by mode m, and

$$a_{in} = \left[\sum_{j=1}^{J} \sum_{m=1}^{M} b_j A_j f_n(C_{ijm}) \right]^{-1}$$

$$b_j = \left[\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} a_{in} P_{in} f_n(C_{ijm}) \right]^{-1}$$

As a singly constrained (or balanced), production model, i.e., with b_j set equal to unity, the model can be written

$$\frac{T_{ijmn}}{P_{in}} = \frac{A_j f_n(C_{ijm})}{\sum_{j=1}^{J} \sum_{m=1}^{M} A_j f_n(C_{ijm})} = \frac{\exp \ln A_j + \beta_n C_{ijm}}{\sum_{j=1}^{J} \sum_{m=1}^{M} \exp \ln A_j + \beta_n C_{ijm}} \quad (4)$$

Equation 4, like equation 2, has a functional form similar to a special case of logit in which the coefficient of the attraction variable, $\ln A_j$, is constrained to 1.0. It is interesting to note that the functional form of the attraction variable, i.e., the logarithmic transformation, is that that has been found to be the most suitable by both Richards and Ben-Akiva (9) and Adler and Ben-Akiva (1) in developing simultaneous destination and modal-choice models for shopping trips. Furthermore, by using retail employment as a proxy for the attractiveness of the shopping center, Richards and Ben-Akiva (9) estimated the coefficient of this variable to have a value of 0.74, which is relatively close to the value of 1.0 implied in equation 4.

Although distribution models are generally applied in the doubly constrained form in which the attraction variable is equal to an independently estimated number of attractions per zone, it is questionable whether this is always a desirable procedure when the attraction model is insensitive to accessibility, as is usually the case; thus, regardless of the effect on accessibility of alternative plans, the total number of trips to a zone remains fixed. The use of a properly specified, singly constrained, production model not only offers the possibility of overcoming this deficiency but also has considerably greater behavioral justification.

The structure of the total transportation model system implies a specific decision-making process on the part of the traveler. Brand (2) summarized the alternative assumptions. If we assume that there is a hierarchy of decisions and that the relative valuation of the choice attributes, or independent variables, remains constant within any given hierarchy, then we have to determine those relative values. It has been argued (4) that it is best, in the case of a sequential destination choice and mode choice situation, to determine the relative valuation of the alternative modes in the modal-split model and then to apply this as a generalized price in the trip distribution model, in which the coefficient of the generalized price is determined.

Conventional urban transportation models have tended to regard all trip makers as having identical valuations of the various attributes affecting the relevant travel choice (e.g., mode) and also as having identical sets of alternatives from which to choose. This practice can give rise to models that fail to adequately explain the behavior of groups within the population and thus lead to prediction errors, especially when the characteristics of the population relevant to travel demand change over time. A particular example of this is the effect of car availability on mode choice; car availability is a function of (among other things) ability to drive. Although Wilson's model permits the use of market segments, it has rarely been applied in transportation planning studies to more than two person types. This can be partly attributed to the trip production modeling procedure that has dominated in the United Kingdom in recent years (13), but it is also due to the problems of calibrating models with a finer system by using traditional procedures. The latter comment also applies to the use of more than two modes.

Although transformation of the disaggregate models into aggregate models was a possible source of problems, it seemed likely that use of a segmentation system based on choice sets as well as a relatively fine zoning system could reduce the aggregate error to an acceptable level. The former of these assumptions has since been given increased credence by Koppelman (6).

TILBURG STUDY

The similarity between logit and Wilson's entropy maximizing model forms the basis for the development of the trip distribution and modal-split models for Tilburg. Such an approach had three major advantages: First it facilitated the calibration of a multimodal model; second it facilitated the application of a number of market segments; and third better models could be developed by using disaggregate rather than aggregate data. Yet the final models are essentially conventional in form; they are compatible with other elements of the model system, and they were developed and can be applied by making extensive use of existing computer programs.

The original intention was to develop a singly constrained, production, simultaneous destination and modal-choice model for all trip purposes except home-based work and home-based school. Work and school were excluded because, with Dutch planning legislation, the absolute number of jobs and school places in any zone can be assumed to be fixed.

Unfortunately, after a series of models for home-based shopping trips with different specifications was calibrated, as well as at least one basic model for each other trip purpose, it appeared that, within the data, time, and budget constraints of this study, no satisfactory specification could be found for a simultaneous destination and modal-choice model that could be readily transformed into an aggregate model and would be independent of zoning systems. The original concept of a simultaneous destination and modal-choice model was therefore abandoned, and a sequential destination choice and modal-choice model in which calibration of the modal-choice model preceded the destination choice model was used instead. The modal-choice model remained a disaggregate model, but the destination choice model became a doubly constrained aggregate model in which the modal-choice utilities were used as generalized prices.

The scope of a market segmentation system for the Tilburg study was constrained by the possibilities offered by both the trip production model and the program to be used for forecasting trip distribution and modal split. The trip production model scheduled for use in the Tilburg study is a person-based cross-classification model. Two dimensions of the classification system are the availability of a car within the household and the personal possession of a driving license. The aggregate trip distribution and modal-split program available for the study was limited to six market segments. Given this, the market segmentation system was based on car and moped availability, availability being defined by simple binary variables:

1. Possession or lack of possession of a driving license,
2. Household possession or lack of possession of at least one car, and

3. Household possession or lack of possession of at least one moped.

All of these variables could then be introduced in the utility function of the disaggregate model as simple dummy variables. Thus the market segmentation system applied in this study related only to vehicle availability and not to the valuation of the level-of-service variables used. Ideally it should have applied to both.

A random sample of 2000 trips for each purpose class (except those for which less than 2000 observations were available) was selected from the home interview files. Although experience to date with disaggregate models has shown that samples of 500 observations can be adequate for model calibration (9), the Tilburg data set presented a particular problem in that the probability of using the bus was very low, between 1 and 3 percent averaged over all trips for a given purpose. Lerman, Manski, and Atherton's (7) work undertaken since the study was completed indicates how this problem could be overcome.

Although five significant models could be defined (car driver and car passenger are different modes), for primarily economic reasons walking and bicycle modes were grouped together. Moped was only considered a valid mode for persons from a household with a moped; car was considered a valid mode for all persons although the probability of choosing car is influenced by the values of the coefficients of a set of dummy variables representing license and car availability. Bus and walk-bicycle were considered to be valid modes for everyone.

The home interview data had been coded to a fine zoning system, consisting of 506 zones; the population of the study area was 170 000. Level-of-service data therefore had to be based on zonal centroids, but to maintain the maximum interzonal variability in the values of the level-of-service variables this zoning system (fine zones) was used for model calibration purposes. For forecasting purposes, however, such a fine zoning system could not be used because of the lack of necessary socioeconomic data at this level and economic constraints. A coarser zoning system was therefore derived. This system, which consisted of 162 zones (superzones), was used for all aggregate model work, including calibration.

In-vehicle travel time data for car, moped, and bus were obtained from modal networks, as were bus access, waiting, and transfer times and costs. In-vehicle travel time for bicycle was derived from the moped network by using a constant speed of 12 km/h. Out-of-pocket travel costs for car and moped were derived by multiplying the distance over the minimum generalized cost path by 7.5 and 2.5 cents/km respectively. Out-of-vehicle and intrazonal travel times for bicycle, moped, and car were estimated manually.

The modal-choice utility functions were originally intended to contain in-vehicle travel time, out-of-vehicle travel time, and out-of-pocket travel costs as independent variables, but early model specifications revealed a major problem due to correlation between in-vehicle travel time and out-of-pocket travel costs for both car and moped and between similar variables for different modes. This was undoubtedly caused by the lack of congestion in Tilburg; journey speeds are thus fairly constant throughout the network. Because the models were to be used to evaluate alternative transportation policies, some of which would be based on various car restraint measures to be represented as additional travel costs, it was decided, reluctantly, to replace the individual variables by a composite generalized time variable, i.e., a conventional generalized cost variable scaled in time (8).

The generalized time variable was applied as a mode-specific variable; i.e., its coefficient was allowed to vary between modes. This was necessary for at least car and moped because generalized cost increases less rapidly with distance for moped than for car (travel times are similar within the urban area but moped is cheaper than car); thus use of a generic variable would imply that moped becomes increasingly attractive relative to car with increasing trip length. Furthermore, the coefficients of the generalized time variables for the other modes were found to be significantly different from each other. This finding is contrary to that reported by Richards and Ben-Akiva (9) for Eindhoven, where the coefficients of in-vehicle travel time for home-work-home journeys were found to be similar for five modes. Nevertheless, the relative values determined for Tilburg seem to reasonably reflect the relative inconvenience or effort associated with the use of the different modes, even though they imply that the value of one unit of generalized time is not constant over modes; a minute is not always perceived as a minute in the choice of modes.

For the models described here, a modal constant was included for each mode except car. Three car-specific dummy variables were used to represent car availability; there was no dummy variable for someone without a license coming from a carless household, and this therefore represents the base situation.

In the singly constrained distribution model, the variable A_j represents the relative attractiveness of zone j, while in a conventional doubly constrained model it represents the absolute number of trip attractions. For the Tilburg study the usual definition of A_j was maintained, i.e., trip attractions. But the observed number of attractions, $A_{j_{obs}}$, was not the relevant variable for use in calibrating a singly constrained production model because it can be expected that this represents a function of the basic attractiveness of the zone, as a function of employment and other content variables, and the accessibility of that zone. The trip attraction model used, however, is a simple cross-classification model in which attractions per land use class (per purpose) are treated as a function of the employment in that class.

HOME-BASED WORK TRIP

Of the modal-choice models calibrated for work trips, the utility function U_m of the one considered the most suitable for use in the forecasting model had the general specification given in Table 1. A full set of statistics for all the models described are given in Table 2. These statistics were based on the following number of observations and cases:

Purpose	Observations	Cases
Work	2135	5170
Social	1933	4458
Recreational	1506	3255

The coefficients of the disaggregate modal-choice model were used in an aggregate modal-choice model by using the observed trip matrices at the superzone level. For the aggregate modal-split model, as well as the trip distribution model, the eight market segments were collapsed to six by grouping people having either a license and no car or no license and a car because the coefficient of the dummy variables for these two had the same value. The calculated and observed model shares per market segment are given in Table 3. The calculated shares compare favorably with observed shares except for the bus mode; this was probably due to its low probability of choice. The calculated shares

Table 1. Utility function for home-based work and social trips.

U_i			
Home-Based Work	Home-Based Social	Item	Mode
-0.03	-0.06	Generalized time	Car
-0.12	-0.19	Generalized time	Moped
-0.15	-0.18	Generalized time	Walk-bicycle
-0.02	-0.03	Generalized time	Bus
+4.28	+3.85	Persons with driving license and car	Car
+1.72	+1.76	Persons with no license but with car	Car
+1.70	+0.82	Persons with license but no car	Car
+4.33	+2.99		Moped
+5.47	+3.98		Walk-bicycle
+0.70	+0.56		Bus

for each of the three main modes are within 2.5 percent. Within the market segments there is greater error, however, especially between walk-bicycle and moped. The similarity of bicycle and moped could be a reason for this, since, except for the third market segment, the share of car is always well reproduced. The observed and calculated average trip costs, a conventional calibration test, were also considered as being satisfactory.

Application of the estimated modal utility functions (per market segment) in the distribution model (with the coefficient of the generalized price variable set equal to 1.0) followed by calculation of modal split yielded the predicted distribution and modal-split values. These results can again generally be considered satisfactory, although there are clearly some specific values that should be improved.

Table 2. Statistics for mode choice models.

	Work		Social		Recreational	
Variable	Coefficent	S.E.	Coefficient	S.E.	Coefficient	S.E.
Car						
License	4.284	0.298	3.853	0.179	3.318	0.199
No license	1.716	0.353	1.757	0.175	0.813	0.192
No car, license	1.702	0.763	0.817	0.316		
Walk-bicycle constant	5.469	0.367	3.981	0.267	22.829	0.341
Moped constant	4.327	0.386	2.987	0.318	13.116	2.344
Bus constant	0.703	0.763	0.563	0.560	30.773	9.885
Generalized time						
Car	0.000 30	0.000 20	-0.000 62	0.000 19		
Walk-bicycle	-0.001 48	0.000 17	-0.001 80	0.000 15		
Moped	-0.001 16	0.000 34	-0.001 86	0.000 32		
Bus	-0.000 24	0.000 12	-0.000 32	0.000 10		
ln generalized time						
Walk-bicycle					-2.867	0.180
Moped					-1.660	0.334
Bus					-3.789	1.160
CBD constant, car					0.377	0.201

Table 3. Observed and calculated modal shares by market segment and trip purpose.

		Home-Based Work				Home-Based Social				Home-Based Recreational			
Market Segment	Model	Car	Walk-Bicycle	Moped	Bus	Car	Walk-Bicycle	Moped	Bus	Car	Walk-Bicycle	Moped	Bus
Car, license, moped	Observed	9 118	4654	3186	75	7 216	1 609	1073	57	2545	1009	222	0
	Predicted (MS)	8 974	4014	4037	1	7 301	1 317	1210	172	2561	785	419	11
	Predicted (D)	9 226	3757	4044	54	7 228	1 392	1208	126	2642	762	364	9
Car, license, no moped	Observed	19 758	9098	80	115	15 643	3 169	—	146	5690	1811	51	51
	Predicted (MS)	19 860	9083	0	30	15 639	3 016	—	268	5911	1665	0	27
	Predicted (D)	20 696	8256	0	123	15 628	3 042	—	277	5951	1631	0	22
Car or license, moped	Observed	615	5848	8403	304								
	Predicted (MS)	1 252	6607	7214	42								
	Predicted (D)	1 239	6626	7212	100								
Car or license, no moped	Observed	843	5335	96	273								
	Predicted (MS)	1 049	5408	0	78								
	Predicted (D)	1 024	5433	0	83								
No car, no license, moped	Observed	253	7310	7842	217								
	Predicted (MS)	212	7679	7865	39								
	Predicted (D)	248	7553	7974	109								
No car, no license, no moped	Observed	353	8064	0	349								
	Predicted (MS)	337	8425	0	124								
	Predicted (D)	262	8531	0	116								
Car, no license, moped	Observed					2 395	4 292	3676	382	732	2922	1687	48
	Predicted (MS)					2 667	4 161	3519	385	971	2616	1749	33
	Predicted (D)					2 285	4 309	3761	390	968	2733	1639	47
Car, no license, no moped	Observed					4 588	6 979	—	465	1665	4423	0	40
	Predicted (MS)					4 711	6 739	—	688	1638	4466	0	94
	Predicted (D)					3 919	7 538	—	672	1613	4512	0	73
No car, moped	Observed					1 071	8 423	6699	1013	650	3240	1548	21
	Predicted (MS)					1 024	7 705	7577	896	481	3009	1907	67
	Predicted (D)					920	8 361	7165	761	468	2848	1989	59
No car, no moped	Observed					2 206	11 247	—	2179	836	6696	0	310
	Predicted (MS)					1 762	12 393	—	1548	1182	6471	0	150
	Predicted (D)					1 389	13 151	—	1163	1267	6405	0	130

Note: Predicted (MS) is modal split only. Predicted (D) is distribution and modal split.

Table 4. Model coefficients for home-based recreational trip.

U_n	Item	Mode
-2.87	ln generalized time	Walk-bicycle
-1.66	ln generalized time	Moped
-3.79	ln generalized time	Bus
+3.32	Persons with driving license and car	Car
+0.81	Persons with no license but with car	Car
+22.83		Walk-bicycle
+13.12		Moped
+30.78		Bus
+0.38	Trips to CBD only	Car

Note: Generalized time is in minutes times 100.

HOME-BASED SOCIAL TRIP

Specifications of the utility function of the mode choice model selected are given in Table 1. For the aggregate models all persons from a carless household were grouped together. Application of the mode choice model specification in the aggregate modal-split model resulted in modal shares given in Table 3.

Application of the values of the modal utility functions in the distribution model, followed by modal split, gave the predicted distribution and modal-split values.

The calculated shares for the four market segments of people from car-owning households are all satisfactory. The modal shares for the two market segments for people from carless households are, however, not so good, and most of the differences in the overall modal shares are due to these two segments. Although the no car, no license, moped and no car, no license, no moped segments represent 39 percent of all home-based social trips in the base year, this proportion will decline with increasing car ownership. It was therefore decided not to apply any adjustment, although better fit could almost certainly have been obtained by setting the generalized coefficient for these market segments to a value other than unity.

HOME-BASED RECREATIONAL TRIP

As with the home-based social model, the original intention of a singly constrained simultaneous trip distribution and modal-split model was replaced by a sequential model system using a doubly constrained distribution model.

Development of a mode choice model proved considerably more involved for recreational trips than for the two purposes discussed previously. A specification similar to that described for home-based work proved satisfactory except that the coefficient of car generalized time was both positive and significant. The coefficient of the dummy variable for people with a license from carless households was not significantly different from zero in this model, indicating that for this purpose possession of a license had no effect on the probability of a person from a carless household choosing car.

After trials with alternative specifications, a model with the natural logarithms of the four mode-specific generalized time variables was tried. This is comparable in aggregate model terms to using a power function (C_{ij}^{λ}) rather than an exponential function ($\exp \beta C_{ij}$). In this model all the coefficients were significant and had the expected sign with the exception of the ln generalized time variable for car, which had a coefficient not significantly different from zero. The model was then rerun, and the coefficients given in Table 4 were obtained. The implication of this model is that choice of car is determined by car availability and the level of service offered by alternative modes; in the base year, choice of car was not directly affected by the level-of-service variables relating directly to car. This could be caused by the correlation problems previously referred to; it could also reflect a definite lack of sensitivity to car level-of-service variables in the choice of car for intraurban recreational trips. Such a lack of sensitivity, within reasonable limits, does not seem totally unreasonable; 72 percent of all trips made by persons from a car-owning household were by car.

Use of such a model for forecasting purposes could create problems if extreme measures relating to car usage were to be applied. However, such extremes are unlikely in the context of the current study, and even if they were the reliability of any of the models calibrated for the base year is questionable for such an application.

Application of the model specified above in the aggregate modal-split program resulted in the modal shares per market segment given in Table 3. These can again be regarded as satisfactory, although some individual values show a difference relative to the observed values that is somewhat larger than might ideally be desired.

Use of the modal-split functions in the aggregate distribution model resulted in a serious overestimation of car trips and an underestimation of walk-bicycle trips. To obtain satisfactory results required that a different generalized price parameter be applied to each pair of market segments. The best values were as follows:

Market Segment	Value
Car and license	2.0
Car, no license	1.2
No car	1.0

The results obtained when these factors were applied are predicted (D) values in Table 3.

CONCLUSIONS

Experience with the application of the basic model philosophy to Tilburg is, in some respects, disappointing. But analysis of the results obtained would seem to indicate that the problem is related more to the characteristics of the area to which the models were applied than to the model system itself. There is, however, a reasonable degree of consistency in the results across the various purposes; for instance, the effect on the probability of choosing car of having a car and license relative to having neither is remarkably constant over all purposes.

The results of the study highlight two particular problems affecting the development of such models. One is that variability is not only required within alternatives but also between alternatives. The second is that of estimating a satisfactory model for alternatives with a low choice probability. Neither of these problems are exclusive to the use of disaggregate models; they are also relevant to aggregate models, even though they are not always apparent.

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