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Disaggregate Travel Demand Models for the San Francisco Bay Area

System Structure, Component Models, and Application Procedures

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Significant advances have recently been made in developing and applying disaggregate behavioral travel demand models to many aspects of urban travel decisions. What has not previously been developed is a full set of urban models integrated into a complete forecasting system for use by a metropolitan planning organization. The purpose of this paper is to describe the first such system, which was developed for the Metropolitan Transportation Commission, the designated metropolitan planning organization for the San Francisco area. First, the background of the current modeling project is briefly set out, followed by a description of the structure of the model system. The model development process—estimation, prediction testing, and validation—is described, and two computerized model application procedures—a regional network analysis system compatible with available urban transportation planning packages and a generalized policy analysis system based on random sample forecasting—are presented. Conclusions concerning the advantages and disadvantages of the system of disaggregate models are presented.

Significant advances have recently been made in developing and applying disaggregate behavioral travel demand models to many aspects of urban travel decisions (1, 2, 3, 4). What has not previously been done is the development of a full set of urban models and their integration into a complete forecasting system for use by a metropolitan planning organization. The purpose of this paper is to describe the first such system, which was developed for the Metropolitan Transportation Commission (MTC), the designated metropolitan planning organization for the San Francisco area. The models have been developed by the Travel Model Development Project, carried out by a consultant team consisting of the COMSIS Corporation, Cambridge Systematics, Inc., and Barton-Aschman Associates. Because of the number of models included in the system, this paper must be an overview of the system as a whole, rather than a detailed description of each individual model. Complete documentation of the project is available in a three-volume final report (5).

BACKGROUND

The MTC is the successor to the Bay Area Transportation Study Commission (BATSC), the original region-wide multimodal transportation planning agency in the Bay Area. Although BATSC carried out the traditional first steps of metropolitan transportation planning—collecting and analyzing land-use and travel data—neither it nor MTC was previously successful in developing an accepted complete land-use and travel modeling system that could be used to forecast future travel patterns. In cooperation with the Association of Bay Area Governments (ABAG), the projective land use model (PLUM) was developed to forecast future land use, employment location, residential location, and socioeconomic characteristics (6).

Although at least two generations of trip-making models that use these forecasts to predict future travel have been developed, both MTC and other Bay Area agencies have been reluctant to use them because of deficiencies in their ability to represent existing travel or to provide reasonable future estimates. The lack of such a travel model system led MTC to fund the Travel Model Development Project and to select an approach to develop a model system that would be, as much as possible, based on disaggregate travel demand modeling techniques.

The domain of the models to be developed was clear. They should begin where PLUM ends, using PLUM's land-use and other travel-related forecasts as input; they should deal with all aspects of urban passenger travel, including the assignment of transit person trips and highway vehicle trips to the appropriate facilities; they should provide the ability to conduct areawide planning studies.

The data base for model development also became clear; although many special purpose surveys collected since 1965 cover specific subareas of the region, the 1965 BATSC travel surveys remain the most recent complete travel data set. In addition, all necessary related data—highway and transit networks, zone level-of-service data (access times and distances and parking costs, for example), and land-use data (obtained largely from "backcasts" to 1965, using PLUM, of data collected in 1970)—were available for 1965. All such data were also available with a common zoning system of 290 zones and 30 districts.

MODEL SYSTEM REQUIREMENTS

Against this background, the following major requirements for the MTC travel demand model system were identified.

1. Validity: The system must accurately represent travel behavior, which occurs as a result of an interconnected set of household and individual decisions;
2. Comprehensiveness: The system must represent the full range of urban travel decisions;
3. Policy relevance: The system must be sensitive to all relevant policy options; and
4. Flexibility: The system must be usable for analysis at varying levels of detail and spatial and time scales.

Because disaggregate travel demand modeling techniques provide significantly improved capabilities to meet each of these requirements, they have been used to develop the MTC model system. Disaggregate models estimated at the household, person, or trip level are used for aggregate forecasting at the zone level. The theoretical and statistical advantages of this approach over conventional aggregate modeling techniques have been extensively discussed in the literature (7). The major characteristics of the resulting model system meet the above requirements in a system that is (a) an operational areawide transportation planning tool, (b) based entirely on disaggregated travel demand models, and (c) estimated by using conventional urban transportation study data.

The remainder of this paper describes the key features of the model system and emphasizes unique characteristics and major improvements over a typical conventional system. The discussion focuses on two major areas: first, the model system structure—the interrelations among travel choices and the structure of individual models—and, second, the model development process—the process of empirical model estimation and testing, and the techniques used for aggregate forecasting. The paper concludes with a summary of the key advantages and disadvantages of the disaggregate approach to travel modeling.

MODEL SYSTEM STRUCTURE

Travel Choices Represented

In general, a travel demand model is concerned with those household and individual decisions that result in trips being made. However, some other choices are so strongly interrelated with actual trip-making choices that it is impossible to separate them from such decisions. For example, the choice of residential location is not in itself a trip-making decision. However, the combination of a worker's employment location choice and his or her household's location decision has as its consequence a trip choice, i.e., daily work trips.

For this reason, the general framework from which the components of the MTC model system are derived begins with a partition of all possible household and household member decisions into two sets: those that are relevant to transportation analysis and those that, for practical purposes, can be ignored. This partition produces the following set of travel-related household decision choices:

1. Employment location (for all workers),
2. Residential location,
3. Housing type,
4. Automobile ownership,
5. Mode to work (for all workers),
6. Frequency (for nonwork trips of each purpose),
7. Destination (for nonwork trips of each purpose),
8. Time of day (for nonwork trips of each purpose),
9. Mode (for nonwork trips of each purpose), and
10. Route (for all trips).

For most situations, this set of decisions must be represented in a complete model system. In theory, each decision may be dependent on the rest. For example, where one chooses to live is obviously linked to the housing type and the level of automobile ownership one selects. Similarly, shopping trip destination and mode are likely to be closely linked.

This perspective, if carried through completely, would produce a model of unmanageable dimensions, since all possible combinations of choices would, for practical purposes, be limitless; useful models would then be impossible to develop. Fortunately, there are some interrelationships among components of this set that are of a fundamentally different character than others. Some of the decisions, such as residential location choice, have high transaction costs and are consequently stable over fairly long intervals; other choices, such as the frequency of social and recreational trips, are altered on a daily basis. Some decisions are more logically represented as being made collectively by the household, while others can be approximated as individual choices. Thus, it is possible to formulate explicit behavioral hypotheses and to establish a structure of the total set of choices as a logical working hypothesis. Such an explicit structure greatly simplifies model development. This structure is termed a hierarchy of choice (8).

Figure 1 illustrates the three-stage choice hierarchy represented by the MTC model system. At the highest level are urban development decisions, which are long run in nature: employers decide where to provide jobs and developers decide where to provide housing of various types. Next come household mobility decisions made more frequently; these include where to live and work, how many household members will have jobs, how often they each will go to work, how many autos to

Figure 1. A three-stage choice hierarchy.

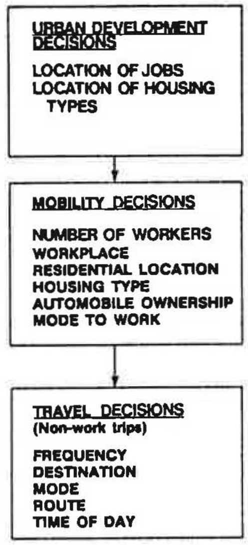
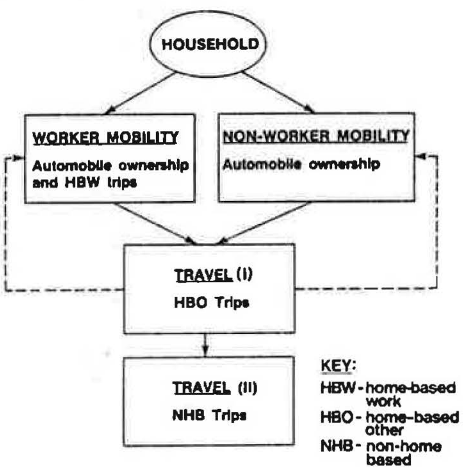


Figure 2. Overall structure of the MTC model system.



own, and which modes will be used to make work trips. Finally come short-run travel decisions made almost daily: frequency, destination, and mode for nonwork trips, and time of day and route for all trips.

The PLUM land-use model used by MTC predicts each of the development decisions shown in Figure 1, plus the residential location decision. The travel demand models described in this paper predict each of the remaining household decisions.

Figure 2 shows in greater detail how the mobility and travel choice levels of this choice hierarchy are represented in the MTC model system; the mobility decisions of households with and without workers are handled separately, and travel decisions are divided into two groups. Home-based other travel (nonwork) is predicted according to all home-based travel decisions. The dotted lines indicate that there is also an indirect provision for nonwork travel (HBO) to affect mobility decisions.

Although the structure shown in Figure 2 is strongly related to the conceptual system of disaggregate travel demand models shown in Figure 1, it incorporates a number of features and approximations necessary for producing a practical regional forecasting system. These include the following.

1. The residential location and housing type choices are external to the present model development effort because they are predicted by the previously developed PLUM system, which also predicts income distributions and work force by zone.

2. The mobility choice block for households with workers distinguishes between primary and secondary workers in a household. Each household with workers has only one primary worker, or breadwinner. All additional workers are termed secondary.

3. The modeling system deals separately with home-based and non-home-based trips. This simplifies the representation of trip chains (a trip from home, followed by one or more non-home-based trips, followed finally by a trip to home), an area in which basic conceptual development is continuing (9). Also, it allows the model system to deal with one-way trips, in accordance with traditional practice, rather than with the roundtrips more commonly considered in disaggregate modeling.

4. For a number of closely related travel decisions for which joint models have been previously predicted, a series of sequential rather than joint models has been developed. Examples are auto ownership and mode choice for primary workers, and nonwork trip frequency, destination, and mode choice. However, due to the structures of these sequential models, joint effects are not ignored.

5. There are exceptions to the hierarchy indicated by the solid-line arrows connecting the choice blocks. These are shown by the dotted-line arrows. Each of these represents an accessibility-like variable in the higher level model (auto ownership for households without workers, for example) that is obtained from a lower level model (home-based other destination and mode choice). Each of these variables is based on the full set of variables of the lower level model. These variables allow consistent representation of level-of-service effects in spite of the sequential structure of the model system.

6. The time-of-day decision is modeled by using historical peaking characteristics rather than a choice model based on the relationship between peak and off-peak transportation system characteristics.

7. The vehicle occupancy choice decision for nonwork travel is made by using historically observed rates rather than disaggregate choice models.

8. The route-choice decision is modeled by using conventional capacity restraint assignment techniques.

Before describing the models in each of the choice blocks illustrated in Figure 2, the definitions of the various trip purposes and modes will be given, the nature of the linkages implied by the dashed lines in the figure will be made explicit, and the types of independent variables used in the system will be described.

Trips Represented

The trip purposes used in model development are: home-based work trips (HBW), or all trips between home and work; home-based other trips (HBO), or home-based nonwork travel represented by two sets of models, one for generalized shopping trips (including also medical-dental, business-related, and serving passenger purposes—HBSH), and one for social-recreational trips (including eating, visiting, and recreation purposes—HBSR); and non-home based (NHB), or all trips that do not begin or end at home. These three purpose groups include all surveyed trips except school trips.

The modes considered in the models include auto and pickup drivers and passengers, as well as all bus, streetcar, railroad, and jitney trips. Trips by trucks and taxi drivers and passengers, and by walkers, are not represented in the models.

Linkages Between the Models

The components of the MTC model system are linked in two ways: first, "lower level" models are conditional on the predicted choices by "higher level" models, as indicated by the solid arrows in Figure 2; second, feedback in the form of composite or accessibility variables are calculated by using lower level models and are included in higher level models, as indicated by the dotted arrows.

The first type of linkage is determined by the assumed choice hierarchy and the resulting sequence of models. Variables resulting from higher level choices are predetermined for lower level choices and are attributes of the household or the individual that do not vary among alternative lower level choices. For example, auto ownership is treated as a household characteristic in the HBO models.

The composite variables represent expectations of the outcomes of lower level choices that could be different among alternatives of higher level choices. For example, level of service by transit for shopping trips affects auto ownership. However, this variable depends on the household choice of shopping trips, a decision made only conditional on the household auto ownership. Thus, the specific shopping level of service is indeterminate in the choice of auto ownership. However, composite variables representing overall shopping level of service for alternative auto ownership levels can be determined. The attributes that vary among lower level choices are aggregated and included as composite variables in the models of higher level choices.

All systems of travel demand models include, to some extent, such composite variables. Examples would be weighted by "inclusive prices" (3) and by the transit accessibility variable used in a trip generation model by the Metropolitan Washington Council of Governments (10). However, the formulation of these composite variables is often arbitrary and results in counterintuitive predictions. The composite variables used in the MTC model system are derived in a way that is consistent with the underlying assumption of the models.

If a lower level choice is modeled by using the logit model, the composite variable defined over these choice alternatives is constructed as the expected maximum utility from this choice process. If the outcome of this choice were known, then the composite variable would be taken as the expected utility of the chosen alternative. However, since it is assumed, in developing a choice model such as logit, that the alternative with the highest utility is selected, then we can calculate the expected value of the maximum utility. For the logit model, this is equal to the natural logarithm of the denominator of the logit probability model (11).

Because the denominator of the logit function must be computed in forecasting anyway, the use of this expression as a variable in related models requires little or no additional computation. In the MTC model system such variables were used in several models as the expected maximum utility from the entire set of alternatives or as the expected maximum utility from a subset of the alternatives. For example, the shopping trip frequency model includes as an independent variable the denominator of the shopping destination and mode-choice model. The auto ownership model includes the ratios of expected maximum utilities from shopping travel by auto and transit for different auto ownership levels, which are calculated by using appropriate partial sums of the denominator. Larger values of this ratio indicate a greater need for a car for shopping travel, which will therefore result in increased auto ownership.

Variables Included

Disaggregate model estimation techniques provide greater efficiency in the use of survey data than aggregate techniques do. As a result, more variables can be included in the model system, thereby increasing the sensitivity of travel forecasts to changes in the urban environment and in government policies.

Figure 3 presents a summary of the independent variables in the MTC model system in terms of the submodels of a conventional system. The independent variables are classified into four groups:

1. Highway level of service (auto travel time and out-of-pocket cost),
2. Transit level of service (fare and wait time),
3. Land use (retail employment), and
4. Socioeconomic attributes of potential travelers (annual income).

These variables affect all the travel-related choices that were described in the previous section. Figure 3 indicates the classes of variables typically omitted from various submodels of conventional systems and the improvements in sensitivity to level of service (LOS) and socioeconomic characteristics in the disaggregate model system. Examples of improved model sensitivity include the impacts of level of service by auto and transit on HBO trip generation and NHB travel and the effect of socioeconomic characteristics on trip distribution. The added sensitivity to LOS characteristics permits a more credible forecasting of the consequences of pricing policies, auto restraint measures, and other service changes that affect not only modal split but generation and distribution as well.

COMPONENT MODELS

In the light of the general material presented in the previous sections, each of the four travel choice blocks shown in Figure 2 can be discussed by presenting the component models and showing their interrelationships.

Worker Mobility Models

Figure 4 displays the details of the worker mobility models, which include a full set of HBW models and a model of auto ownership for households with workers. Workers are differentiated into primary (one per working household, chosen on the basis of income per worker) and secondary (all other workers) groups. For each, sequential models of trip frequency, work place choice (distribution), and mode choice are provided. The work place choice models use accessibility terms for each destination by all modes obtained from the mode-choice models. Household auto ownership is affected by the work place choice of the primary worker, by means of an expected utility variable that measures the relative ease of traveling to this destination by auto and transit. In addition, the relative ease of traveling to all shopping destinations by auto and transit is allowed to influence household auto ownership levels.

Nonworker Mobility Models

Because they make no work trips, only auto ownership is predicted for households without workers. The model uses information on the relative accessibility to shopping destinations by auto and transit, as well as per capita household income and residential density measures to predict probabilities of owning a given number of autos.

Travel Models I: Home-Based Other

As shown in Figure 5, for each home-based other trip purpose—shopping and social-recreational—two models exist. These models predict trip frequency and the joint choice of destination and mode. Trip frequency is dependent on the auto ownership predicted in the mobility blocks, the autos remaining after all work travel is predicted, and the expected utility of travel to all available destinations by either auto or transit. This structure allows the amount of nonwork travel to vary as auto use for work travel varies, and as the level of service in the transportation system varies.

Travel Models II: Non-Home Based

Figure 6 presents the structure of the NHB models. Home-based trip attractions by mode are put directly into a joint model of NHB frequency and destination choice. The frequency decision is binary; i.e., either the traveler goes home (frequency = 0) or he or she makes an NHB trip (frequency = 1) to one of the destination alternatives in the choice set. The details of these NHB models are in another paper in this Record by Ben-Akiva, Sherman, and Kullman. Explicit modeling of mode choice can be omitted if the observed frequency of tours involving mode switching is negligible. In this case, the mode choice for NHB trips can be assumed to be determined by the home-based trip mode choices; i.e., separate NHB models could be estimated for each mode, and the trip table inputs to the NHB models are for a specific mode.

MODEL DEVELOPMENT PROCESS

An aggregate forecasting system based on disaggregate models offers more opportunities for refinement and validation than does a system based on purely aggregate models. This is because, with disaggregate model systems, the individual models can be tested in both their aggregate (e.g., at the zone level) and disaggregate forms.

Estimation and Validation

Figure 7 presents a schematic outline of the overall model development process starting with estimation. Disaggregate estimation requires a sample of observed

Figure 3. A comparison of variables included in the MTC and conventional model systems.

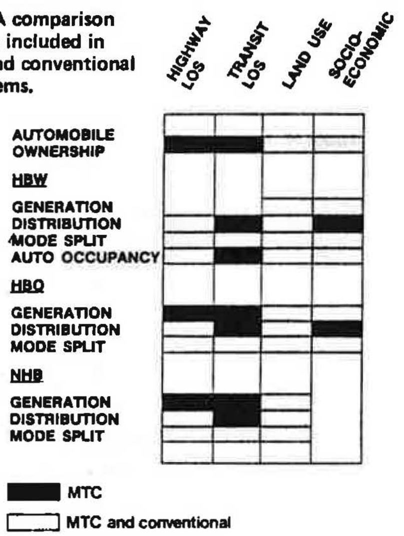


Figure 4. Worker mobility models.

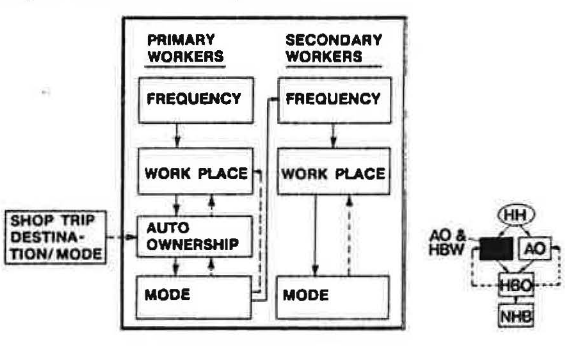


Figure 5. Travel models I: home-based other trips.

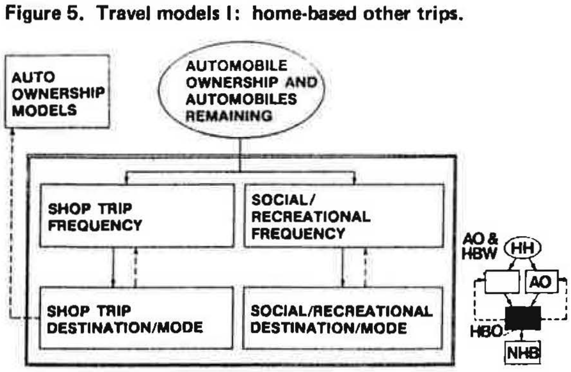


Figure 6. Travel models II: non-home-based trips.

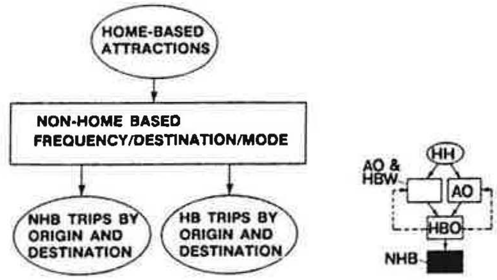
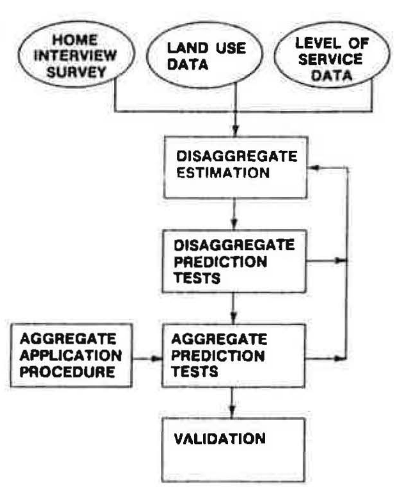


Figure 7. Disaggregate model development process.



travel decisions and socioeconomic characteristics from a home interview or other survey, land-use data to describe the attractiveness of destinations, and level-of-service data to describe model alternatives. In terms of types of data required, the aggregate and disaggregate approaches are identical. The key difference for disaggregate systems arises from the significant reduction in sample size required to yield statistically significant parameters.

As shown in Figure 7, following model estimation, the next step in the overall model development process is a series of disaggregate prediction tests, a step unique to the disaggregate approach. The estimated component models can be tested one at a time, passing each observed trip in the estimation data set through the disaggregate model system to produce tables of predicted and observed choices. Weaknesses in model specification may show up as systematic mispredictions by market segment (such as income) or by explanatory variable (such as travel time). The feedback loop from disaggregate prediction to disaggregate estimation in Figure 7 represents the decision to return to the estimation step based on the failure of a given model specification. Only after each model has passed the disaggregate tests does the process proceed to aggregate prediction and validation.

The base-year aggregate validation procedure for a disaggregate model system is essentially the same as for conventional aggregate systems. With disaggregate models it may be necessary to modify the forecasts by making transformations of the utilities. This requirement arises from the use of average households per zone to represent all households in a zone. The difference between the average behavior of all households and the behavior of an average household is referred to as aggregation bias (12, 13).

We found it necessary in the MTC model system to add distance-related factors to the utilities of the destination choice alternatives to match the observed trip length distribution. Also, in attempting to match zone-to-zone or district-to-district interchanges, we had to add trip interchange adjustment factors (in some cases) to obtain the equivalence between observed and predicted data. In this context, however, one important difference exists between traditional aggregate and disaggregate model systems. A complete disaggregate model system can be estimated with data from as few as 1000 households. The zone interchanges obtained from a sample that small are too sparse to use as the basis of zone interchange adjustments. Either one must rely on the trip length adjustments as the sole means of validating the distribution models with the survey data or one must augment the survey sample used for model estimation with additional observations. In the case of the MTC models, this sample was used in its entirety to ensure that the aggregate versions of the models matched observed travel patterns.

If the disaggregate testing procedure in Figure 7 is followed carefully, there should be no need to return from the aggregate tests to the disaggregate estimation, since the only changes made in the models involve adjustment of the utilities.

Disaggregate estimation and disaggregate and aggregate prediction testing were carried out iteratively as a part of the MTC model development process. As a result, the model system matches observed data in all of the following respects, at the district and district-to-district levels (there are 30 districts in the MTC analysis area): (a) person trips produced and attracted, (b) average trip length for person trips by production district, (c) mode choice by production district, and (d) trip interchanges by mode.

The final validation of the model requires external data sources and preferably data from before and after a change in the transportation system that can directly be compared with the model predictions. This step is being carried out by MTC in their continuing use of the model system.

Model Application Procedures

As part of the travel model development project, two computerized procedures have been developed to apply the demand models described in this paper. The first is oriented toward the application of an aggregate version of the model system for detailed regional network analysis in either the short- or long-range time frame. The second is oriented to more rapid generalized policy analysis in the short- to medium-range time frame. Each of these procedures is described in this section.

MTC Regional Network Analysis

MTC regional network analysis (MTCFCAST) is a package of programs based on all of the MTC travel demand models that predicts regional travel patterns and volumes from regional socioeconomic information and the level of service data for existing and proposed modes of transportation. This computer system represents an alternative to the demand estimation portions of the traditional urban transportation planning (UTPS) packages (14, 15) and is integrated with them in its external data structure and its use of their data-processing, report-formatting, and traffic-assigning programs. This compatibility with the UTPS package greatly enhances the effectiveness of MTCFCAST. This system provides the aggregate application procedure used for aggregate prediction tests, as shown in Figure 7.

The primary product of MTCFCAST is a set of eleven 24-h person-trip tables on

1. Driving alone home-based work trips,
2. Shared ride home-based work trips,
3. Transit home-based work trips,
4. Auto home-based shopping trips,
5. Transit home-based shopping trips,
6. Auto home-based social-recreational trips,
7. Transit home-based social-recreational trips,
8. Auto non-home-based trips,
9. Transit non-home-based trips,
10. Auto home-based trips, and
11. Transit home-based trips.

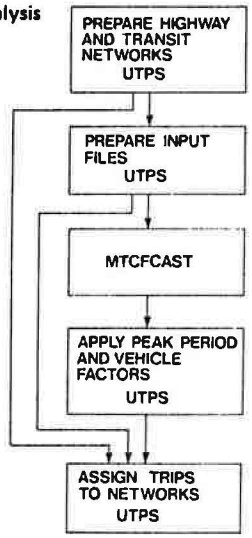
These trip tables may be put directly into the UTPS matrix manipulation and network assignment routines to produce 24-h or peak-hour highway vehicle and transit person-trip assignments. The entire composite MTCFCAST-UTPS analysis framework is shown in Figure 8.

The MTCFCAST forecasting system is similar to but more sophisticated than the conventional trip generation-trip distribution-modal split methodology. It incorporates or provides the necessary inputs to UTPS routines that incorporate each of the models described in the previous section. Its structure is essentially that shown in Figure 2. Aggregation is performed by market segmentation by using average socioeconomic values for each of three income groups initially, followed by segmentation based on auto ownership level after the prediction of auto ownership in the mobility blocks.

Short-Range Generalized Policy Analysis

Short-range generalized policy analysis (SRGP) is a

Figure 8. The MTCFCAST analysis framework.



computerized procedure that applies a subset of the MTC travel demand models for analysis. The procedure is designed to produce rapid turnaround estimates of the consequences of broadly defined transportation policy options. SRGP processing and outputs are based on an input sample of home interview survey households. The program estimates the travel behavior of the individual households subject to user-controlled facilities for expanding the results in whatever manner is appropriate to the problem universe. This approach takes full advantage of the disaggregate nature of the demand models. Aggregation does not take place until the expansion, after all estimation is complete, and can be straightforward and without bias.

It is the use of sample households that also lends SRGP its short-range applicability. The procedure has no facilities for modeling the long-range dynamics of attributes of households, such as location and life cycle progression or the number of workers and their choice of occupations and job locations. Activity distributions (the zone extent and intensity of employment, shopping facilities, social and recreational opportunities, etc.) are also provided exogenously to the procedure. It was previously applied to other urban areas using alternative disaggregate models (16, 17).

Because of its orientation to short-range analysis, only the following models, which represent short-range choices, of the full MTC model system are included: auto ownership for worker households, auto ownership for nonworker households, HBW mode choice, HBSH trip production, HBSR trip production, HBSH destination-mode choice, and HBSR destination-mode choice.

As these models are applied to each household in turn, summary impacts are accumulated and reported for household income class groups or other segmentation. SRGP also has the capability to retrieve the results of a previous run to produce comparison tables.

CONCLUSIONS

As the first production-oriented system developed for use by a metropolitan planning organization that is based on a consistent theory of traveler behavior and disaggregate model estimation, the MTC model system has achieved the following major accomplishments.

Disaggregate models have been integrated into a working aggregate model system that resembles the conventional systems with which planners are familiar.

The model system is a reasonable compromise between validly representing the theories of individual travel behavior and developing a practical, large-scale planning model.

The model system has improved behavioral properties compared to its previous aggregate counterpart. It is relevant to the low capital cost alternatives that must be evaluated now and is sensitive to a wider range of variables than aggregate models.

The model system provides an additional option over the full detail and sketch planning approaches supported by conventional aggregate models. Random sample enumeration is a valuable, quick, low-cost method of analyzing a wide range of policies and projects.

Cost reductions in the development of disaggregate model systems arise from the vastly reduced amount of data needed. Employing random sample enumeration techniques also reduces costs of using the models in certain situations.

The only disadvantage that exists in the use of this approach relative to conventional aggregate models is the increased complexity of the system. Due to improved behavioral representation, more models are estimated; they are closely interconnected; and they are not yet well understood by practitioners. The cost of a full zone aggregate application of a disaggregate model system is marginally higher than its aggregate counterpart, but this cost differential is not a significant issue since the major costs of both types of systems are network skimming and assigning.

Work undertaken to date has shown that this modeling approach is feasible, that careful estimation and testing are necessary during the model development phase, that extensive training is necessary to familiarize planners with the new approach, and, of course, that the resulting model systems are sufficiently improved over the conventional system they replace to warrant the investment in training and model development.

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Non-Home-Based Models

Moshe E. Ben-Akiva, Cambridge Systematics, Inc., and Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge
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This paper describes a practical model of non-home-based travel that can be incorporated in existing urban transportation model systems. The model is estimated by using a disaggregate sample of trips drawn from the 1965 home interview survey of the San Francisco Bay Area for the Metropolitan Transportation Commission. The model predicts trip generation, distribution, and mode split with full sensitivity to travel times, costs, and zone characteristics. The paper describes the overall model structure and estimation results. Comparisons with other research on non-home-based travel are drawn and recommendations for future research presented.

There is a clear need to better understand non-home-based (NHB) travel behavior. In large urban areas, NHB travel may represent over 20 percent of total vehicle trips, and an even larger proportion when pedestrian travel is counted. Moreover, emerging transport policies focusing on downtown people-mover systems, free or reduced-fare transit circulation systems within central business districts (CBDs), auto restricted zones, and activity center connectors have drawn increased attention to NHB travel patterns.

In modeling urban travel patterns, it has been traditional to classify trips into three categories: home-based work (HBW) trips, home-based other (HBO) trips, and non-home-based (NHB) trips. Models of non-home-based travel have received the least attention. From a behavioral standpoint, non-home-based travel should be sensitive to the same factors that are conventionally associated with HBW and HBO travel patterns. For example, accessibility and the spatial distribution of opportunities should clearly influence the generation and distribution of NHB trips, and yet most existing model systems treat NHB travel as a fixed proportion of home-based trips or use simple generation rates that take no account of transport accessibility. Also lacking from most conventional approaches is a behaviorally plausible representation of trip chaining.

Some recent research has attempted to develop explicit models of trip chaining. Adler, for example (18, 19), has estimated disaggregate choice models in which the choice set consists of alternative trip chains with two or more links. Each alternative's utility was characterized by a total tour level of service and spatial opportunities at the destinations included in the tour. Another approach was taken by Horowitz (20), who used regression analysis to model the frequency and number of stops made on household trip chains as a function of level of service. Because of their complexity or structure, neither of these approaches is suitable for inclusion in an urban area travel demand forecasting system, but they do establish the importance of characterizing the interdependence of non-home-based and home-based travel.

The models reported here explicitly represent this interdependence as a Markovian process where the decision of an individual to continue a tour with a non-home-based trip depends only on conditions at a specific trip end, not on the sequence of trips that may have led

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The models reported here explicitly represent this interdependence as a Markovian process where the decision of an individual to continue a tour with a non-home-based trip depends only on conditions at a specific trip end, not on the sequence of trips that may have led to the trip end. This structure was dictated by practical considerations, since in aggregate forecasting applications it is not computationally feasible to treat specific tour sequences as explicit choice alternatives.

While the theory, estimation, and preliminary validation of the NHB models reported here were developed at the disaggregate level, the models were designed to be incorporated into an aggregate travel demand forecasting system to be used by the Metropolitan Transportation Commission (MTC) of the San Francisco Bay Area (21, and the paper by Ruiter and Ben-Akiva in this Record). Thus, from the beginning, model development was concerned with balancing theoretical and behavioral plausibility with model practicality and ease of use. The key advantages of the resulting models are their sensitivity to transportation level of service and their explicit representation of the interdependence of home-based and non-home-based travel.

DEFINITIONS AND TERMINOLOGY

Non-home-based travel consists of all trips made between two non-home locations. Examples of NHB trips are a journey from work to a place to eat lunch or the journey from a shopping location to work. While it is possible to further differentiate NHB travel by trip purpose, in the empirical work of this study all travel purposes were grouped together.

In developing a theory of NHB travel behavior, it is convenient to adopt a notation where trips are defined by purpose at the origin and destination. Trip end purposes can then be classified into three groups: home (H), work (W), and other (O). In these terms, NHB travel occurs whenever a trip has W or O purposes at each end. Thus, the number of NHB trips between zones e and k can be written as the sum of the following sets of trips:

$$\text{NHB trips from e to k} = W_eO_k + O_eW_k + O_eO_k + W_eW_k \tag{1}$$

where

W_eO_k = trips with purpose W at origin e to destination k with purpose O,
O_eW_k = trips with purpose O at origin e to destination k with purpose W,
O_eO_k = trips with purpose O at origin e to destination k with purpose O, and
W_eW_k = trips with purpose W at origin e to destination k with purpose W.

Similarly, home-based (HB) trips may be defined as follows (ignoring home-to-work trips):

$$\text{HB trips from e to k} = H_eW_k + H_eO_k + W_eH_k + O_eH_k \tag{2}$$

where

H_eW_k = trips with purpose H at origin e to destination k with purpose W,
H_eO_k = trips with purpose H at origin e to destination k with purpose O,
W_eH_k = trips with purpose W at origin e to destination k with purpose H, and
O_eH_k = trips with purpose O at origin e to destination k with purpose H.

It was assumed in this study that there is no need to differentiate between work-based and non-work-based, non-home-based trips. Accordingly the above notation can be greatly simplified by designating A to stand for any non-home-based purpose, i.e., A = W + O. This definition leads, for example, to the following relations:

$$H_eA_k = H_eW_k + H_eO_k \tag{3}$$

$$A_eA_k = W_eO_k + O_eW_k + O_eO_k + W_eW_k \tag{4}$$

The symbols A and H can be used to represent both the type and the direction of trips as indicated in Figure 9. The terminology and definitions in Figure 9 are essential for the development of the model described below.

THEORETICAL MODEL DEVELOPMENT

Each trip maker at a non-home location is always faced with the choice between returning home or traveling to a non-home location. If the traveler returns home, then one may say that a NHB trip was not made. If a traveler does continue on to another non-home location, then the traveler must choose between alternative destinations and modes. This sequence is repeated until the traveler eventually returns home. This view of the NHB choice process makes it clear that the traveler's decision process can be associated with the trip end. That is, each home-based trip (and succeeding NHB trips) constitutes a potential NHB trip.

Given this general framework, two assumptions were adopted to simplify the empirical analysis and to facilitate the use of the models in aggregate forecasting. First, it was assumed that each traveler's decision is independent of previous decisions, i.e., that the decision maker has no memory of past decisions. This assumption obviates the need to represent several alternative trip chains (e.g., two-leg versus three-leg versus four- or five-leg tours) as explicit choice alternatives. Second, it was assumed that travelers making NHB vehicle trips would continue on the same mode as their outbound home-based trip; i.e., mode switching is not explicitly modeled. Analysis of San Francisco travel data indicated an extremely low incidence of vehicle mode switching between HB and NHB trip legs. The models, in any event, do not ignore trips that switch mode. They simply predict these trips as if they continued on the same mode as on the HB trip. As a result of this assumption, separate NHB models could be estimated conditional on auto or transit choice for the home-based trip.

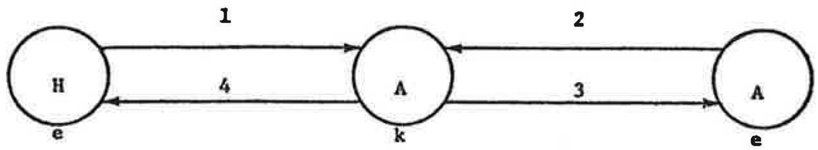
It is apparent from the above discussion that the analysis assumes that a traveler at a non-home location has choices over two dimensions: either to return home (NHB frequency = 0) or to make an NHB trip (NHB frequency = 1) to a specific alternative trip end. Using the approach of random utility choice models employed in disaggregate travel demand models, the preferences of an individual for these choice alternatives can be represented by the following probabilities:

1. The first is $p(f = 1, e|k)$ = probability of making an NHB trip (f = 1) to trip end location e, which could be either an origin or a destination depending on the form of the model—a point that will be discussed below—given that the opposite trip end is in zone k; and
2. The second is $p(f = 0|k)$ = probability that an NHB trip is not made given a trip end, either origin or destination, in zone k.

There will be one such probability for each mode. For simplicity, we will not carry the mode subscript in our notation.

It is possible to model NHB trips from either a destination or an origin perspective. The former represents a traveler choosing from alternative non-home destinations (NHB f = 1) given a non-home trip origin,

Figure 9. Non-home-based trip types.



$$\left.\begin{array}{l} H_eA_k = \text{type 1 trips} \\ A_kH_e = \text{type 3 trips} \end{array}\right\} \text{HB}$$

$$\left.\begin{array}{l} A_eA_k = \text{type 2 trips} \\ A_kA_e = \text{type 4 trips} \end{array}\right\} \text{NHB}$$

while the latter represents alternative non-home origins from which a traveler could have reached a non-home destination. Although the former approach appears more reasonable, both types of models were estimated in this study in order to calculate directional splits by trip purpose.

The disaggregate model of NHB frequency and trip end was specified as a joint choice logit model:

$$p(f = 1, e \mid k) = \exp V_{ek} \Big/ \left(\exp V_{ok} + \sum_{e' \epsilon A_k} \exp V_{e'k}\right) \qquad (5)$$

$$p(f = 0 \mid k) = \exp V_{ok} \Big/ \left(\exp V_{ok} + \sum_{e' \epsilon A_k} \exp V_{e'k}\right) \qquad (6)$$

where

A_k = set of feasible trip end choices from trip end k (note that this set may depend on the mode), and

V_{ok}, V_{ek} = linear parameter utility functions for the alternatives f = 0 and f = 1 and trip end e, respectively.

The utility associated with choosing trip end (zone) e was represented by the cost and travel time between zones k and e and zone e's attractiveness in terms of the density and level of its population and employment. The zero frequency function contained proxy measures for factors that would decrease the probability of NHB travel.

MODEL ESTIMATION

Definition of Choice Set

The San Francisco MTC region was divided into 30 districts, each of which represented a possible trip end choice. In addition, in NHB destination (origin) choice models, all zones in the origin (destination) district were considered as possible choices. This procedure was designed to reduce the variance associated with the level-of-service measures. Analysis of our data showed that over 85 percent of NHB trips were intradistrict. Hence, for the great majority of the chosen trips, level of service was represented at the zone interchange level, rather than district to district. In the NHB transit models a potential destination was considered unavailable if transit service was unavailable. The maximum size of the choice set was 29 districts (not including the trip end district k) plus 26 zones (maximum; many districts have fewer) plus 1 zero frequency alternative which equals 56 alternatives maximum.

Estimation Data Set

The estimation data set for the NHB models consisted of a sample of 11 249 trip records from 1347 households randomly drawn from MTC's 1965 home interview survey tape. Screening of all the trips for invalid modes (taxi, truck, walk) and purpose (school) reduced the set of valid observations to 8216 records, of which 3214 were NHB f = 1 and 5092 NHB f = 0. These resulting data were subdivided into four files corresponding to auto, transit, origin choice, and destination choice model forms. The resulting numbers of trip records are shown below.

Model Type	Population	Freq = 1	Freq = 0
Auto, destination choice	4730	1789	2941
Transit, destination choice	308	57	251
Auto, origin choice	4759	1789	2970
Transit, origin choice	265	57	208

The small differences in the population of trips from which NHB trips could be made as represented in the origin and destination choice models are due to incomplete trip chains contained in the survey data.

Specification of Independent Variables

The variables that were used in the models are listed below.

Variable	Description
ZEROFCON	1 in zero frequency utility function, 0 otherwise
CBDOCON	1 in zero frequency utility function if origin zone (destination zone if NHB origin choice model) is in CBD, 0 otherwise
LN(TT)	Natural log of total travel time in f = 1 utility functions, in minutes
COST	Travel cost in f = 1 utility functions, in cents
EMPDENS	Employment density: total employment divided by total area at the destination (origin if NHB origin choice model) alternative in f = 1 utility functions, in employees per square kilometer
LN(P/E)	Natural log of the zone fraction of regional population divided by zone fraction of regional total employment at the destination (origin if NHB origin choice model) alternative in f = 1 utility functions
LN(EMP)	Natural log of the zone fraction of regional total employment at the destination (origin if NHB origin choice model) alternative in f = 1 utility functions

Table 1. Structure of the NHB models.

Model	Variable: ZEROFCON	CBDOCON	LN(TT)	COST	EMPDENS	LN(P/E)	LN(EMP)
Auto destination choice							
f = 0	α_1	α_2					
f = 1			β_1	β_2	β_3	β_4	1.0
Transit destination choice							
f = 0	γ_1	γ_2					
f = 1			δ_1	δ_2	δ_3	δ_4	1.0
Auto origin choice							
f = 0	θ_1	θ_2					
f = 1			ϕ_1	ϕ_2	ϕ_3	ϕ_4	1.0
Transit origin choice							
f = 0	π_1	π_2					
f = 1			ϵ_1	ϵ_2	ϵ_3	ϵ_4	1.0

Table 2. Summary of model estimation results.

	Destination Choice						Origin Choice					
	Auto			Transit			Auto			Transit		
Variable	EC[a]	SE[b]	t-Statistic	EC[a]	SE[b]	t-Statistic	EC[a]	SE[b]	t-Statistic	EC[a]	SE[b]	t-Statistic
CBDOCON	0.313 5	0.068 2	4.59	-	-	-	0.368 4	0.068 3	5.39	1.880	0.458 0	4.11
ZEROFCON	-11.22	14.39	-0.78	-7.57	1.47	5.14	-10.75	7.90	-1.36	-4.53	1.37	3.32
LN(TT)	-2.294	0.073 6	31.2	-1.033	0.306 1	-3.38	-2.418	0.074 0	-32.7	-0.898 2	0.239 8	-3.75
COST	-0.015 18	0.001 51	-10.1	-0.016 08	0.006 91	-2.33	-0.013 38	0.001 47	-9.09	-0.017 75	0.006 09	-2.65
LN(P/E)	0.470 0	0.030 6	15.38	0.608 8	0.209 9	2.90	0.398 1	0.030 0	13.26	-	-	-
EMPDD	0.002 242	0.000 6	3.87	0.003 566	0.002 0	1.77	0.001 887	0.000 5	3.72	-	-	-
LN(EMP)		1.0			1.0			1.0			1.0	
Percent correct predictions		11.9			55.9			11.8			50.0	
ρ^{-2}		0.546 4			0.724 5			0.552 7			0.716 3	
Likelihood ratio statistic		19 341			1554			19 681			1322	

[a]EC = estimated coefficient. [b]SE = standard error.

The structure of the model showing how each variable enters in the f = 0 and f = 1 utility function is given in Table 1, which emphasizes the fact that no assumptions were made that the coefficients of identical variables in the origin and destination choice models would be the same. The variable LN (EMP) is a measure of the size of a destination alternative and its coefficient is constrained to take the value of 1.0. This constraint is necessary if the model is independent of the zone system used for estimation. In fact, in aggregate forecasts made with the NHB models described here, a different zone system has been used.

Estimation Results

Estimation results for the four model types are shown in Table 2. For each variable the cell entries indicate estimated coefficient, standard error, and t-statistic. In preliminary estimations not reported here, gross employment density was used as a variable to explain walk trip propensity (i.e., in the f = 0 alternative), but its estimated coefficient was insignificant. Also, in preliminary runs, it was determined that in- and out-of-vehicle travel time could not be statistically distinguished, so only total travel time was ultimately used. The coefficient of the size variable LN(EMP) is constrained to 1.0 in all cases.

The relatively high value for the ρ^{-2}-statistic derives from the fact that the f = 0 alternative is chosen with high frequency, while it is presumed in the "equally likely" case that it has only an equal chance of being chosen along with each f = 1 destination.

An indication of the reasonableness of the model results is the implied value of time (VOT). For the recommended models, the values of time for a range of travel times between 20 and 60 min were calculated. These results, based on the estimated models in Table 2, are shown below.

Model	Total Travel Time (min): 20	40	60
NHB destination choice, auto	4.53	2.27	1.51
NHB origin choice, auto	5.42	2.71	1.81
NHB destination choice, transit	1.92	0.96	0.64
NHB origin choice, transit	1.52	0.76	0.51

Auto VOT is higher than transit VOT for every travel time and model type (origin or destination choice). For both modes, travelers show a decreasing sensitivity to marginal time savings as total travel time rises. These results are similar to those obtained from the HBO destination and mode-choice models estimated from the same data set (21).

FORECASTING WITH THE NHB MODELS

Forecasting with the NHB models is complicated by two factors. First, the models predict the non-home-based travel decision of a traveler at the trip end of either a home-based or a non-home-based trip; and, second, the directional split of the home-based trip is unknown.

Consider, for example, using a destination choice approach where the directional split of home-based trips is known. In this case, non-home-based trips could be determined by predicting trips in sequence: first HB and then NHB. However, since the models will predict a non-zero probability to every possible destination zone, this approach is computationally infeasible for application to large networks that typify major urban areas. Lerman and others (22) used a variant of this procedure by simulating each trip leg of a tour conditional on the previous trip end, but their approach is far too complex to be practical for aggregate forecasting applications.

Assuming that there are N possible zones, the total number of NHB flows is N^2, and this prediction problem could be viewed as a solution of a system of N^2 simultaneous equations. Each equation expresses the expected number of non-home-based trips from a given origin to a given destination as follows:

$$A_k A_e = P(f = 1, e \mid k) \left(HA_k + \sum_{e'} A_{e'} A_k \right) \quad (7)$$

where HA_k is $\sum_{e'} H_{e'} A_k$. The unknown directional split of the home-based trips adds 2N more equations and unknowns. The first N of these equations defines the directional split of the home-based attractions:

$$HA_k + A_k H = HBA_k \quad (8)$$

where HBA_k is home-based attractions at k.

The second set of N equations defines the conservation of flows at the non-home ends:

$$HA_k + \sum_e A_e A_k = A_k H + \sum_e A_k A_e \quad (9)$$

These systems of equations (with known or unknown HB direction split) are too complex to be solved directly. Therefore, a simplified method based on the use of both origin and destination choice models was devised.

To distinguish between the two NHB model types, we introduce the subscript i = 1, 2 to refer to the choice of NHB destination (i = 1) or NHB origin (i = 2):

$$P_i(f = 1, e \mid k) = \exp V^i_{ek} \Big/ \left(\exp V^i_{ok} + \sum_{e'} \exp V^i_{e'k} \right) \quad (10)$$

where

i = 1 implies e = destination, k = origin, and
i = 2 implies e = origin, k = destination.

The equations predicting NHB trips are

$$A_k A_e = P_1(f = 1, e \mid k) \left(HA_k + \sum_{e'} A_{e'} A_k \right) \quad (11)$$

$$A_e A_k = P_2(f = 1, e \mid k) \left(A_k H + \sum_{e'} A_k A_{e'} \right) \quad (12)$$

Summing both sides of these equations over trip ends and denoting the summation over trip ends e by the absence of the subscript e, we may write

$$A_k A = F_{1k} \times (HA_k + AA_k) \quad (13)$$

$$AA_k = F_{2k} \times (A_k H + A_k A) \quad (14)$$

where F_{1k} and F_{2k} are the fraction of potential NHB trips choosing zone k as the origin or destination of an NHB trip. Specifically these fractions may be written as

$$F_{1k} = \sum_e P_1 (f = 1, e \mid k) \quad (15)$$

$$F_{2k} = \sum_e P_2 (f = 1, e \mid k) \quad (16)$$

Equations 13 and 14 can now be solved for $A_k A$ and AA_k:

$$A_k A = (F_{1k} HA_k + F_{1k} F_{2k} A_k H)/(1 - F_{1k} F_{2k}) \quad (17)$$

$$AA_k = (F_{2k} A_k H + F_{1k} HA_k)/(1 - F_{2k} F_{1k}) \quad (18)$$

Substituting Equations 17 and 18 into 11 and 12 yields

$$A_k A_e = P_1 (f = 1, e \mid k) [(HA_k + F_{2k} A_k H)/(1 - F_{1k} F_{2k})] \quad (19)$$

$$A_e A_k = P_2 (f = 1, e \mid k) [(A_k H + F_{1k} HA_k)/(1 - F_{1k} F_{2k})] \quad (20)$$

Either Equation 19 or Equation 20 could be used to forecast trips, but not both, since these equations predict opposite ends of the same NHB trips. It is more natural to use Equation 19, which predicts NHB trips from origin zone k to destination zone e based on both the home-to-any and the any-to-home trip ends in zone k. Although only one of the equations is needed to forecast, note that the influence of both origin and destination models enters in Equations 19 and 20 through the terms F_{1k} and F_{2k}.

Starting from Equations 13 and 14, the complete set of relations used for NHB aggregate forecasting can now be derived by adding the two equations for the directional split of home-based attractions at k and flow conservation at k. The entire set of equations can then be solved simultaneously to obtain expressions for HA_k, $A_k H$, $A_k A$, and AA_k, which depend only on F_{1k}, F_{2k}, and known HBA_k:

$$HA_k = [(1 - F_{2k})/(2 - F_{1k} - F_{2k})] \, HBA_k \quad (21)$$

$$A_k H = [(1 - F_{1k})/(2 - F_{1k} - F_{2k})] \, HBA_k \quad (22)$$

$$AA_k = [F_{2k}/(2 - F_{1k} - F_{2k})] \, HBA_k \quad (23)$$

$$A_k A = [F_{1k}/(2 - F_{1k} - F_{2k})] \, HBA_k \quad (24)$$

The equations serve two purposes: they directionally split the forecasts of HBA_k (home-based trips; use Equations 21 and 22), and they directly predict NHB generations and distribution (use Equation 23 or Equation 24).

CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

The models presented in this paper were developed as part of a complete system of disaggregate travel demand models. However, they can be used in a conventional urban transportation model system to replace existing NHB trip models.

The simplifying assumptions of the model structure presented were dictated by practical considerations of model development resources and computer cost for model application.

Given the overall model structure developed in this paper, the specific models could be improved by further disaggregation of purposes, inclusion of mode choice, and addition of other variables to better represent attractions of travel opportunities and transport services.

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Discussions

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Urban travel demand research in the 1960s and early 1970s gave rise to the hope that travel forecasting models could be developed that would satisfy the following objectives. They would predict the changes in travel demand from adding new modes or other new transportation alternatives, evaluate the consequences of alternative policy options applied to the existing transportation system, be easily transferred from one urban area to others, and make full use of disaggregate data to properly specify travel behavior.

In a major step toward these objectives, McFadden and Domencich (23) showed that probability choice models could be extended using multinomial logit (MNL) to estimate equations representing a wide range of travel decisions. These models were designed to predict the short-run responses of trip makers to transportation system changes. In addition to mode choice, which had traditionally been analyzed with probability choice models, MNL was applied to trip time of day, destination, and frequency decisions. These separate models were linked with accessibility measures to form an integrated travel forecasting structure.

The San Francisco MTC system is an initial attempt to utilize this basic MNL model structure in a large-scale urban transportation planning package. It also incorporates some important refinements in travel demand model estimation with MNL. The first of these is a rigorous definition of the choice structure of mobility decisions based on the work of Ben-Akiva and Lerman (1, 24). The second refinement is an appropriate specification for sequential models with inclusive prices (25). Finally, there has been some attempt to adjust the attraction variables in the destination and frequency choice models to make the equations transferable to alternative zone systems.

Given the scope of the MTC system, it is appropriate to review it in terms of the four objectives of travel demand models presented above. The major advances in large-scale travel forecasting procedures represented by the MTC system appear to be that

1. Policy-sensitive accessibility measures have been incorporated in the separate components of travel demand,
2. New alternatives to the traveler choice set, such as new modes, can be unambiguously forecast by using the independence from irrelevant alternatives (IIA) property of multinomial logit [see Charles River Associates (26) for a discussion of the strengths and limitations of this capability], and
3. The destination choice models make better use of trip record data than does the traditional gravity model calibration approach, thereby gaining, potentially, greater accuracy in forecasting the trip distribution effects of transportation system and land-use changes.

There are several major limitations on the MTC system that are discussed in more detail below. These include, first, problems with model estimation and model specification that combine to prevent isolation of short-run travel response from other effects; these problems should lead to forecasts that are overly responsive to system changes and to biased policy evaluations. Second, the destination and frequency choice model is not generally transferable, and, third, potential advantages of disaggregate data analysis have gone unrealized, perhaps because of the dependence upon the traditional large-scale home interview survey.

POLICY SENSITIVITY

The MTC system should give biased travel demand forecasts and policy evaluations. This results, in part, from using relatively simple model structures estimated on cross-section data. This statistical design is an unfortunate constraint on most travel demand analysis. In addition, there appear to be model specification errors that compound the drawbacks of using cross-section data.

CROSS-SECTION BIAS

Not enough attention has been given to cross-section bias in travel demand model estimation. As an example of this type of problem, consider either of the MTC system's disaggregate models of nonwork trip frequency estimated from a household travel survey. These households will have chosen locations for themselves based on, among other things, their preferences for accessibility to alternative activities. Households with low preferences for accessibility will live in areas with high impedance measures for nonwork trips. Households with high preferences for accessibility will live where there are low travel times and costs to a large number of trip-generating activities.

The frequency choice model will use the correlation between trip frequency and accessibility and incorrectly assign an increased frequency response to a policy that increases accessibility.

In fact, households will have revealed their preference for trip frequency by their location decisions. Rather than forecasting trip frequency, the model is partially distributing households to locations as a result of accessibility, given their demands for a certain number of trips. As a result, the model should overpredict the travel demand response to increased trip frequency.

Practitioners should be cognizant of potential cross-section bias, not only in frequency models but also in destination and mode-choice estimates and forecasts. A lack of appreciation of this problem can lead to model specifications that fit the data better than alternatives but lead to worse forecasts of traveler responses to transportation systems. Two examples of model specification problems are discussed below.

MARGINAL VALUE OF TIME IN THE NON-HOME-BASED DESTINATION/ FREQUENCY MODEL

Specification of the utility function in the travel models will in some ways exacerbate cross-section bias. The MTC system's non-home-based destination and frequency choice model, for example, has the logarithm of travel time as an argument in the utility function. Thus, the marginal value of time is inversely proportional to the amount of travel time between an origin and a destination (O-D); that is, the marginal value of time declines with respect to time spent in travel.

This formulation is inconsistent with the behavior of travelers who maximize utility under time constraints.

The policy implications of this model specification are that for two zone pairs with equal flows, the time benefits of improving travel time by 1 min for an O-D link of 10 min is equivalent to improving travel time by 6 min for an O-D link of 60 min. Project evaluation will be biased toward improving links associated with short origins and destinations inasmuch as cost per kilometer of an improvement is constant or increasing. Thus, the model is policy sensitive, but it may give the wrong priorities to policy alternatives because of its specification.

One problem with estimating the marginal value of time from cross-section data is that people with a low value of time will take longer journeys, which creates a negative statistical correlation between marginal value of time and length of the trip. However, this correlation does not tell us that any given individual has a decreasing marginal value of time when choosing among alternative destinations. This latter concept of value of time is what is relevant in analyzing traveler responses to system changes and in evaluating projects.

WORK-TRIP DISTRIBUTION

The purpose of the MTC model is to forecast travel demand with exogenously determined land-use patterns. Presumably, the land-use model (PLUM) forecasts zone aggregates of employment and residences that are input to the MTC travel demand system. Thus, long-run residence and employment choice decisions are modeled in PLUM. A transportation policy that redistributes work trips would do so primarily by redistributing zone household locations and employment opportunities. However, the MTC travel demand model keeps these elements constant and reallocates workers among existing places of employment.

For short-run travel demand analysis, it is preferable to keep work-trip distribution constant (as is done in the short-range generalized policy analysis package). For long-run travel demand analysis, work-trip redistribution should be included in the land-use forecasting system with a methodologically sound linkage to the travel demand models.

TRANSFERABILITY

Strong conditions are required on the use of zone activity variables in the MNL model in order to ensure that arbitrary repartitioning of the zones does not violate conservation of travel flows (27). Even more stringent conditions are required either if the nontrip alternative is included in the model or if the inclusive price (the log of the denominator) from the destination choice model is to be in the utility function of a higher level frequency choice model.

The non-home-based travel model in the MTC system can be used as an example of the problems in transferring destination and frequency choice models. The developers of the model use total zone employment as an attractor variable; it is specified in log form with the coefficient constrained to unity. If this were the only activity variable in the utility function, then the model could be transferred without arbitrarily changing travel demand forecasts. Unfortunately, including other activity variables such as zone attractors in the model leads to a violation of conditions that would ensure transferability. To see this, we rewrite the MTC non-home-based model as follows, ignoring the employment density variable and the zero frequency alternative:

$$P_i = e^{V_i} E_i^{1-a} Y_i^a \Big/ \sum_{j=1}^{n} e^{V_j} E_j^{1-a} Y_j^a \tag{25}$$

where

P_i = probability of the ith alternative;
V_i = level of service component of the utility function;
E_i = employment in the ith destination zone;
Y_i = population in the ith destination zone; and
a = estimated coefficient.

If a repartitioning of the zones occurs such that ΔE and ΔY are taken from destination zone 1 and added to destination zone 2, then the conservation of trips would require the following equality:

$$\begin{aligned}(e^{V_1}E_1^{1-a}Y_1^a + e^{V_2}E_2^{1-a}Y_2^a) \Big/ \sum_{j=1}^{n} e^{V_j}E_j^{1-a}Y_j^a = \\ [e^{V_1}(E_1-\Delta E)^{1-a}(Y_1-\Delta Y)^a + e^{V_2}(E_2+\Delta E)^{1-a}(Y_2+\Delta Y)]^a \\ \div [e^{V_1}(E_1-\Delta E)^{1-a}(Y_1-\Delta Y)^a + e^{V_2}(E_2+\Delta E)^{1-a}(Y_2+\Delta Y)^a \\ + \sum_{j=3}^{n} e^{V_j}E_j^{1-a}Y_j^a]\end{aligned} \tag{26}$$

With population and employment acting as attractors, it is necessary for a to be within the unit interval so that the coefficients on zone attraction are positive. However, if trips are to be conserved in cases where the number of choices is three or greater, it will in general be necessary for a to be either zero or one. The values for a estimated in the MTC model are within the unit interval but tend to be around 0.5, which would lead to forecasting error if the model were transferred to an alternative zone system.

Another problem in transferability arises because changing the number of destination alternatives will, in and of itself, affect the frequency of travel. In a joint frequency and destination choice model, such as the non-home-based model in the MTC system, this effect is quite direct.

Suppose, for example, that the denominator in Equation 25 doubles with a twofold increase in destination possibilities. Then, using numbers from the destination sample for the MTC model, the probability of taking a trip would increase from, say, 0.38 (the proportion of nonzero frequency records in the destination sample) to 0.55. This implies a much higher elasticity of trip frequency than is intuitively plausible. Note that, if frequency choice is modeled separately from destination choice, the coefficient on accessibility in the frequency choice model could be less than unity, which would moderate this effect.

DISAGGREGATE DATA ANALYSIS

As a closing and hopefully constructive comment, disaggregate data analysis should focus more on distinguishing variations among households' travel behavior. Different trip makers in a zone have different choice constraints and different sensitivities to transportation LOS variables. These distinctions are now blurred when one model structure is applied to a zone containing a heterogeneous population. In this regard, large-scale planning models have not been significantly improved with the application of disaggregate travel demand models. An important topic for future research is how zone forecasting can be made more precise through the use of disaggregate data analysis that would segment trip makers demographically into groups with distinct travel behavior.

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This discussion is a comment from the user's perspective rather than a critique of the content of the papers. We feel that the papers adequately represent the work done for MTC by the authors. Further discussion of theory and technique does not seem as important as a few comments about the experience we have had in using the models. This is important to anyone considering development or use of such models.

A little background is appropriate first. MTC contracted with the consultant team (COMSIS, Cambridge Systematics, and Barton-Aschman Associates) in 1975 to develop a complete set of travel forecasting models. In phase one of that project the consultants reviewed the needs of MTC for travel forecasting models and reviewed the MTC data base. Then they recommended how we should proceed and told us what it would cost. We accepted their recommendations, and phase two began late in 1975. The model system was delivered about a year later. Some additional validation work was necessary and was completed by mid-1977. The entire effort took about two years and cost nearly $250 000.

MTC gained knowledge and experience with the models as we monitored the consultants' work. MTC conducted the aggregate validation for 1975 for the HBW models and has been using only those models, preparing travel forecasts in one study. MTC also had some brief experience with the entire model system early in 1977, before the models were finally validated for 1965. Our experience has been primarily with the regional network analysis system. We have done some further development work on the policy analysis system, but that is not reported here.

Our position is one of concern that the models may not do the job we need or may not do it within reasonable time and resource constraints. The models may be excellent theoretically and quite accurate—or as accurate as possible given the data base. We shall deal with the behavioral nature purported for the models, some changes necessary to validate and use the models, and their cost effectiveness.

A claim made for these models is that they represent traveler decision-making behavior. Experience with our models indicates that such claims may be somewhat inflated. Our opinion is based on the kinds of adjustments needed to make the models match various measures of existing trip patterns. This judgment is partly the result of our feeling that models should be reasonably consistent within a given data base. We have not found this to be true with our models and data base, but either might be suspect.

What concerns us most are the dramatic changes to the constants of the estimated models to eliminate large prediction errors. The constants represent the unknown or nonquantifiable factors and therefore are subject to considerable estimation error. Even when they are changed, there is no assurance that the constants will retain their values in the future or, if they do not, how they might change.

A second major problem was the inability to identify a function that adequately and consistently reproduced trip distribution behavior. The need for a trip length adjustment variable became apparent in disaggregate validation when estimated models overpredicted long trips. A distance correction variable by district of production was introduced into the utility equation. Its coefficient was developed by trial and error to match observed trip lengths. This is reminiscent of the traditional fitting of older trip distribution functions (friction factors). The consultants interpret this variable as representing travelers' decreasing knowledge of potential attractions as trip length increases. We disagree, since such an adjustment is applied more often to work trips than nonwork trips. It seems that travelers should be much more familiar with work-trip attraction alternatives farther from home than nonwork alternatives.

MTC is performing the 1975 validation by comparing model predictions to estimates from other sources. There was no regional travel survey in 1975, but 1970 census journey-to-work data have been used in this validation. Traffic counts, transit ridership, and numerous special purpose surveys have also been used to check the models.

The performance of the HB work models in 1975 validation indicated that the distribution models require unique adjustment factors similar to traditional K-factors. The K-factor approach was implemented by adding a term to the utility functions for specific i-j pairs (county or district interchanges). This is similar to changes in modal constants of the utility functions. The K-factors were developed first for county interchanges and then for district interchanges.

Since most of the disaggregate research and model development work had been done in the area of work mode choice, the expectations for the performance of these models were high. The results did not measure up to expectations. The mode-choice models also required transit trip production and district interchange adjustment factors.

The results of disaggregate validation showed that the model estimated from 1972 data overpredicted transit in the 1965 disaggregate data set by 80 percent. This required adjustments to the constants of the driving alone and carpooling modes. The prediction error was eliminated by increasing the driving alone constant by 31 percent and increasing the carpooling constant by 26 percent. The reverse happened in aggregate validation. HB work transit prediction using the disaggregately validated model was 42 percent under the 1965 observed regional transit trips. This required a decrease of 43 percent in the constant for the driving alone mode and a decrease of 30 percent in the constant for the carpooling mode.

After pondering these results one wonders which disaggregate data set to believe and if the changes in the constants of the utility functions are more behavioral than shifting empirically derived mode-split diversion curves to match the overall level of transit patronage.

The 1965 aggregate validation of the work mode-split model also showed that even though the total regional transit trips matched the home interview survey data, it was necessary to further adjust the model constants to match transit productions by district. When applying the mode-split model to 1975 estimated conditions, the results showed that different utility adjustment factors than those for 1965 validation were needed. In addition, the model overpredicted intracounty (short) transit trips and underpredicted intercounty (long) transit trips. This meant further intercounty or interdistrict adjustments. The 1975 results were purely mode-choice prediction errors, since the model-simulated person trip table was generated by the distribution model that incorporated K-factors that matched the observed 1975 person trips quite well.

The final aspect of our concern about the models is the resources required to operate them. This includes extensive data processing to prepare a multitude of variables in the proper formats and functions for use by the models. The simplicity of the papers and this discussion belies the extensive directories and cross-references required to use, understand, and interpret these models.

Add to that the problem of expense. To run a complete pass of our model system requires about one week of elapsed time, despite a computer system that gives us the best turnaround in the Bay Area. A complete model run costs over $6000 in computer charges, including all network processing for peak and off-peak transit and highway networks. The demand models themselves cost something over $2700 for a complete run. A complete run includes peak and off-peak networks, four purposes, and all-or-nothing assignment.

Our concerns about these models can be summarized in the following way:

1. The validity and behavioral claims are suspect because of the significant changes in constants and coefficients required to make estimated models reproduce an independent disaggregate data set and an aggregate data set;
2. The particular subsets chosen from the home interview survey data set for disaggregate estimation and validation have too great an effect on estimation results; and
3. The extensive work and reiteration from estimation through validation calls into serious question the claims by some advocates that disaggregate behavioral models are transferable.

Authors' Closure

We appreciate having this opportunity to respond to the discussions by Dunbar and by Shunk and Kollo. Their review of our papers, and of the MTC model system in its entirety, provides insights from the varying perspectives of the econometrician and tne practitioner. We will respond briefly to the critical comments made by each.

Dunbar's comments deal with potential specification errors in the travel demand models. We note that all of Dunbar's critical comments apply to all existing travel demand models and are not specific to the MTC model system. We will respond briefly to three of these.

Dunbar's comment on cross-section bias may be important only because an ordinary least-squares approach was used to estimate the travel frequency models in the MTC system. In on-going studies, a probabilistic choice structure is used for trip generation models as well as for distribution and mode-choice models. This avoids the type of cross-section bias pointed out in Dunbar's discussion, since estimation of conditional choice probability (i.e., frequency given location) is unbiased.

On value of time Dunbar states that it is inconsistent for a marginal rate of substitution (MRS) between time and cost of travel (i.e., value of time) to decline with respect to time spent in travel. This MRS not only is the result of the effect of time and cost constraints, as Dunbar suggests, but also represents consumers' trade-offs between time and cost that exist when the constraints are not binding. In this case, a declining MRS is perfectly reasonable, matches a wide range of empirical data, and is indeed a property of many existing aggregate and disaggregate travel demand models. The time and cost constraints that do exist are represented indirectly in the MTC model system, as in all others, by limiting predictions of internal travel to the set of zone pairs that exist within some specified analysis area.

Dunbar points out that the zone activity variables used in a number of the MTC destination choice models present potential problems when the models are transferred to other zone systems and other areas. As shown in Dunbar's Equation 25, and using his notation, the total attraction component of a typical model of this type is $E_i^{1-a} Y_i^a$. However, this can also be expressed as:

$$(E_i/Y_i)^{1-a} Y_i \tag{27}$$

This form supports the interpretation of Y_i as the only size variable, and E_i/Y_i as a rate or density-type variable. The single size variable does lead to the conservation of trips, and any deviations in predictions caused by the rate variable due to changes in zones are no different than deviations in level of service variables—both represent unavoidable aggregation errors inherent in any aggregate application of travel demand models.

Shunk and Kollo comment on questions that have arisen at MTC about the behavioral nature of the models, especially as evidenced by the changes in constants and the distance corrections required for validation, and the cost and effectiveness of model application. We will respond to their major points.

NATURE OF CONSTANTS IN LOGIT MODELS

Constants in logit models represent more than the unknown and unquantifiable characteristics of travel alternatives mentioned by Shunk and Kollo. When the models are applied at the aggregate (zone) level, these constants must also compensate for whatever biases exist due to the approximations and averages used to characterize the aggregated regional system. The important thing to note is that these adjustments do not change in any way the behavioral validity of the relative weights estimated statistically for the variables of the models. The advantages of disaggregate models in including more relevant variables than is possible in aggregate models, and in requiring fewer observations for model estimation, are also not affected by constants and the need to adjust them in aggregate applications.

TRIP LENGTH ADJUSTMENTS

Shunk and Kollo miss the importance of trip length adjustments when they state that these adjustments are applied more often to work trips than to nonwork trips. The magnitude of these corrections is more relevant than their frequency of application, and the relative magnitudes for work and nonwork purposes vary with trip length. For all trips less than 5 km (3 miles) in length, no correction is applied for either purpose. In the 5- to 24-km (3- to 15-mile) range, work corrections exceed those for nonwork travel. For trips longer than 24 km, the home-based shop corrections are the largest.

COST AND EFFECTIVENESS

Our paper mentions the expanded resource requirements, both in terms of staff understanding and in terms of analysis costs. Shunk and Kollo quote computer costs of $6000; we maintain that these compare favorably with the costs of traditional aggregate systems, which can be as high as $10 000 for a full analysis. In addition, it must be noted that these costs apply only to the full network analysis system, MTCFCAST. For many problems faced by MPO's, SRGP can provide the required information at costs per alternative in the $100-$200 range, after one-time costs of approximately $5000, to prepare a data base of household and level-of-service data. It is also worth noting that further work is being done to expand the SRGP approach to be compatible with network assignments. The computer costs of this approach fall in the $1500-$2000 range when an iterative procedure is used to predict both demand and network equilibrium, two aspects that cannot be addressed at all for the quoted $6000 cost.

Fred Reid raised another important question. He asked both Shunk and Ben-Akiva, "If you had the project to do over again, what would you do differently?" This is a question to which we have given considerable thought, because the technical quality and capability of the model system are not being taken full advantage of by the agency for which it has been developed.

One important aspect of the project that would be done differently is that less effort would be spent formulating and estimating additional model components; instead, more effort would be spent on thoroughly testing and validating the fewer model components estimated. This strategy is required to prevent the disillusionment likely to occur when, near the end of the model development process, some component produces unreasonable results under certain input assumptions.

Two other redirections of effort would have increased the usefulness of the modeling work done. First, rather than the almost exclusive emphasis, in the prediction testing and validation portions of the project, on the full network analysis system, MTCFCAST, more effort would have been devoted to demonstrating the value and usefulness of the SRGP program, which is potentially more cost effective for many of the policy questions addressed by an MPO. Second, more emphasis would be placed on ensuring, throughout the project, that the end product be precisely what is needed to meet the agency's planning needs and that the agency staff have full knowledge of the end product and complete facility in using it.

The problems of implementing and successfully using a major new model system require a large amount of cooperative effort by modelers and practitioners to be completely solved.

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Effects of Transportation Service on Automobile Ownership in an Urban Area

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A disaggregate automobile ownership choice model is applied to estimating the elasticities of automobile ownership with respect to household income, fixed costs of automobiles, travel times on urban roadways, and public transit service in a case study urban area. Focus is on the aggregate stock of automobiles held by all households and on the distribution of households owning zero, one, two, and three or more autos. Automobile ownership behavior of sociodemographic segments in the total population is also compared. Results indicate that the total number of automobiles owned is approximately three times more sensitive to household income than to automobile travel times. Furthermore, automobile ownership is twice as sensitive to automobile travel times as it is to public transit travel times. Finally, the automobile ownership decisions of inner-city dwellers and older families are more sensitive to all of these factors than are the decisions of suburban dwellers and younger families. It is demonstrated that transportation policies affecting urban traffic efficiency and public transit service are likely to impact on automobile ownership and these impacts will vary with geographical location and population sociodemographic segment.

The purpose of this research is to estimate the relative sensitivities of urban automobile ownership levels with respect to household income, automobile costs, ef-