ABSTRACT

Most research on logit models of mode choice has concentrated on the work trip, a fact frequently commented on by critics for some years. With the increasingly widespread adoption of the logit model as the basic mode-choice model of practical transportation planning, more logit models for nonwork purposes are being installed in travel forecasting procedures. In this paper the form that most of these models take and the assumptions on which they are based are examined. It is shown that the majority of these are not calibrated, but are updated from the work models. The inappropriateness of this is demonstrated through selected case studies, and the types of models that can be built are described. It is shown that calibration of nonwork models is feasible and presents no new problems over the work mode-choice models, and that the relative weights of cost and time components in work models are different from those found for fully calibrated nonwork models. The data requirements and calibration needs are also discussed.

Throughout most of the development of disaggregate models of mode choice, research concentrated almost exclusively on developing models of choices for the work trip. This was justified on a number of grounds, including the importance of the work trip in planning and policy decisions, and the convenience and appropriateness of the work trip for research. In this respect, it was often pointed out that collecting data on work trips presents a relatively simple and inexpensive data-collection activity; and that, because of the habitual nature of the trip, there is a greater chance that the work trip represents a rational choice of mode and that knowledge may exist about the alternatives. It is not the purpose of this paper to deliberate over these reasons or to produce evidence as to whether or not there exist foundations for them. Suffice it to say that there are published research results that cast some doubt on each of these basic assumptions and reasons, but that these still appear to have been insufficient to generate any significant change in the direction of research.

Of course the authors do not claim that there has been no research on nonwork models. There are several published papers about models for shopping trips (1-4), and a few instances of other nonwork models as well (5,6). However, the total number of such publications is insignificant in comparison with those on work trips. Furthermore, the logit model for the work trip has remained relatively simple, certainly in the perception of practicing transportation planners, whereas much of the research on nonwork models has generated more complex models in the stream, such as destination choice (trip distribution) or route choice. Given the added complexity stemming from this, the fact that most practical travel forecasters are reasonably content with existing aggregate trip-distribution models, and that aggregate versions of these more complex models are largely unknown, the few nonwork models that have been developed have largely failed, so far, to penetrate practice.

In this paper the pros and cons of substituting aggregate or disaggregate mode-choice models in the standard travel-forecasting procedure for work trips, and for making radical changes in the modeling process and its structure, are not discussed. Rather, it is accepted that the majority of planning regions in the United States use the conventional four-step modeling process for travel forecasting, as exemplified by the Urban Transportation Planning System (UTPS) program of the U.S. Department of Transportation, and they have simply chosen to replace or update the modal-split models in this process. Also, it should be noted that the authors use the term "modal split" to refer to models that are conceptually and structurally aggregate, while the term "modal choice" for models and procedures that are either disaggregate entirely or are based on use of disaggregate data for their development.

PRACTICAL IMPLEMENTATION

For more than two decades of modern regional transportation planning, no agreement could be reached on the form and structure of the modal-split model. It was frequently stated that, although only two types of trip-distribution models (gravity and intervening opportunity) were to be found in use, there were as many different modal-split models as there were urban areas that had completed a long-range transportation planning activity. Documentation of modal-split models tended to demonstrate the range of different types and structures of models (2,11). In the past few years this situation has changed quite dramatically. Almost every urbanized area that has updated or improved their model stream, and every area that has considered seriously the potential building of a line-haul transit service, has introduced a set of logit models of modal split. Such models are currently in use in Los Angeles and San Francisco, California; Washington, D.C.; Miami, Florida; Honolulu, Hawaii; Detroit, Michigan; Minneapolis-St. Paul, Minnesota; New Orleans, Louisiana; and San Juan, Puerto Rico, to name a few.

As noted previously, there has been considerable research on the mode-choice logit model for work trips, but relatively little for any other trip purposes. In applying logit methods to the standard travel forecasting stream, models are required to cover all purposes. In practical transportation planning, the emerging standard appears to be to use about six trip purposes for trip generation and trip distribution, but to aggregate these purposes to three or four for mode choice. In most of the cities previously mentioned, there are three models for the purposes of home-based work (HBW), home-based other (HBO), and non-home-based (NHB) trips. In one or two...
instances, an additional model exists for home-based
school (HBS) trips, but these are more usually left
as part of the HBO trips or excluded altogether, and
dealt with in some other estimation procedure that
implies an allocation of trips by school bus.

Clearly, then, every locality that has introduced
logit models of modal split has had the need to
build not only the well-researched, reasonably well-
derstood work trip model for HBO trips, but has
also had to develop models for at least two other
purposes, HBO and NHB, neither of which has been
studied or understood to any great extent.

Knowledge of how to build a model for shopping trips
has not helped the definition of models for
shopping trips. This assumes that the relative
weights of components of travel time, travel cost, and any user
characteristics in the models are the same for all
trip purposes. There is no research or other litera-
ture to support this position, but it is widely
held. In some instances the models so developed are
even further removed from calibration, because the
work model may in some cases have been built with
predetermined relationships between some of the
variables. Illustrations of this are discussed later
in the paper.

The second method of building the needed addi-
tional models--factoring--is to build factor models
that use the zonal market shares from the work model
and apply this, usually through some factoring pro-
cedure, to NHB trips. In many respects this differs
from quasi-updating only in that the factor is
derived by a different procedure.

One may question to what extent this treatment of
nonwork trips is of any real importance. It is clear
that most conventional bus systems derive most of
their ridership from the peak periods, carrying pri-
arily work and school trips. Even systems that in-
clude some form of rapid transit are still likely to
carry significantly more trips in the peak period
and to derive a large portion of their patronage
from the work trip. Nevertheless, these statistics
do not indicate that the nonwork, nonpeak trips can
be dismissed and can be treated substantially less
accurately than the work trips. In most large urban
areas work trips represent about 20 to 25 percent of
total daily trips. Home-based nonwork trips gen-
erally constitute a further 50 to 55 percent of
trips, whereas NHB trips make up the balance (20 to
30 percent) of regional person trips. In a typical
medium or large urban area in the United States, the
transit share of the market ranges from 2 to 15 per-
cent of all trips, and about 50 percent of this
transit share comes from the work trip.

As examples of these figures, 1980 statistics for
the Los Angeles region show that work trips consti-
tute about 18 percent of daily person trips, home-
based nonwork trips are about 52 percent, and NHB
trips are 30 percent. The bus system carries about 3
percent of these trips, with 45 percent of transit
trips being HBO trips. Overall, transit carries 7.5
percent of HBO trips, 2.4 percent of HBO trips, and
1.3 percent of NHB trips.

In Houston, it is estimated that 16 percent of
regional trips are HBO trips (including NHB trips), with 36 percent being
NHB trips. Transit carries about 14.9 percent of the
HBO trips, 7.9 percent of HBO trips, and 5.4 percent
of NHB trips. Because of the high use of the public
bus system for HBO trips, which are included in the
HBO total, Houston buses derive only 30 percent of
their patronage (not including the substantial tour-
ist ridership in Houston) from the work trip. If school trips are added to this, most of
which also occur in the peak periods, the percentage
of patronage for HBO and NHB trips becomes 36 per-
cent. The Houston bus system carries 9.2 percent of
the resident person trips plus an additional 29,000
non-work trips on an average weekday.

Finally, in Miami the regional split of trips
among purposes is 26 percent for HBO trips, 60 per-
cent HBO trips, and 14 percent NHB trips. The re-
gional transit share is 4.2 percent, consisting of
7.8 percent of HBO trips, 1.7 percent of HBO trips,
and 9.1 percent of NHB trips (the latter being high
because of the relatively high proportion of NHB
trips for Miami Beach and the high transit share of
all trips in Miami Beach) (9).

ILLUSTRATIVE EXAMPLES

It is useful to see the form of the models that are
produced by the alternative methods of building HBO
and NHB mode-choice models. Several examples have been selected from reported models that are in cur-
cent use in several different locations.

Minneapolis-St. Paul

This is one of the earliest models to have been
developed and applied for regional travel forecast-
ing (10). The coefficients for these models are
given in Table 1. The ratio of out-of-vehicle time
to in-vehicle time coefficients in the HBO model is exactly 2.5, and the ratio of the cost
and in-vehicle time coefficients is 1.5. Neither of
these ratios appears as such in the work model, al-
though both represent values that have been stated
frequently to represent the conventional wisdom of
the relative values of these in logit models. Over-
all, these ratios appear to have been established
and only the absolute values of the coefficients and
the values of the modal constants were fitted to
transit share data. In the HBO model the ratio of
2.5 between out-of-vehicle time and in-vehicle time
is maintained, generating coefficients of -0.025 for
out-of-vehicle time constant coefficients and -0.01 for in-
vehicle time. The cost coefficient is -0.0039, which
appears as almost the same ratio as the ratio of HBO
in-vehicle time to cost. Although this is not a pure
example of the types described earlier, these models
appear to be generally of the form of the ones that
define the HBO and NHB models from the HBO models,
calculating only an overall multiplier to fit ob-
erved transit share data.

Miami

The Miami model was built in 1976 and revised in 1978 (9). It was built under difficult circumstances
in that no calibration data were available for con-
structing it. Therefore, it was built from existing
trip tables, estimated modal splits, and information from other logit models, principally those for Wash-

Transportation Research Record 987
TABLE 1 Cost and Time Coefficients of Models for Minneapolis-St. Paul

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Wait Time</th>
<th>Walk Time</th>
<th>Out-of-Vehicle Time</th>
<th>In-Vehicle Time</th>
<th>Parking Cost</th>
<th>Running Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>HBW</td>
<td>-0.044</td>
<td>-0.030</td>
<td>-0.031</td>
<td>-0.014</td>
<td></td>
<td></td>
<td>-0.014</td>
</tr>
<tr>
<td>HB-nonwork</td>
<td>-0.020</td>
<td>-0.020</td>
<td>-0.008</td>
<td>-0.012</td>
<td></td>
<td></td>
<td>-0.012</td>
</tr>
<tr>
<td>NHB</td>
<td>-0.025</td>
<td>-0.025</td>
<td>-0.0100</td>
<td>-0.0039</td>
<td></td>
<td></td>
<td>-0.0039</td>
</tr>
</tbody>
</table>

aSeveral alternative coefficients are used for out-of-vehicle time for automobiles, depending on occupancy.

itington, D.C. The coefficients for these models are given in Table 2. In every case the ratio between the excess-time coefficient and the in-vehicle time coefficient is 2.5, and the ratio between the in-vehicle time coefficient and the cost coefficient is -0.3333. The cost coefficient is, in this case, the coefficient for a variable of cost divided by income.

This model is an excellent example of the first type of construction, in which the ratios among the coefficients are prespecified, and fitting of the model is concerned only with an overall factor for the model coefficients and any mode-specific constants.

New Orleans

This model was built in 1981 and incorporates some additional sophistications not apparent in the previous two models. (Note that the data for this model are from unpublished reports by Barton-Aschman Associates, Inc.) These sophistications include using different coefficients for walk time and wait time and introducing yet a further coefficient for automobile time when used as access to transit. The coefficients for these models are given in Table 3. In the HBW model the ratios between each of walk time and wait time and in-vehicle time are approximately 2.3 and 5.3; whereas the ratio between cost and in-vehicle time is 0.53. Notwithstanding these values, the model reverts to a 2.5 ratio for both walk and wait times to in-vehicle times for both the HBW and NHB models. The cost coefficients demonstrate almost exactly the same relationship to in-vehicle time as the Minneapolis models, which suggests that this model may have been used as the basis for the cost coefficient to replicate observed transit shares more accurately.

TABLE 2 Cost and Time Coefficients of Models for Miami

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Wait Time</th>
<th>Walk Time</th>
<th>Out-of-Vehicle Time</th>
<th>In-Vehicle Time</th>
<th>Parking Cost</th>
<th>Running Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>HBW</td>
<td>-0.0515</td>
<td>-0.0206</td>
<td>-0.0618</td>
<td>-0.0078</td>
<td></td>
<td></td>
<td>-0.0618</td>
</tr>
<tr>
<td>HB-nonwork</td>
<td>-0.0415</td>
<td>-0.0166</td>
<td>-0.0498</td>
<td>-0.0116</td>
<td></td>
<td></td>
<td>-0.0498</td>
</tr>
<tr>
<td>NHB</td>
<td>-0.0193</td>
<td>-0.0077</td>
<td>-0.0231</td>
<td>-0.0047</td>
<td></td>
<td></td>
<td>-0.0231</td>
</tr>
</tbody>
</table>

Note: The cost and time coefficients are for transit, nonbeach traffic only. Models exist for each of transit and highway for both beach and nonbeach zones. Each model contains different coefficients, but the ratios among coefficients are the same.

TABLE 3 Cost and Time Coefficients of Models for New Orleans

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Wait Time</th>
<th>Walk Time</th>
<th>Out-of-Vehicle Time</th>
<th>In-Vehicle Time</th>
<th>Parking Cost</th>
<th>Running Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>HBW</td>
<td>-0.0332</td>
<td>-0.0769</td>
<td>-0.014</td>
<td>-0.0078</td>
<td></td>
<td></td>
<td>-0.0078</td>
</tr>
<tr>
<td>HB-nonwork</td>
<td>-0.0165</td>
<td>-0.0165</td>
<td>-0.0116</td>
<td>-0.0047</td>
<td></td>
<td></td>
<td>-0.0047</td>
</tr>
<tr>
<td>NHB</td>
<td>-0.0328</td>
<td>-0.0328</td>
<td>-0.3048</td>
<td>-0.0131</td>
<td></td>
<td></td>
<td>-0.0131</td>
</tr>
</tbody>
</table>

aOut-of-vehicle time is for automobile only, and several coefficients exist for the occupancy levels for HBO and NHB.

Los Angeles I

The first Los Angeles model to be described is the one built for the Los Angeles Rapid Transit System in 1976. The time and cost coefficients for the HBW model are as follows [1]: out-of-vehicle travel time/distance = 24.37, in-vehicle travel time = -0.01465, cost/income = -0.1860, and the factor = 2.332. This model, which was never adopted for regional forecasts by the local agencies, consisted of a logit work mode-choice model and a factoring procedure for nonwork trips. The factoring procedure is based on the observation that approximately 43 percent of transit trips are work trips. After estimating the HBW trips, the trip interchange totals of transit trips generated by the work model are multiplied by 2.332, which represents the inverse of the proportion of transit trips that are work trips. This is an excellent example of the second method of developing nonwork mode-choice models.

Los Angeles II

The second Los Angeles model was built in 1982. The coefficients are given in Table 4. (Note that these data are from unpublished reports for the Southern California Association of Governments by Cambridge Systematics, Inc., 1982.) This model represents an exception to the previous ones, insofar as the HBO model is concerned. This model was calibrated to data, and no use was made of relationships between coefficients in the work model for devising this model. The ratio of the coefficients of excess time and in-vehicle time is 5.6 for the HBW model and 3.1 for the HBO model. In these models cost is divided by income, thus making comparison with some of the other models more difficult. However, the ratio of the cost coefficient to in-vehicle travel time is 2.01 for the HBW model and 3.17 for the HBO model.
Again, these values serve primarily to demonstrate that the HBO model was calibrated freely and that the assumed values from the earlier models do not appear to be replicated by these calibrated values. This is discussed at more length later in the paper.

In this model set the NHB transit trips are estimated by multiplying the HBO share of transit trips (expressed as a fraction) by a fractional constant to determine the transit share of NHB trips. NHB trips are subdivided into other-to-work and other-to-other trips. For the former, the fractional multiplier of the HBO modal split is 0.2608, and for the latter, it is 0.3431. In the event that a trip interchange has no HBO trips, the NHB transit market shares are set at 0.0182 for other-to-work trips and at 0.0156 for other-to-other trips. These values are approximately the regional modal splits for these two purposes.

The NHB model is an example of the factor model, whereas the HBO model represents one of the still-few instances of the free calibration of a model for nonwork trips.

More examples could be drawn from those that are in current use, but those documented in the preceding paragraphs provide adequate illustrations of the types of models that are in current use and that are based on the noted methods of calibration.

### FULL CALIBRATION

The alternative to the foregoing procedures is to calibrate the home-based nonwork and NHB models directly from available data. As noted earlier in the paper, there appear to be certain myths surrounding full calibration of these models that have led to the preponderance of the model-fitting procedures described in the previous section of the paper. In this section two case studies are described that should expose the myths. The first of these case studies deals with what is likely to be the most common case for practical transportation planning, in which the region does not have household data that have been collected recently with calibration of logit mode-choice models in mind. Rather, the data are likely to be of the form required for updating earlier types of forecasting models. In the second case study data were collected expressly to allow calibration of logit models of mode choice for all purposes. This is closer to the ideal situation, but is likely to occur far less often than the first case.

#### Case Study 1

This case study is for San Juan, Puerto Rico (12). New modal-split models were to be constructed for use in a conventional UTPS-based forecasting procedure, but the modal-split models were to be aggregate logit models. The work plan for this activity did not include either time or money to permit collection of data for constructing new models. However, a data set existed that had been collected in 1977 for updating a fully conventional set of home-interview data. The data set consisted of 1,178 households, from which standard trip data for 24-hr, household demographics, and locational data had been obtained. The trip data consisted primarily of the mode of travel, the origin and destination, the time of day, and the purpose of the trip. Information existed on whether or not the household had automobiles available and how many automobiles were available. The number of licensed drivers was not included in the data.

A calibration data set was developed for mode choice by subdividing the reported trips into the purposes of HBW, HBO, NHB, and HBS. Data were compiled for each trip from the path characteristics of the highway and transit networks to represent the travel characteristics for each trip. For HBW and the HBS trips, the travel characteristics were developed from the peak networks, whereas the characteristics for HBO and NHB trips were drawn from the midday or 24-hr networks. Paths were defined for three primary mode alternatives: automobile, bus, and publico ( jitney). It was assumed that access to bus was by walk only, whereas publico could be accessed by either walk or walk and bus. No distinction was obtained in the travel characteristics for automobile based on the occupancy, except to divide the cost among the occupants. The trip characteristics obtained from the path files and zonal characteristics were walking time, waiting time, in-vehicle time, parking cost, and running cost (running cost is total out-of-pocket costs, not including parking).

The calibration was achieved by using ULOGIT in the UTPS program package. This model required that trips be deleted from the calibration file if any of the alternatives had no path and therefore no trip characteristics. From the 1,178 households, the calibration data set consisted of 564 HBW trips, 579 HBO trips, 798 HBO trips, and 346 NHB trips. The lack of captivity data prevented removal of captives from the calibration data. The coefficients of the models are given in Table 5.

First, it may be observed that the models for all four purposes produced sensible results in terms of the signs and magnitudes of the coefficients. Hence concerns that models for nonwork trip purposes cannot be calibrated from conventional data appear to be unfounded. Second, note that the relative values of the coefficients differ from those described in the quasi-updated models. In the HBW model walking time and waiting time each have about the same coefficient, and it is more than 3 times the value of the in-vehicle time coefficient. The cost coefficient is about 0.31 of the in-vehicle time coefficient. For HBO trips, the coefficients of walking and waiting time are again similar, but are 12 times the value of the in-vehicle time. The cost coefficient is equal to the in-vehicle time coefficient in this case.

The HBS model is substantially different. In this case the in-vehicle time coefficient was so insignificant and small that the variable was not used in the final model. The walking time coefficient was

### TABLE 4 Cost and Time Coefficients of Models for Los Angeles (1982)

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Wait Time</th>
<th>Walk Time</th>
<th>Out-of-Vehicle Time</th>
<th>In-Vehicle Time</th>
<th>Parking Cost</th>
<th>Running Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>HBW</td>
<td>-0.157</td>
<td>-0.0329</td>
<td>-0.0557</td>
<td>-0.0111</td>
<td>-0.0256</td>
<td>-0.0293</td>
<td>-0.19</td>
</tr>
<tr>
<td>HBO-nonwork</td>
<td>-0.0746</td>
<td>-0.0256</td>
<td>-0.0293</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>NHB</td>
<td>-</td>
<td>-</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: The NHB transit share is factored from the work modal split.
more than twice the size of the waiting time coefficient, and is 4 times the size of the in-vehicle time coefficient for the work model. Parking cost has a coefficient that is nearly 5 times the size of running cost. The latter coefficient is about 0.2 of the work model in-vehicle travel time coefficient, and is about 0.12 of the waiting time coefficient of this HBW model. Finally, the NHB model shows a further set of different relationships. In this case walking time is weighted 4.5 times more heavily than waiting time and almost 12 times as heavily as in-vehicle time. The cost variable is again divided into the two components of parking and running cost, with the former having a coefficient that is 6 times the value of the latter, and 1.6 times the in-vehicle time coefficient. The ratio of the cost coefficient to the in-vehicle time coefficient is 0.2.

Generally, there is little support from this model for the ratios assumed in many of the noncalibrated models. The work mode-choice model exhibits coefficient relationships that are well within the range of those that have been reported in a variety of other localities. The lack of importance of in-vehicle travel time for school trips is reasonably acceptable, suggesting that, given the necessity to go to school and the relative lack of choice in school location, in-vehicle travel time is of little consequence in choosing among available travel modes. In all models both walking and waiting times are weighted much more heavily than in-vehicle travel time, although walking is considered far more onerous for HBO and NHB trips than for the other purposes.

Case Study 2

The second case study is from Honolulu, Hawaii (13). In this study data were collected expressly for calibration of a set of logit mode-choice models, although it was decided that network (aggregate) data should be used for the calibration data set. Data were collected by means of a travel diary from 1,370 households (see paper by Ohstrom et al. elsewhere in this Record), and the calibration data set was developed by geocoding the origins and destinations of the trips and again extracting the travel characteristics from the path files. The models were structured around the alternatives of automobile (with three occupancy levels), local bus, and express bus. Express bus could be accessed by walk or local bus, while local bus had walk access alone. Express bus was available for only HBW and HBS trips, and both of these purposes again used the peak transit network characteristics, with congested highway speeds, whereas midday transit network characteristics and free-flow highway conditions were used for the HBO and NHB models. As with the San Juan model, no distinction in the characteristics of midday and peak period automobile trips could be obtained beyond the division of cost among the occupants. Again, the characteristics used were walking time, waiting time, in-vehicle time, parking cost, and running cost. Sociodemographic variables were also tested, but the only one found to affect the models significantly was the ratio of available vehicles to licensed drivers (minimum value of 0.0 and maximum value of 1.0). This variable was not retained in the final models because of concerns about the ability of local agencies to forecast it. Retention of the calibration values, in place of forecasts, would leave the variable as little more than a constant term.

Calibration was achieved by using the QUAL program developed at the University of California at Berkeley (14), which permits calibration data to contain a variety of subsets of alternative modes. Therefore, the only discarded data were for any trips where only one mode had a path between a pair of zones or where the trip was totally within the zone. From the 1,370 households, the calibration data sets consisted of 458 HBW trips, 329 HBS trips, 361 HBO trips, and 277 NHB trips. In this case the data included information on captivity, and captives were excluded from the calibration data. In addition, a number of data points were lost because the network characteristics created outliers that would bias the calibration results. An outlier was defined as arising when the chosen mode had travel characteristics (times and costs) that were all inferior to those of any of the nonchosen modes and the sum of the time component was more than 20 min in excess of the worst alternative not chosen. Alternatively, if the total travel time for the chosen mode was more than 3 times the travel time of the next alternative, it was also considered an outlier. The results of the calibration are given in Table 5.

The conclusions to be drawn from these models are similar to those from the San Juan models in their essential points for this paper. Again, the results clearly show that logit models can be calibrated satisfactorily for all of the purposes. Likewise, the relative values of coefficients differ substantially from the assumed values, and show significant differences from purpose to purpose. In the HBW model walking time is valued at 6.6 times in-vehicle time, whereas waiting time has a coefficient of 5.7 times that of in-vehicle time. Costs are split, with running cost having a coefficient that is 0.17 of in-vehicle time and parking cost a coefficient that is 0.72 of in-vehicle time. In the HBO model walking time is valued at 6.6 times in-vehicle time and waiting time is valued at 4.5 times, whereas cost is 0.47 times the in-vehicle time. In this case in-vehicle travel time did not appear in either the HBO or NHB models. This may signify a problem with the midday and uncongested networks, but it also may be a realistic reflection of behavior. For the HBO model, walking time is considered about 2.5 times as onerous as waiting time, and about 3.5 times as onerous as in-vehicle time for the work trip. Parking cost is 3.5 times as important as running cost, whereas the latter has a coefficient somewhat smaller than for the HBO model.

Finally, the NHB model shows walking time to be more than 3 times as onerous as waiting time and has cost coefficients for both parking and running costs that are almost identical to the HBO values. The
The authors would like to thank the Oahu Metropolitan Planning Organization (OMPO) for permission to use the results described for the Honolulu case study and for their active support on the presentation of this paper. The authors particularly would like to thank Cathy Arthur and Gordon Lum of OMPO for their suggestions and help both in the original work and in the documentation of the results in this paper. The authors would also like to thank the Department of Transportation and Public Works of the Commonwealth of Puerto Rico for permission to use the results described for the San Juan case study.

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REFERENCES


TABLE 6 Cost and Time Coefficients of Models for Honolulu

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Wait Time</th>
<th>Walk Time</th>
<th>Out-of-Vehicle Time</th>
<th>In-Vehicle Time</th>
<th>Parking Cost</th>
<th>Running Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>HBS</td>
<td>-0.099</td>
<td>-0.068</td>
<td></td>
<td>-0.0015</td>
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<td>-0.007</td>
</tr>
<tr>
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<td>-0.006</td>
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results of the NHB and HBO models are similar to those of San Juan, and suggest a radically different weighting of coefficients to any of the noncalibrated models discussed. (It should be noted that the Honolulu models have been recalibrated subsequently, with minor changes in certain inputs, and some changes have occurred in final coefficient values.)

CONCLUSIONS

Three conclusions are in order from the cases discussed in this paper. First, planning agencies and their consultants should not conclude that the lack of reported research on nonwork models is in any way indicative of potential problems in fitting the models. Although not discussed here, it is appropriate to observe that the statistics of goodness-of-fit for the NHB models are generally inferior to those of the HBW models, which is consistent with experience in fitting trip-generation models for NHB trips. Nevertheless, the values of these statistics are adequate to indicate a useful model. This is further borne out by obtaining coefficients that are reasonable and that also show consistency between two localities described herein. The statistics for HBS models were found to be comparable with the HBW models. In all cases coefficients were found to have t-scores well in excess of 2.0 for included variables, and chi-square values were, as usual, far larger than any table values for the appropriate degrees of freedom. For details, however, the reader is referred to the original reports.

Second, although it is clearly desirable that data be collected that are designed for the purpose of calibrating logit models, it is possible to obtain adequate fits from data that may have been collected several years previously and that were not collected specifically for logit modeling. A cautionary note is appropriate to the effect that use of network-derived characteristics requires great care in path building, a topic that is too extensive to deal with in this paper.

Finally, the transferability of HBW logit-model coefficients that have been assumed in building models for other purposes is not borne out by true calibration. The relationships tend to be significantly different from those in the work models, and may exhibit variation from locality to locality. Similar local differences are also to be found among HBW models when unconstrained calibration is performed. Furthermore, not all of the travel characteristics found to be significant in work mode-choice models are significant in nonwork models. Therefore, factoring from work models, or defining a multiplier for a predefined combination of times and costs for nonwork models, is not an appropriate procedure to use.

ACKNOWLEDGMENTS

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REFERENCES

Sequential Model of Interdependent Activity and Destination Choices

RYUICHI KITAMURA and MOHAMMAD KERMANSHAH

ABSTRACT

A sequential model of daily travel patterns that consists of activity and destination choice submodels is developed in this study. The model development takes into account the interdependencies among the choices and the constraints imposed on the movement in time and space. The empirical analysis indicates that non-home-based destination choice is critically dependent on the residence location of the individual and that activity choice is influenced only marginally by the accessibility of the origin location. As a practical and immediate modification of non-home-based destination choice models, it is proposed in this study that destination-to-home travel time be included as a factor that enables a more realistic depiction of spatial travel patterns.

In previous efforts (1,2) the authors have examined the properties of activity choice that are directly related to generation of trips and their temporal distribution over a 1-day period. The results have revealed the characteristics of time-of-day dependencies of activity choice and revealed patterns in sequencing activities in trip chains. Analysis of the dependence of activity choice on its own history indicated that activity history may be represented in a simple manner for use in travel behavior analysis. This study draws on the previous efforts and expands it by introducing the spatial dimension into its scope.

The ultimate objective of this continuing effort is to develop a practical model system that makes possible a more realistic depiction of complex daily travel behavior. The effort and the resulting models can be characterized by the following two aspects.

The first is its explicit recognition and incorporation into the model structure of the fact that trips made by an individual are linked to each other. This leads to the emphasis in this study of the interdependencies among choices that underlie the entire daily travel and activity pattern. In other words, this study does not isolate a trip or a travel choice from the rest to be analyzed independently. Second, the effort acknowledges that the movement of an individual is constrained in time and space because of various factors, including the social commitments, obligations, limited transportation capabilities, and physiological needs of the individual (3-8). The constraints are most typically associated with activities that allow little scheduling flexibility such as work, chauffeuring children to school, or having lunch during a lunch break. This study therefore emphasizes, among others, time-of-day dependencies of activities and trips.

A system of models is developed in this study. It consists of home-based and non-home-based destination choice models that incorporate the effects of trip continuity together with those of time of day. The activity choice models of this study are expanded to include, in addition to the variables used in the previous study (2), spatial factors such as the travel time between the home base and the origin activity location and the accessibility from that location.

The objective of this study is, first, to identify the extent to which destination choice is influenced by factors other than the traditional variables (i.e., the origin-destination travel time and the attributes of alternative destination locations). More specifically, the study is an endeavor to show that the location of an individual's home and the locations of alternative destinations relative to the home location critically influence non-home-based destination choice. The second objective is to identify the effects that spatial factors have on activity choice, either independently or jointly with other factors, including time of day, activity history, and socioeconomic characteristics of the