Comparison of Models of Individual Choice in a Complex Setting

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Abstract

In response to gasoline shortages, pollution problems and the rise in oil prices, it is clear that individual commuting habits may be modified. To assist planners in evaluating the impact of alternative policies, models of individual behavior in complex mode choice environments are necessary. This paper examines the use of simulation in association with statistical methodologies to verify models of traveler behavior. The data employed in the calibration and evaluation of the models was derived in a large scale longitudinal study. In conjunction with an UMTA demonstration project, policy makers were able to manipulate the cost and service of the transportation alternatives and observe in detail the responses over time of a large sample of individual users for whom extensive amounts of socio-economic data had been collected.

INTRODUCTION

Studies of individual beahvior and choice often emphasize the calibration and validation of well-established models. The extent of reliance on "classical" models is often a function of particular application areas. For example, in studying transportation and travel choice, the most commonly used methodologies address the question, "who will use mass transit (or some other mode) and who will not?"

In response to gas shortages, pollution problems, and the rise in oil prices, it is clear that individual commuting habits may be modified. Responding to external circumstances, local, state, and federal governments attempt to meet pressures by such means as:

- shifting funds from highway to rapid transit
- requiring tighter auto emission standards
- enforcing parking restrictions and/or auto free zones
- charging tolls on highways, bridges, and tunnels
- establishing priority schemes to encourage the use of carpools/mass transit
- establishing restrictions on the access to to gasoline

However, not all government policy is directed to reduce automobile usage. For example, recent Congressional cutbacks in AMTRAK and rail transit severely restrict the capacity of railway systems. Also, the requirement (in the state of California) that gas stations remain open at least one day of the weekend is designed to alleviate the problems of the motorist. The mode choice environment becomes more complex, and as one might assume, so would any model of behavioral choice. Of course, it isn't that the underlying thinking of the traveler or commuter changes, it is just that the travel commuting options become more complex. Any useful model of travel choice must be capable of reflecting the various significant influences on the traveler.

The simple binary models do not provide adequate planning information about travel chioce when the user is confronted with a more complicated mode mix. Travel planners can no longer simply calibrate some existing model, but must address the underlying mechanism of individual, or disaggregate, travel choice. This may involve structuring many alternative models which allow for a wide variety of choice options. For example, no matter how entrenched an individual's auto commuting habit may be, the long-distance commuter may have to face the realities of long gas lines and the inability to obtain gas on a regular basis. Perhaps, such an individual could be induced to make at least occasional use of public transportation or carpool systems.

Evaluating alternative choice models may present an imposing task; a whole new dimension is added to the problem which the transportation planner is required to solve. A major difficulty derives from the data and information available to the transportation planner; the data gathering effort must be comprehensive enough to respond to

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the needs of model structure formulation as well as model calibration.

Underlying the possible disaggregate choice schemes is the fact that any individual faces only a finite number of choices. No matter how complex the mode setting, or how numerous the options, there can only be a countable number of alternatives. The evaluation of the alternatives can be incorporated in a more general statistical analysis effort. Of course, it is necessary to adopt some measure of model performance, or more specifically, a measure of how well the model reflects observed behavior.

The mechanics of model evaluation requires the prediction of individual choice under each model structure proposed; predicted behaviors may be retained as variates along with the initial data base. It is then an easy matter to compare statistical measures of model performance. An obvious performance criterion is the mean-square error (of predicted relative to actual behavior). If the original data base is large enough, this criterion should pose no potential hardships. There may be some subtle difficulties inherent in the model structure (due to biases unrelated to sample size). However, there are often easily implemented procedures for eliminating such biases.

It is relatively easy to consider a large number of models, if model evaluation is performed as part of statistical data analysis programs. This is particularly critical, since each model structure may be implemented in a number of ways. For example, if the process of model choice involves some sequential process, different choice mechanisms may be operative at each stage of the choice sequence. Thus, multiple "cases" need to be considered for each proposed model structure.

Of course, the price we pay for seeking a general model structure is the additional burden placed on the data base. Model calibration (generating coefficient estimators and conducting tests of significance) goes hand-in-hand with the model selected; a different model gives a different set of calibration values. What we can do, is to determine the "best" model and assess the adequacy of this model in explaining behavior.

Unless a new data set is gathered in exactly the same setting, it is not possible to validate the model. The process discussed above is really a model verification effort, and is weaker than the validation process. If a new setting is to be examined, the merits of adopting models from other settings need to be carefully considered. It is possible that the new setting involves an entirely different structural choice mechanism (e.g., differences in demographic, socioeconomic characteristics). Calibrating an erroneous model would yield specious predictions of response to transportation system changes.

So why bother with the more complex model? Of course, one could attempt so comprehensive a data collection and modeling effort that the model could "absorb" regional differences in setting and individual characteristics. However, with the rapid expansion of demonstration projects and accumulation of data bases, it may be possible to select a "microcosm" of a particular setting, to act as a surrogate in model building. Specifically, large urban areas, with their variegated populations, complex transportation networks, and concommitant transportation problems, may not prove tractable as the bases for structuring behavioral choice models. Choosing some smaller, but representative setting might provide the basis for establishing an appropriate behavioral model structure in the larger setting.

CASE STUDY

Most probabilistic models of commuter mode choice emphasize the decision to use one out of two or more modes, with the total exclusion of other modes. It is desired to establish a model of mode choice (specifically, mass transit) which allows for the simultaneous decision to use two or more modes in some supplementary fashion. This is of particular concern in medium or smaller size communities, such as the one in this study, where such modes as bicycle, walking, and hitchhiking attract sizeable portions of commuter population. The use of such modes will, of course, be dependent on such factors as topography, climate, and origin-destination distances.

The data base used for model calibration was developed as part of a no-fare commuter bus Demonstration Project conducted at the University of Massachusett/Amherst. Specifically, the data was collected in a series of longitudinally stratified telephone surveys. The intent of the surveys was to assess the impact of successive modifications to existing transportation facilities and policies.

The importance of the multiple mode option to the University of Massachusetts setting is seen below in Table 1. The percentages for successive modes represent the portion of users relying solely on that mode to meet their commuting requirements. The surveys were conducted over successive academic semesters.

The transit choice (as well as other mode choice) option was treated as discrete. It was assumed that the individual commuter chooses an integer number of trips per week to be made via mass transit. There did not appear to be any simple underlying distribution to the number of trips per week. This is clear when one considers an individual more likely to make an even number of trips using a particular mode than an odd number. Also, it should be clear that "peaks" to any distribution of number of trips would be at zero (mode non-use) and ten (regular commuting mode).

The underlying mechanism of transit choice was assumed to follow one of three basic decision-making sequences. Part of the function of this study was to determine which mechanism most closely forecast actual transit use. The mechanisms are shown in Figure 1. In addition to the mechanisms shown, various assignment methods (i.e., probabilistic vs. deterministic at each stage of the model) were examined. In all, nine different models were evaluated.

TABLE 1

PROPORTION OF MODE USERS INDICATING EXCLUSIVE USE OF THAT MODE FOR COMMUTING

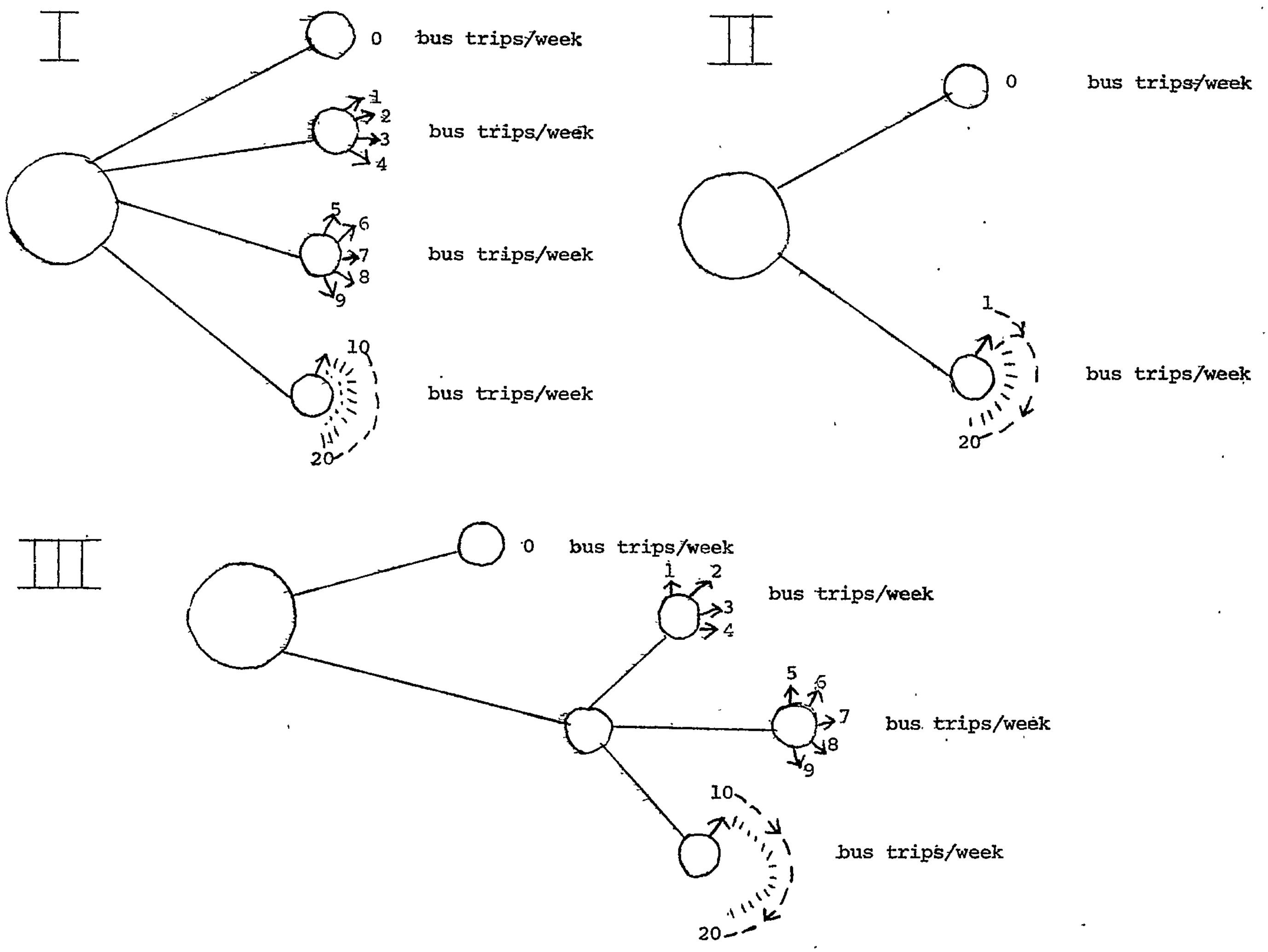
	MODE USERS MAKING EXCLUSIVE USE OF MODE							
	TELEPHONE SURVEY 1		TELEPHONE SURVEY 2		TELEPHONE SURVEY 3		TELEPHONE& SURVEY 4	
MODE	COUNT	%	COUNT	%	COUNT	%	COUNT	%
Auto to Peripheral Lot	---	---	---	---	18	72	12	39
Auto to Core or Edge Lot	---	---	---	---	181	83	92	53
Private Auto	446	80	328	69	---	---	---	---
Bus	11	22	120	49	114	62	15	13
Bicycle	13	22	13	27	15	39	1	5
Walk	92	50	65	47	60	62	24	33
Hitchhike	15	30	*	*	*	*	*	*

* Sample size inadequate

& Telephone survey 4 responses are not directly comparable with the other telephone surveys, because of format change in mode choice questions.

FIGURE 1

BASIC CONFIGURATIONS OF TRANSIT CHOICE MODELS



For each of the models, calibration was conducted via regression estimates, with interaction terms generated as products of canonical component pairs. The canonical components were selected from specified categories of variables (e.g., socioeconomic characteristics, experiential variables, attitudes). A scheme for developing efficient parameter estimates had to be employed, since the choice options were binary (e.g., choose or don't choose a specific transit option).

Because of the current interest in evaluating aggregate vs. disaggregate models, two model evaluation schemes were used. The first used all the calibration data (corresponding to the disaggregate model). The second used only information concerning the stratification variables; this served as a comparative aggregate model. After adjusting for degree of freedom in obtaining estimates, the two approaches are compared.

In addition, linear and logit models were tried. The advantage of the linear model is computational ease. The advantage of the logit model lies in ease of interpreting results. The logic estimation model required a "two-pass" data evaluation procedure.

A schematic of procedures for evaluating the proposed transit use models is shown below in Figure 2.

The model with the smallest mean-square error of predicted transit choice had the following characteristics (note that the mean-square error was significantly smaller, in a statistical sense, than for the other models):

1 - two stage assignment mechanism
2 - transit use or non-use assigned in a deterministic manner
3 - level of transit use (for those forecast to use transit) modeled as a continuous function (normal distribution used in this study)

The implications of the above results should be clear. It appears that individual make decisions of whether or not to use transit based on some composite index of utility for that individual. If that index exceeds some specified level, the individual will adopt transit; if the index does not exceed that level, he/she will not. Thus, from a marketing standpoint, it would make sense to direct promotional efforts at those individuals nearest to (but not exceeding) their "threshold" levels. In addition, emphasis should be directed to individuals who are potential regular (as opposed to partial) transit users. (Specifically, it may be of little value to encourage a nonuser of transit to become a user when he is likely to make only a small number of his commuting trips by transit.).

Of even greater interest are those variables found to be significant in the estimation of choice for the two stages of the model. The key variables in the decision of whether or not to use transit were time to walk to bus stop and level of service attributes. The significant variables in the estimation of number of transit trips (by transit users) were socioeconomic variables and prior community behavior (i.e., mode choice). Since the transportation planner can more readily manipulate attributes associated with the first set of variables, it is suggested that emphasis be placed on modifying the individual composite index of utility. What is desired is a numerical value for the composite index which exceeds the "threshold" level, as discussed above. The predicted level of usage should be used only as a guide for establishing "target" population stratification groups most likely to use transit on a regular basis.

FIGURE 2

SCHEMATIC OF EVALUATION PROCEDURES FOR PROPOSED DISAGGREGATE TRANSIT CHOICE MODELS