ACTIVITY-BASED MODELING SYSTEM FOR TRAVEL DEMAND FORECASTING

Travel Model Improvement Program

Submitted to:

Metropolitan Washington Council of Governments
777 North Capitol Street, N.E.
Washington, D.C. 20002-4226

Sponsored by:

U.S. Department of Transportation
400 7th Street, SW
Washington, D.C. 20590

and

U.S. Environmental Protection Agency
401 M Street, SW
Washington, D.C. 20460

Prepared by:

RDC, Inc.
311 California Street, Suite 620
San Francisco, CA 94109

September 1, 1995

NOTE: This project was jointly sponsored as part of the Travel Model Improvement Program (TMIP), by the U.S. Department of Transportation (US DOT) and U.S. Environmental Protection Agency (US EPA). The sponsors' intent behind the project was to investigate and develop the idea of activity-based forecasting in an applied setting. RDC, Inc. developed the Activity-Mobility Simulator, or AMOS, as a tool in this regard.

The information contained in this report represents the views of RDC, Inc., and is not necessarily endorsed or recommended by the US DOT or US EPA.

The project sponsors ***are*** *interested, however, in articulating their support for continued investigation and assessment of activity-based forecasting techniques, and studying their potential for: (1) applications in transportation, and (2) any improvements to modeling practice. To date, several metropolitan areas have demonstrated an interest in activity modeling, and have started to undertake activity surveys for their regions; among these are Boston, Oahu, Detroit, Dallas/Ft. Worth, Raleigh/Durham, and Portland, OR. As part of TMIP, US DOT and*

US EPA anticipate continued exploration of the role an activity-based approach can play in travel forecasting.

Abstract: Activity Based Modeling System for Travel Demand Forecasting - Travel Model Improvement Program

This study is probably the first attempt to develop and implement a full-fledged activity-based policy analysis tool for a metropolitan region and thereby examine whether activity-based approaches can be put to practical use. In particular, the study attempts to determine whether an operational activity-based tool can be developed while utilizing available data, supplemented by a medium-scale survey that can be conducted with modest mounts of monetary and time resources.

Author: RDC, Inc.
Publication Year: September 1995
Sponsor(s): Metropolitan Washington Council of Governments; U.S. Department of Transportation; U.S. Environmental Protection Agency

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Chapter 1: Introduction

1.1 Background

Over the past couple of decades, the emphasis of transportation planning has shifted from the construction of new infrastructure to the effective management of travel demand. This shift has been brought about by rising social, environmental, and economic concerns coupled with a realization that building one's way out of congestion is only a temporary solution to serving the increasingly complex patterns of travel demand that evolve over time. Federal legislative acts such as the Clean Air Act Amendments, 1990 and the Intermodal Surface Transportation Efficiency Act, 1991, serve as key examples of this shift in transportation planning emphasis.

In this regard, the decade of the 1980s saw an increased interest in the development and implementation of Travel Demand Management (TDM) strategies. These strategies were aimed at effectively managing and distributing travel demand, both in the spatial and temporal dimensions. For example, flexible work hours helped shift commute related peak-period trips to off-peak periods. However, these strategies alone were not able to alleviate air quality, traffic congestion, noise, and safety problems associated with an ever-rising travel demand. As a result, new strategies termed Transportation Control Measures (TCMs) have been embraced by the transportation planning community. These measures are sophisticated and complex in nature, the exact impacts of which are unknown. However, they are not only intended to effectively manage existing travel demand, but also to reduce travel demand through the suppression and selective elimination of trips. Specifically, these measures tend to target peak-period commute trips and single-occupant vehicle (SOV) automobile trips, the two types of trips that contribute most to traffic congestion, fuel consumption, and emissions.

As increasing numbers of urban areas began considering TCMs, it became apparent that traditional travel demand forecasting and planning methods, that are primarily derived from trip-based four-step procedures, are not able to address the complex questions raised by TCM implementation. Relationships among human travel behavior patterns and the attitudes, values, and constraints that determine these patterns are extremely complex in nature, and traditional forecasting methods do not explicitly model these relationships in a theoretically sound framework.

An alternative approach which has the potential of offering effective and practical tools for TDM and TDM analysis is the activity-based approach. It was conceived in the travel behavior research arena in 1970s. Activity-based approaches explicitly recognize that travel demand is derived from the need to pursue activities that are dispersed in time and space. Moreover, these approaches recognize the inter-dependence among decisions for a series of trips made by an individual. They also recognize the interactions among various members of the household, that arise when household members allocate resources (such as household vehicles) to themselves, assign and share tasks, and jointly engage in activities. As such, it has been argued that activity-based approaches provide a theoretically and conceptually stronger framework within which travel demand modeling may be performed.

Because activity-based approaches attempt to treat travel behavior in more rigorous and realistic manners, they tend to focus on details and demand more data. Furthermore, activity-based approaches have been more of a conceptual framework than specific methods that are accompanied with quantitative tools. In fact, applications of activity-based approaches to travel demand forecasting or quantitative policy analysis are practically non-existent. Activity-based approaches are by no means a "proven" concept.

This study is probably the first attempt to develop and implement a full-fledged activity-based policy analysis tool for a metropolitan region and thereby examine whether activity-based approaches can be put to practical use. In particular, the study attempts to determine whether an operational activity-based tool can be developed while utilizing available data, supplemented by a medium-scale survey that can be conducted with modest mounts of monetary and time resources.

Although results of this study indicate that activity-based approaches in fact lead to viable policy tools, the experimental nature of this study must be born in mind by the reader of this report. It is also noted that it is not the intent of the report to assert in any way that activity-based approaches are the only approaches to travel demand forecasting and policy analysis. To the contrary, it is believed that non single approach or model system is suited for all study objectives; activity-based approaches are believed to be effective in the types of analysis contained in this report, while other approaches, including the trip-based, four step model systems, will continue to be useful tools in other types of analysis.

1.2 Study Objectives

The Metropolitan Washington Council of Governments (MWCOG) as part of the Travel Model Improvement Program (TMIP), jointly sponsored by the U.S. Department of Transportation (DOT) and the U.S. Environmental Protection Agency (EPA) engaged RDC, Inc. to conduct an applied research study to determine the feasibility of using activity-based methodologies to evaluate selected TDM policies. To perform this study using large-scale regional data, RDC, Inc., implemented a prototype of its Activity-Mobility Simulator (AMOS) which is a dynamic micro-simulator that replicates household responses to TDM measures.

To implement and test AMOS in the Washington, D.C. metropolitan area, RDC's approach consisted of the following activities:

- The TDM measures to be tested within the activity-based framework of AMOS were selected in collaboration with MWCOG and Federal sponsors. Of the more than 50 identified individual and combined TDM measures, six were selected for evaluation ranging from targeted premium charges for using personal vehicles (e.g., congestion pricing) to incentives for using alternatives to personal vehicles (e.g., improved pedestrian facilities). Appendix A describes the initial set of TDM measures identified, and the process used in selecting the TDM measures addressed in the study.

- In collaboration with MWCOG, RDC administered an elaborate survey of over 650 commuters in the metropolitan area designed to collect stated-preference responses to the selected TDM measures, revealed by daily time-use (activity) patterns both inside and outside the home, daily travel patterns, detailed commute trip attributes, and demographic and socio-economic data. This AMOS survey was the basis for estimating AMOS model parameters essential in evaluating TDM responses in the Washington, D.C. metropolitan area.

- The AMOS prototype system was configured to maximize the use of existing pertinent data available within the MWCOG jurisdiction. MWCOG's data bases including the MWCOG 1994 Household Travel Survey data (trip diary data) and relevant network data provided baseline travel patterns for the Washington, D.C. metropolitan area.

- The AMOS prototype system was tested and used to assess the selected TCMs in the Washington, D.C. metropolitan area. MWCOG provided the necessary sample data on nearly 100 households located in the study area to evaluate the commuter responsiveness to the selected TCMs.

1.3 AMOS Features

Over the past two years, the RDC, Inc., research team has developed and implemented the AMOS prototype intended to serve as a short-term transportation planning and policy analysis tool. AMOS is an activity-based micro-simulator of daily human activity and travel patterns, which focuses on the adaptation and learning process that people exhibit when faced with a change in the transportation environment. AMOS simulates a new activity-travel pattern that a person is likely to adopt in response to a TDM measure. This is accomplished through the implementation of several AMOS modules, namely:

- ***Baseline Activity-Travel Analyzer***. The baseline activity-travel analyzer reads individual trip records, compares them with the network data for logical consistency and missing information, and then generates a coherent baseline activity-travel pattern for each individual. All consistent baseline activity-travel patterns are used by the remaining AMOS system components.

- ***TDM Response Option Generator***. This module creates the "basic" response of an individual to a TDM strategy. It is a neural network model that is trained by using revealed-preference and stated-preference data obtained from AMOS survey. The baseline travel pattern from the Baseline Activity-Travel Analyzer, demographic and socio-economic attributes, and TDM characteristics under investigation serve as inputs to this module. The outputs of this module are the behavioral responses. The TDM measures are characterized by their cost changes, travel time changes, mode attribute changes, and imposition or relaxation of constraints.

- ***Activity-Travel Pattern Modifier***: This module constitutes the activity-trip re-sequencing and re-scheduling algorithm. It provides one or more alternative activity-travel patterns based on the response provided by the TDM Response Option Generator. The inputs of this module include the baseline activity-travel patterns, network data, land-use data, socio-economic and demographic characteristics, and the response options from the TDM Response Option Generator. The output of this module is a modified activity-travel pattern. The feasibility of a modified activity-travel pattern is checked for consistency and logic against a set of rule-based constraints.

- ***Evaluation Module and Acceptance Routines***: This component evaluates the utility associated with a modified activity-travel pattern generated by the Activity-Travel Pattern Modifier. Operationally, its built-in acceptance routines assess whether a modified activity-travel pattern will be accepted or rejected on the basis of a human adaptation and learning model incorporating a set of search termination rules.

- ***Statistics Accumulator***: This module reads all feasible accepted activity-travel patterns provided by the Evaluation Module and generates descriptive and frequency statistics on a daily basis. These descriptive and frequency statistics include vehicle miles traveled, number of trips by mode and by time of day, number of stops by purpose, trip chains, activity duration by purpose, travel times by purpose, vehicle occupancy, cold and hot starts, etc. In conjunction with baseline travel patterns, it can provide measures of *change* in travel characteristics.

As such, AMOS consists of a series of inter-related components that collectively serve as a comprehensive transportation planning and policy analysis tool. AMOS abandons some of the questionable assumptions in the trip-based four-step procedures, and embraces several new concepts that are theoretically sound and lead to more robust TCM impact predictions.

1.4 Study Conclusions

This project represents the first implementation of a full-fledged activity-based model system for transportation planning and policy analysis. Despite the theoretical arguments that warrant their practical applications, activity-based approaches remained within the domain of academia for nearly two decades. The development of AMOS and its implementation in the Washington, D.C., metropolitan area, therefore, represents a significant step forward in transportation planning and policy analysis. The development is especially significant considering the importance of travel demand management in the current planning contexts set forth by the Clean Air Act Amendments and Intermodal Surface Transportation Efficiency Act.

In the project, a micro-simulation model system which is capable of producing travel demand forecasts based on principles of activity-based analysis has been constructed and implemented in the Washington, D.C., metropolitan area, and applied to a selection of TDM measures using a sample of trip diaries from the 1994 MWCOG survey. The achievements of this effort can be summarized as follows.

- The project has demonstrated that the activity-based model system can be implemented in a metropolitan area using data available from a typical metropolitan planning organization (MPO), such as trip diary data, network travel time data, and land-use inventory data (the only additional data needed for AMOS implementation are stated-preference survey results from the area which are used to customize a component of AMOS to the area residents' responsiveness to TDM measures).

- It has been shown that travel demand forecasts can be developed while treating the daily travel pattern in its entirety, without breaking it into individual trips and thereby compromising the interdependencies and continuities that exist across the series of trips made by a traveler.

- This also implies that practical capabilities have been developed to assess TDM impacts more cohesively while accounting for secondary and tertiary changes in a traveler's daily travel pattern that are brought about as results of a primary change in response to a TDM measure (for example, if a SOV (single-occupant vehicle) commuter, who stops on the way to and from work to drop off and pick up a child at day-care, switches to carpooling in response to congestion pricing (*primary change*), then new, two round-trip SOV trips may be made between the home and day-care to drop off and pick up the child).

- The AMOS survey designed in this project has shown that the stated-preference questions developed in this project have produced credible results (except for the case of a particular synergy combination of two TDM measures), and that the survey can be applied to obtain information vital for the assessment of potential effectiveness of alternative TDM measures.

- The AMOS survey data produced rich statistical results that have revealed the characteristics of responses commuters would show when faced with TDM measures; for example, female commuters who make stops on the way to or from work tend not to change their travel in response to a TDM measure.

- The numerical examples using the sample of MWCOG trip diary data have shown the AMOS prototype is capable of producing aggregate statistics of travel demand at levels that are comparable to the conventional trip-based model systems (except that the current version of AMOS operates with static zone-to-zone travel time matrices rather than internally conducting network assignment).

It is worthy to note that the development of the AMOS prototype incorporates a number of theoretical concepts, such as "adaptation behavior" and "time-space constraints," into a practical model system which fully utilizes the data that are maintained by a typical MPO.

1.5 Outline of Report

This report consists of eight more sections. Sections 2 and 3 discuss the trip-based four step process, and the features that can be either augmented or replaced by an activity-based travel demand methodology such as AMOS. Sections 4 and 5 discuss the basic concepts and analytical techniques which are the foundation of AMOS, and its applicability in evaluating TDM policies. Section 6 defines the TDM policies selected for evaluation in the Washington, D.C. metropolitan area, implementation of AMOS with the MWCOG network data, and the application of AMOS to MWCOG household records. Sections 7 and 8 discuss the results of the TDM policy analysis, and implications for future activity-based travel demand modeling.

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Chapter 2: A Critical Review of the Trip-Based, Four Step Procedure of Urban Passenger Demand

Practically all tools currently available for passenger travel demand forecasting and policy analysis are based on the four-step procedure. The procedure was developed in the 1950s and 1960s during the post-war expansion period, when:

- Urban population was rapidly growing,
- Motorization was progressing, and
- Suburban sprawling was starting.

The emphasis in transportation planning at that time was infrastructure development. The issue at hand was where to build a new freeway and how many lanes were needed. Because of such straightforward planning contexts, coarse forecasting procedures sufficed at that time. In fact, it is not difficult to see that when the population of a metropolitan area doubles, the total number of trips will approximately double and increases in trips can be relatively easily forecast once one can determine in which parts of the metropolitan area increases in residential and work populations will take place.

Planning emphasis has changed substantially since then. In the 1970s Transportation Systems Management (TSM) was promoted, while in the 1980s Travel Demand Management (TDM) was proposed. Currently the transportation planning community embraces a more inclusive concept of Transportation Control Measures (TCM). The measures being considered are extensive and increasingly more sophisticated and are fine-tuned to target specific traveler segments. The trip-based four-step procedure, developed to serve the planning needs of decades ago, is not best suited to address these new transportation measures.

2.1 Advantages

The simplification incorporated into the four-step procedure made urban passenger travel demand forecasting practicable using standard survey methods, census and other existing data, and computational capabilities that had been available. The simplifying assumptions adopted in the procedure facilitated quantitative analysis of travel demand, which is a result of complex (to analyze) travel behavior. In particular, the development of a standard analysis package, Urban Transportation Planning System (UTPS), led to the development of PC-based transportation planning packages, which in turn have made the forecasting procedure affordable to practically any MPO.

2.2 Internal Inconsistencies

The procedure, however, contains several well acknowledged internal inconsistencies. For example, the area-wide totals of zonal trip productions and attractions normally do not coincide with each other, requiring some adjustment; zone-to-zone travel times used as input to trip distribution and modal split are not necessarily consistent with travel times that are derived from the network assignment; and trips are assigned to different time periods of the day (e.g., peak vs. off-peak) prior to network assignment, usually using heuristic procedures. For additional issues involved in the application of the four-step procedure, see Table 2.1.

Table 2.1: Sample of Recognized Issues Involved in the Application of the Four-Step Procedure

- Agreement between trip generation and trip production
- Estimation of external-to-internal and internal-to-external traffic
- Estimation of directional traffic flows by time of day (peak vs. off-peak), estimation of peak hour flows
- Conversion of person trips to vehicle trips (estimation of vehicle occupancy by time of day, by purpose)
- Estimation of intra-zonal travel times
- Assignment of intra-zonal trips to the network
- Estimation of access walk time to public transit, access time to freeways or major arterials
- Special trip generators
- Creation of new zones, grouping of existing zones
- Determination of speed-volume relationship
- Temporal stability in model parameters (e.g., K-factors and friction factors; value of time)
- Determination of inter-zonal travel times in pre-modal-split trip distribution
- Consistency in the travel time variables across trip distribution, modal split and network assignment (can be resolved by implementing feedback loops)

2.3 Data Inefficiency

When disaggregate choice models were proposed in the 1970s, it was argued that the aggregate four-step procedure was not data-efficient. This is mainly because the procedure was developed when available computational capabilities were very limited and costly and statistical theory for model estimation was not well advanced. As a result, model calibration procedures adopted inefficient data use (especially the aggregation of household survey results into zonal averages) led to an inefficient parameter estimation (e.g., trip distribution models).

2.4 Lack of Behavioral Foundation

More problematic are the implicit assumptions in the four-step model components which lack behavioral foundation. For example, consider trip generation models. Implicit in typical linear-regression or cross-classification models of trip generation is the assumption that the number of trips generated by a household is a function of the number of its members and the number of vehicles available. This assumption does not reflect the well known behavioral fact that employment status affects travel behavior. Therefore, the number of workers in the household affects trip generation.

2.5 Resulting Problems as a Policy Tool

Suppose parking pricing is implemented in the downtown area. This event may cause some travelers to choose suburban destinations. This result, however, is not accounted for by the four-step procedure because the total number of trips attracted to the downtown area is determined in the trip generation phase, which typically does not incorporate parking cost. The procedure would indicate no change in the number of trips attracted to the downtown area before and after the implementation of parking pricing. Likewise, effects of congestion on travel demand cannot be fully accounted for by the four-step procedure because trip generation models are typically insensitive to travel time (this problem cannot be alleviated by incorporating feedback loops).

Trip-Based*:* The four-step procedure treats each trip as an independent entity for analysis. This assumption is central to the four-step procedure in the sense that its model structure hinges on it. This dependence, however, leads to a number of serious limitations, especially when its application to TCMs is considered. The problems stem from the fact that trips made by an individual are linked to each other and the decisions underlying the respective trips are all inter-related.

Example of Travel Mode Choice for Multi-Stop Trip Chains*:* Consider a home-based trip chain (a series of linked trips that starts and ends at the home base) that contains two or more stops. The four-step procedure looks at each trip at a time and determines the best mode for it. Let h be the home base and i and j be the destination zones visited in a trip chain. There are three trips, (h, i), (i, j), and (j, h). When a trip-based, post-distribution mode choice model is applied while comparing the alternative modes available between each pair of zones, it is entirely possible that bus is assigned for (h, i), drive alone for (i, j), and carpool for (j, h). This contains two major problems. First, the result violates the modal continuity condition. Mode choice for a trip with non-home origin is regulated by the mode selected for the first home-based trip; if one leaves home by bus, it is normally not possible to choose the drive-alone mode in subsequent trips. On the other hand, once one leaves home by driving alone, all subsequent trips tend to be made by driving alone. Second, the result ignores the behavioral fact that one will most likely plan ahead and choose a mode while considering the entire trip chain, not just each individual trip. One may decide to take the auto even when good bus service is available between h and i and between j and h, but because no bus service is available between i and j.

Treating each individual trip in isolation becomes a problem on many occasions. For example, commuters who make trips on the way to or from work (e.g., dropping off/picking up children) are less likely to switch from the drive-alone mode when TDM measures such as congestion pricing are implemented. What is termed "activity re-sequencing" in this study is another example. Suppose a drive-alone commuter stops by at a grocery store on the way home from work. Faced with congestion pricing, this commuter may choose to take the bus to commute, and go shopping by auto at a grocery store near home after returning home by bus. The trip-based four-step procedure is not capable of addressing such secondary and tertiary changes brought about by the primary commute mode change.

Over-Predicted Mode Shift*:* Because its trip-based structure does not recognize the mode continuity condition, it is logically expected that the procedure over-predicts mode changes. The problem is multiplied by the fact that the modal split phase tends to be most sensitive to changes in the travel environment because it often incorporates disaggregate choice models. As a result, the four-step procedure may grossly over-estimate mode shift, when in fact travel mode may be the last thing travelers wish to change.

No Time Dimension*:* The fact that the four-step procedure does not incorporate the time-of-day dimension is curious when congestion -- which has been the single most important concern of transportation planning -- occurs with the concentration of demand in the same area at the same time. The absence of the time dimension is behind some of the recognized issues listed in Table 2.1. In addition, it implies that departure time choice cannot be incorporated into the forecasting procedure (without introducing ad hoc assumptions). This in turn implies that the four-step procedure cannot be effective in the analysis of peak spreading in general and congestion pricing in particular.

The time dimension is crucial in air quality analysis. Because air quality is a function of complex meteorological relationships, it is important to be able to predict when within the day pollutants are emitted, not just the total amount of emissions. Determining the split between hot and cold starts in any consistent manner would also require the introduction of the time dimension into the analytical scope. Furthermore, recent interest in Intelligent Transportation Systems (ITS) technologies calls for the ability to predict traffic dynamics on the network.

Vehicle Ownership*:* An area where very little effort has been directed at the Metropolitan Planning Organization (MPO) level is vehicle ownership modeling. This may not be a problem if the number of vehicles available to the household is the only concern (which in fact was the case at the time when motorization was progressing at fast rates). Recent concerns with air quality and fuel consumption, however, imply that increased importance is assigned to which types of vehicles are chosen by households and how much and where each type of vehicle tends to be used. This calls for the implementation of vehicle type choice models, and development of vehicle allocation models that predict which vehicle will be used for which trip.

Representing Accessibility and Land-Use*:* The state-of-the-art has not advanced enough to incorporate into the forecasting process:

- Impact of new highway and transit facilities on land-use,
- Impact of travel patterns (materialized demand) on land-use,
- Impact of accessibility (congestion) on trip generation and attraction, and
- Impact of multiple-activity land-use development (e.g., shopping malls) on travel demand.

2.6 Summary

In summary, the following can be listed as the limitations of the four-step procedure in the current policy contexts:

- Trip-based, sequential structure,
- Lack of the time-of-day dimension,
- Limited sets of explanatory variables,
- Limited behavioral responses,
- Consequently unresponsive to most TDM measures,
- Trip generation unresponsive to congestion and pricing,
- Consequently the trip distribution phase is not fully responsive to system change,
- Inability to address vehicle fleet mix evolution, and
- Totally exogenous land-use, economic and socio-demographic input.

While some of the problems discussed in this section may be resolved for certain situations by introducing new model elements, the problems stemming from its atemporal, trip-based structure are difficult targets for improvement within the framework of the four-step procedure.
Before closing this section, it is emphasized that no single model system is suited for all study objectives. The trip-based, four-step procedure continues to be an effective demand forecasting procedure for certain types of problems. Yet, current policy contexts call for alternative models. The array of transportation planning tools available to policy makers needs to be expanded.

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Chapter 3: Why the Activity-Based Approach?

As noted earlier, the activity-based approach explicitly recognizes the fact that the demand for activities produces the demand for travel. In other words the need or desire to engage in an activity at a different location generates a trip. Then once we understand how activities are engaged in the course of a day or a week, a rigorous understanding of travel demand will follow.

The activity-based approach thus aims at the prediction of travel demand based on a thorough understanding of the decision process underlying travel behavior. In this sense the activity-based approach is entirely different from the approach taken for the development of the four-step procedure where statistical associations, rather than behavioral relationships, drove model development. Another important distinction is the following recognition: as the activities engaged in a day are linked to each other, trips made to pursue them are also linked to each other; they cannot be analyzed separately one by one.

Although the activity-based approach was conceived in the 1970s by a group of researchers at Oxford University, it largely remained within the domain of academic research. The practitioners' community has paid little attention to it until very recently. Kitamura (1988a) attributed this inattention to the fact

that the activity-based approach is not suited for the evaluation of capital-intensive large-scale projects, but better suited for refined, often small-scale transportation policy measures, and that small-scale projects can hardly afford elaborate analysis. This is no longer the case, at least in the United States. The importance of refined TDMs are well recognized and efforts are being made to promote their implementation and to assess their potential effectiveness.
Aside from this rather drastic change in transportation planning contexts, several important advances have taken place:

- Accumulation of activity-based research results,
- Advances in survey methods (e.g., stated-preference (SP) and time-use survey methodologies) and statistical estimation methods, and
- Advances in computational capabilities and supporting software (database software, GIS, etc.).

All these changes have created an environment where a model of travel behavior can be developed while adhering to the principles of the activity-based approach. More specifically, these changes have made activity-based micro-simulation of travel behavior a practical tool for transportation planning and policy analysis.

Activity-based studies of travel behavior have led to the following emphases:

- Constraints which govern activity engagement and travel behavior (e.g., store opening hours, vehicle availability),
- Behavioral changes, or behavioral dynamics which are exhibited when an individual is faced with changes in the travel environment (e.g., switching between driving alone and carpooling to work),
- Adaptation as a special case of behavioral dynamics (e.g., a new baby prompting the acquisition of a large-screen TV set by the parents who gave up evening outings),
- The time dimension which is implicit in the emphasis of behavioral changes as changes taking place over time,
- Day-to-day variability in behavior and demand, as another special aspect of behavioral dynamics (e.g., part-time carpooling),
- Scheduling of activities and trips over a span of time; when to engage in what type of activities, and in what sequence,
- Trip chaining: combining stops into a trip chain,
- In-home/out-of-home activity substitution (e.g., going out for a movie vs. watching TV at home), which is directly related to trip generation,
- Inter-personal linkages, which may take on the form of task and resource assignment (e.g., vehicle allocation within a household) and resource sharing (e.g., carpooling by family members), joint activity engagement (a Sunday family outing), and activity generation (e.g., a child's ballet lesson generating the parent's activity of chauffeuring the child to ballet school), and
- Household life-cycle stage, which is strongly associated with the level of inter-personal interaction.

Studies with these emphases have individually and collectively contributed to the revelation of the mechanism of trip making.

The activity-based approach implies an expansion of the analytical scope because its subject is not limited to the trip. This naturally leads to increased levels of difficulty in the analysis because activity engagement is a complex behavior. Conventional trip diary data do not offer sufficient information on activities. Partly because of such data limitations, little effort has been made to explain the behavior over a span of time (say, a day or a week). Difficulties are compounded because modeling time allocation into activity categories by itself is not sufficient; activity engagement episodes need to be modeled for travel demand analysis. In other words, the link between activity engagement and trip making is yet to be established.

Despite these difficulties, the activity-based approach is more than worthy to pursue because it offers advantages that outweigh the cost of increased levels of analytical complexity. In fact some of the problems raised above have been resolved in this AMOS implementation project where micro-simulation is deployed as a tool for demand analysis.

The advantages of the activity-based micro-simulation approach adopted in this project include:

- **Time Of Day:** predicts travel behavior along a continuous time axis;
- **Not Trip-Based:** treats a daily activity-travel pattern as a whole, thus avoiding the shortcomings of conventional trip-based methods;
- **Realism:** incorporates various constraints governing trip making, facilitating realistic prediction and scenario analyses;
- **TDM Evaluation:** is capable of realistically assessing the impact of TDMs on the entire daily travel demand;
- **Versatile:** can address various policy scenarios using special-purpose SP surveys;
- **Flexible:** can be modified for specific study objectives, e.g., to evaluate the effects of day-care facilities at work, extended transit service hours, or transit lines;
- **Induced Demand:** the activity-based approach is a key to address the issue of induced or suppressed demand; and
- **Accuracy Control:** using synthetic household samples, can produce results with desired levels of spatial and temporal resolutions.
- **Comprehensive Evaluation Tool:** activity-based approach simulates the entire daily activities and travel. Therefore, the effect of a transportation policy on the entire daily activity, not just commute trips, can be evaluated, leading to better benefit measures.

The activity-based micro-simulation approach resolves much of the problems in the trip-based, four-step procedure. This will be illustrated using more specific examples in later sections of this report.

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Chapter 4: Overview of AMOS

AMOS is an activity-based micro-simulator of daily human activity and travel patterns. In a nutshell, AMOS takes an observed ("baseline") daily travel pattern of an individual; generates an adaptation option (e.g., change commute travel mode) that may be adopted by the individual when faced with the TCM under consideration; adjusts the baseline pattern (e.g., re-sequences activities, selects new destinations) to produce a modified activity-travel pattern; evaluates the utility of the modified pattern; based on a satisficing rule, accepts one of the modified patterns so far generated and terminates the search, or continues to search for alternatives.

AMOS consists of a series of inter-related components that collectively serve as a comprehensive transportation policy analysis tool. AMOS departs from the restrictive assumptions in the trip-based four-step procedures and adopts new paradigms that are theoretically sound and practical.

4.1 Paradigm Shifts

AMOS is fundamentally different from conventional forecasting model systems in several crucial aspects. In addition, AMOS represents the following paradigm shifts:

- from trip-based analysis to activity-based analysis,
- from static, cross-sectional analysis to dynamic, longitudinal analysis,
- from deterministic demand equation to stochastic micro-simulation,
- from optimization to satisficing, and
- from capacity- and level-of-service-based capital project evaluation to time-use-based assessment of TDM effectiveness as well as capital project evaluation.

The activity-based approach as described in detail in Section 3 is the central principle of the AMOS development effort. Because of this, the entire daily itinerary, not each individual trip, is the focus of the analysis. Derived from this focus is the rule-based heuristics that are embedded in the AMOS algorithms (see Section 5).

Another critical paradigm shift is from static approach to *dynamic approach* for both model development and data collection ("static" analysis assumes that the behavioral relation is atemporal and the time dimension is irrelevant, while "dynamic" analysis focuses on behavioral changes over time). This shift is based on critical appraisals of the following well-accepted and well-practiced, yet not validated assumption: Future behavior can be predicted based on the extrapolation of cross-sectional observations of individuals of different characteristics and behaviors, and that future behavior can be predicted without observing behavioral changes for each individual ("cross-sectional" observations or data refer to a set of observations obtained at one point in time from the respective behavioral units such as individuals or households, while "longitudinal" observations comprise repeated observations taken from the same behavioral units).

Application of a model estimated on a cross-sectional data set taken at one point in time represents the "longitudinal extrapolation of cross-sectional variations" (Kitamura, 1990). In such extrapolations cross-sectional elasticities observed across different individuals are applied as if they represent longitudinal elasticities that capture the change in behavior that follows a change in a contributing factor within each behavioral unit. Unfortunately this approach is valid only under very restrictive conditions (see Goodwin et al., 1990). For example, it requires that behavioral response is immediate without any time lag; that the magnitude of response is invariant regardless of the direction of change; and that behavioral response is independent of the past history of behavior.

The assumption of the equivalence between cross-sectional and longitudinal elasticities has yet to be validated, while empirical evidence is accumulating that these assumptions do not hold (e.g., Kitamura & van der Hoorn, 1987; Goodwin, 1992). This critical appraisal of cross-sectional analysis and forecasting of travel demand, combined with the emphasis of activity-based analysis on adaptation behavior, leads to dynamic analysis and modeling being emphasized throughout the construction of AMOS.

Another important paradigm shift is the transition from the extrapolation based on deterministic demand equations to forecasting using *stochastic micro-simulation*. The motivating factor for the adoption of micro-simulation as a central driving force of AMOS is the fact that activity-travel behavior is a process that is governed by layers of constraints and influenced by numerous factors many of which are stochastic. Arranging activities and trips into a daily itinerary itself is a complex operations research problem to which individuals have devised routines to find a (not necessarily optimum) solution. Despite the simplicity of the activity-based approach that arises from its focus on human behavior without introducing artificial constructs, the behavior under investigation is indeed complex to analyze (for example, it has been proven that no analytical solutions exist for even simpler "traveling salesman problems" where an optimum sequence is sought to visit a pre-determined set of locations, a problem by far simpler than an individual's daily activity-travel decision). Given the complexity and stochastic elements inherent in transportation system performance, constraints and motivating factors for activity-travel behavior, and in human decision and behavior themselves, micro-simulation is the only feasible approach that need not embrace over-simplifying assumptions that, unfortunately, reduce the complexity and hence, realism of response and adaptation patterns that are being modeled.

It has been customary to view travel behavior as the outcome of an optimization process in which the most superior travel option is identified and pursued by the individual (e.g., Recker, 1995; Recker et al., 1986a, 1986b). Practically all discrete choice models of travel behavior are based on this premise. Although elegant, the assumption of optimization is unrealistic when applied to everyday behavior of activity engagement and travel by individuals and households. For example, the individual must possess complete information to be able to locate an optimum solution, and must be capable of sorting out an enormous number of possible options and discriminating among them. It also assumes that the individual can perfectly detect minute differences among options. These assumptions presume super-human abilities in ordinary travelers, and therefore are unrealistic as behavioral propositions. On the contrary, the information individuals have is partial and incomplete; the number of items individuals can incorporate into their cognitive system is limited; their perceptive ability to discriminate between stimuli is limited; the outcome of a decision is usually highly uncertain; and individuals' decisions may not be internally coherent and consistently rational. Moreover, there is evidence that behavioral inertia is prevalent, and that individuals tend to resist behavioral changes. Our travel behavior is most probably not in the state of equilibrium which the paradigm of optimization assumes (Goodwin et al., 1987).

AMOS, on the other hand, emphasizes trial-and-error and learning activities along with the satisficing principle which is viewed to govern the adaptation process. The optimization principle may be applied to observed behavior as an operational (as opposed to behavioral) axiom with the premise that a central tendency exists and embodies the optimization principle, and that deviations of individual observations from that central tendency can be accounted for by error components. This premise, however, is valid only when deviations from the central tendency are purely random. The development of AMOS, on the other hand, reflects the intention to adopt the most realistic modeling framework that best replicates activity-travel behavior. Instead of assuming the presence of cross-sectional equilibrium based on optimization, the behavioral process of adaptation is explicitly modeled in AMOS.

Finally, evaluation of transportation projects has traditionally been based on capacity and level of service. Given the cost, an alternative that delivers the most capacity and highest level of service is considered as the best alternative; or given a minimum capacity or level of service, the least cost alternative is considered as best. This is a trip-based approach to project evaluation. An activity-based project evaluation and policy analysis is adopted in AMOS. Since activity engagement is synonymous as time use, time-use-based policy analysis and project evaluation are proposed here. In short, the new approach aims at evaluating the impact of a transportation policy measure or capital project on urban residents' daily life as represented by time-use patterns, and attempts to derive evaluation measures based on time-use utility. More discussion can be found in Section 5.4 of this report.

4.2 Structure of the Model System

Figure 4.1 is a flowchart showing how the five primary modules relate to one another within the overall AMOS framework.

The first module is the Baseline Activity-Travel Analyzer. It reads trip records, checks them against transportation network data, and assembles coherent baseline activity-travel patterns. The next module, TDM Response Option Generator, reads these baseline patterns and provides a basic behavioral response that an individual may exhibit when subjected to a TDM strategy. The third module, Activity-Travel Pattern Modifier, uses the basic response to determine secondary and tertiary changes that may occur in the baseline travel itinerary as a result of the TDM policy. It offers multiple alternative activity-travel patterns that may be considered by an individual. The Evaluation and Search Termination module evaluates these alternative patterns and determines the one that is most likely to be adopted by the individual. Finally, the Statistics Accumulator computes individual and aggregate travel indicators for the adopted modified activity-travel patterns. Section 5 provides detailed discussions on each of the modules comprising AMOS.

Figure 4.1 AMOS Model Structure

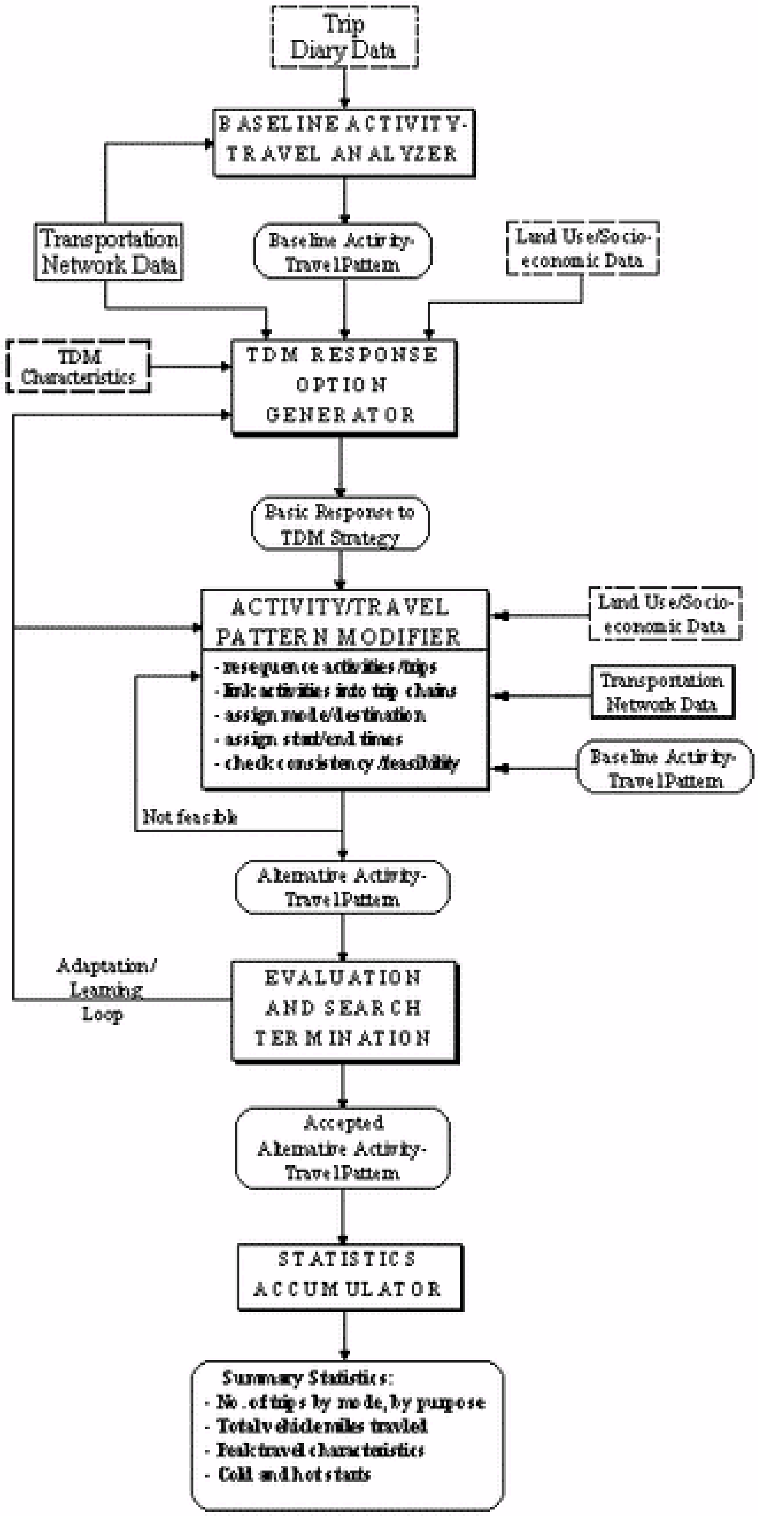

Table 4.1 describes the output information provided by each AMOS module. Most of these output variables also constitute input variables of other AMOS modules as shown in Figure 4.1.

Table 4.1: Output Variables for AMOS Modules

AMOS Module	Output Variable
Baseline Activity-Travel Analyzer	Coherent and logically consistent baseline travel pattern and activity engagement profile
TDM Response Option Generator	Basic behavioral response of individual to TDM strategy under investigation
Activity-Travel Pattern Modifier	Alternative activity-travel patterns that may be considered after introduction of TDM strategy
Evaluation and Search Termination	Alternative activity-travel pattern that is most
Module	likely to be adopted by individual after introduction of TDM strategy
Statistics Accumulator	Individual and aggregate travel indicators describing characteristics of adopted alternative activity-travel pattern

4.3 Data Needs

The AMOS prototype has been developed to fully utilize data bases that are available from typical MPOs while minimizing the need for non-existent data. Despite the paradigm shifts discussed in Section 4.1, in particular the focus on activities rather than trips, shift in data requirements has been kept to a minimum.

Implementing AMOS in a region requires the following data that are typically available from the area MPO:

- traffic analysis zone (TAZ) system,
- TAZ-to-TAZ network travel time by mode and distance,
- land-use inventory by TAZ,
- existing mode choice models and trip distribution models, and
- standard trip diary data of household members with basic trip information such as origin, destination, trip purpose, departure and arrival times, and mode.

Based on these regional data, the AMOS prototype develops regional forecasts using a pivot method (see Section 6.5).

In the near future more rigorous regional forecasting will be made by generating synthetic households for micro-simulation. For this, will be needed. It is believed that these distributions can be obtained from publicly available census tape.

- the distributions of household size, vehicle ownership and income by TAZ, and
- the joint distribution of household size, vehicle ownership and income for the region,

In addition, if AMOS is being implemented as a policy tool for TDM evaluation, it is required that those TDM strategies that are considered for potential implementation be identified and their characteristics be determined, namely,

- the types and characteristics of TDM strategies under consideration (policy input).

Finally it is desirable that study area residents' responsiveness to the TDM strategies under consideration be accurately reflected when implementing AMOS to the region. This calls for

- individuals' potential responses to TDM strategies, along with their demographic, socio-economic, and travel characteristics.

The last requirement calls for a survey which involves stated-preference questions to potential TDM strategies. This survey requires only a moderate size of sample (about 500). The results of this survey will be used to customize the response option generator (see Section 5.2) and other AMOS components to the region. The survey conducted in the Washington, D.C. area is described in Section 6.

In sum, most AMOS data requirements can be satisfied with data that are maintained by, and available from, most MPOs. The only exception is TDM response data for which a special survey is required.

Since this project represents the first implementation of an AMOS prototype, the survey described in Section 6 has been designed to collect information for prototype development. In the future as AMOS becomes more complete and refined, information required from the survey is expected to decrease. Exactly how much information needs to be collected in a survey for each installation, and whether a survey needs to be repeated in every installation, need to be determined in the future.

4.4 Areas of Application

AMOS is being developed as an extremely versatile transportation policy analysis tool. It may be considered a comprehensive activity-based travel demand forecasting system that is truly behavioral in nature. As such, AMOS is able to serve a host of applications including:

- ***Travel Demand Forecasting***: First and foremost, AMOS is the first operational activity-based travel demand forecasting system. AMOS is a dynamic micro-simulator of individual activity-travel patterns and therefore can be used to predict travel demand under various future scenarios.
- ***Policy Analysis***: AMOS can be used as a comprehensive policy analysis tool. For example, AMOS can predict changes in travel patterns that may result from the introduction of a wide variety of TDM measures.

- ***Activity Engagement and Time-Use Modeling***: The activity-based approach underlying AMOS allows the explicit modeling of individual activity engagement and time-use. The model system can in turn be used in several research areas including transportation, psychology, sociology, and health sciences.
- ***Air Quality Analysis***: The statistics accumulator provides information on cold and hot starts, fuel consumption, and vehicle miles traveled for activity-travel patterns that may be adopted as a result of a TDM strategy. These statistics can be used in conjunction with air quality and energy models to perform emissions analyses and fuel consumption analyses.

AMOS is capable of addressing many of the issues and questions raised by ISTEA, of 1991 and CAAA, of 1990 that have set a new stage for transportation planning and policy analysis. On the other hand, traditional four-step procedures are not able to address these issues. In the next few sections of this report, the components of AMOS are described in detail and its implementation in the Washington, D.C. metropolitan area is discussed.

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Chapter 5: AMOS System Components

AMOS is a system of integrated computer models designed to predict traveler behavior through a micro-simulation of transportation activities and decisions. AMOS will provide, in response to a TDM measure, a modified activity and travel pattern that satisfies a person given his or her socio-economic and demographic characteristics, and baseline travel pattern. AMOS consists of five main computer models (or components) that collectively and systematically accomplish this objective. The five main components that comprise the AMOS system, shown in **Figure 5.1**, are described as follows:

- ***Baseline Activity-Travel Analyzer***. The baseline activity-travel analyzer reads individual trip records, compares them with the network data for logical consistency and missing information, and then generates a coherent baseline activity-travel pattern for each individual. Baseline activity-travel patterns (or profiles) of all documented individuals are used by the remaining AMOS system components.

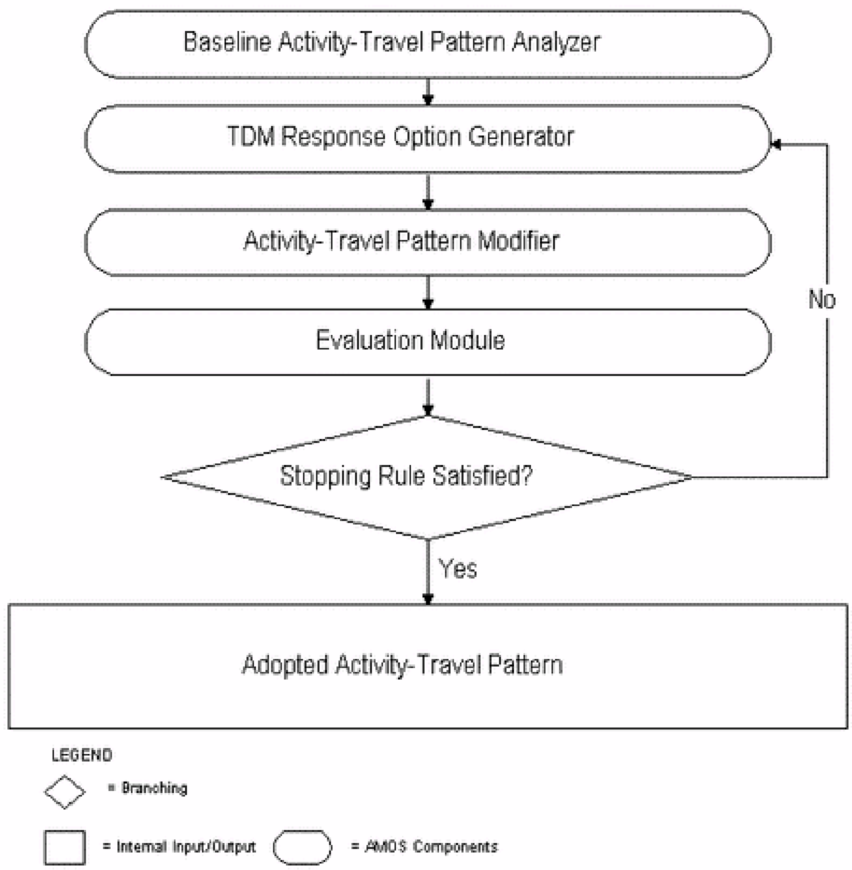
- ***TDM Response Option Generator***. This module creates the “basic” response of an individual to a TDM strategy. It is a neural network model that is trained by using revealed-preference and stated-preference data. The modified baseline travel pattern from the Baseline Activity-Travel Analyzer, demographic and socio-economic attributes, and TDM characteristics under investigation serve as inputs to this module. The outputs of this module are the behavioral responses. The TDM measures are characterized by their cost changes, travel time changes, mode attribute changes, and imposition or relaxation of constraints.

- ***Activity-Travel Pattern Modifier***: This module constitutes the activity-trip re-sequencing and re-scheduling algorithm. It provides one or more modified but feasible alternative activity-travel patterns based on the responses provided by the TDM Response Option Generator. The inputs of this module include the baseline activity-travel patterns, network data, land-use data, socio-economic and demographic characteristics, and the response options from the TDM Response Option Generator. The output of this module is a modified activity-travel pattern. The feasibility of a modified activity-travel pattern is checked for consistency and logic against a set of rule-based constraints.

- ***Evaluation Module and Acceptance Routines***: This component evaluates the utility associated with a modified activity-travel pattern generated by the Activity-Travel Pattern Modifier. Operationally, its built-in acceptance routines assess whether a modified activity-travel pattern will be accepted or rejected on the basis of a human adaptation and learning model incorporating a set of search termination rules.

- ***Statistics Accumulator***: This module reads all feasible accepted activity-travel patterns provided by the Evaluation Module and generates descriptive and frequency statistics on a daily basis. These descriptive and frequency statistics include vehicle miles traveled, number of trips by mode and by time of day, number of stops by purpose, trip chains, activity duration by purpose, travel times by purpose, vehicle occupancy, cold and hot starts, etc. In conjunction with baseline travel patterns, it can provide measures of *change* in travel characteristics.

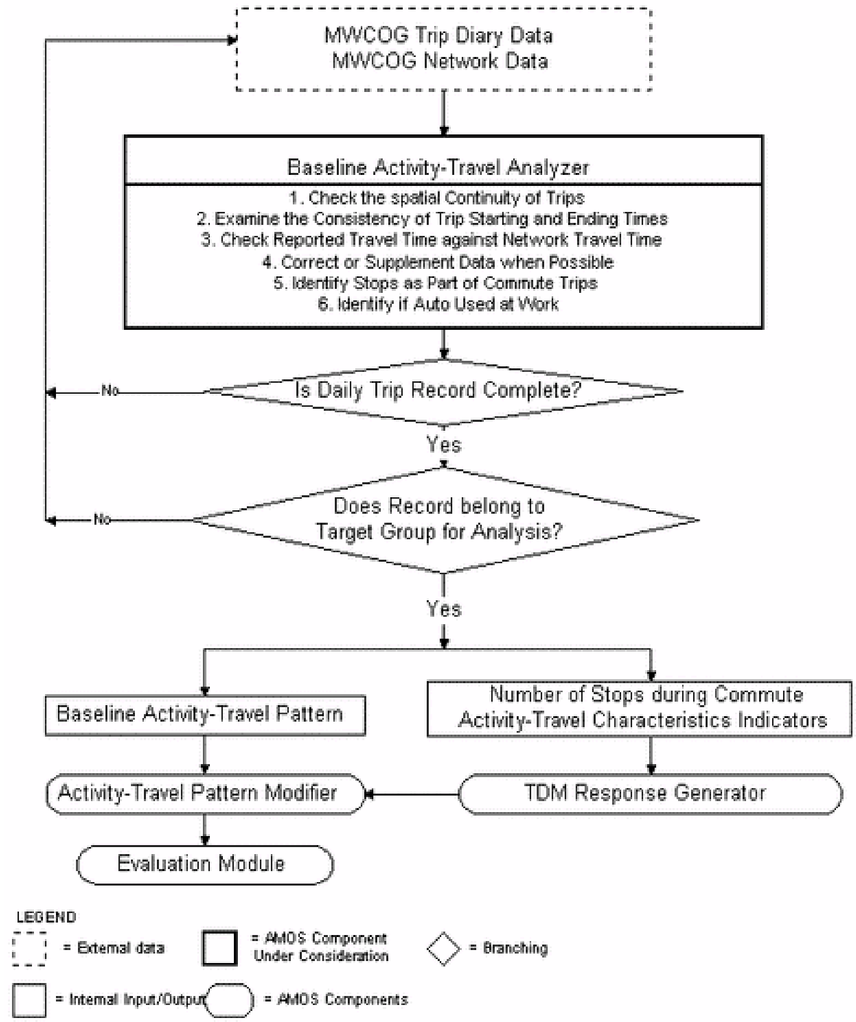
Figure 5.1: Activity-Mobility Simulator (AMOS)



5.1 Baseline Activity - Travel Analyzer

The Baseline Activity-Travel Analyzer is the first module of the AMOS model system. Its flow structure is shown in the Figure 5.2. The module reads individual trip records from the MWCOG Household Travel Diary Survey Data and compares them with network data for logical consistency on the basis of certain criteria. These criteria include spatial continuity, temporal continuity, and modal continuity. Spatial continuity states that the origin of a trip should match the destination of the previous trip. Temporal continuity guarantees that the beginning time of a trip should be always greater than or equal to the ending time of the previous trip. Finally, modal continuity states that the mode of a trip is dependent upon the mode used in the previous trip. Any logical inconsistency against these criteria will be corrected by the analyzer and missing information will be supplemented.

Figure 5.2: Baseline Activity-Travel Analyzer



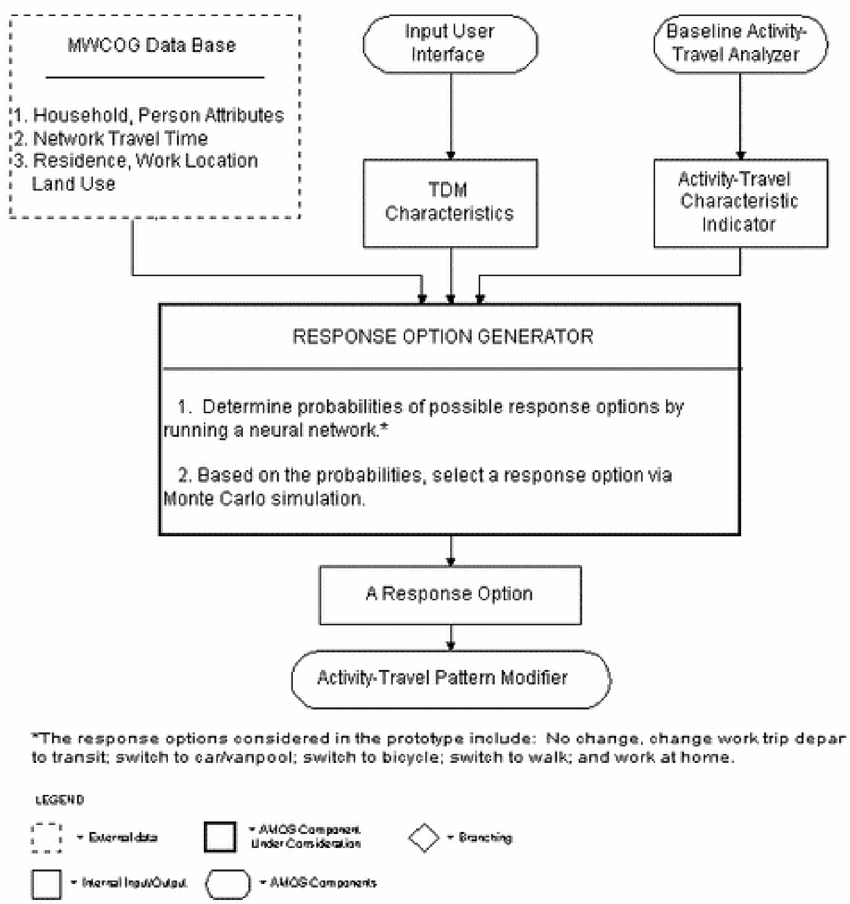
Following the logical consistency checks, the analyzer will identify certain activity-travel characteristics that are key parameters in subsequent components of the AMOS model system. For example, the analyzer will determine whether stops are made on the way to or from work and whether auto trips are made while the individual is at the work place. Identification of these parameters helps define the constraints under which the TDM Response Option Generator and the Activity-Travel Pattern Modifier must search for feasible behavioral responses.

The Baseline Activity-Travel Analyzer then generates a screened baseline daily activity-travel pattern. All corrected and supplementary information is flagged appropriately as a note of change introduced by the program. The analyzer determines whether the activity-travel records fall within the purview of the TDM options and provides these records as input to the TDM Response Option Generator and the Activity-Travel Pattern Modifier.

5.2 TDM Response Option Generator

The flow structure of the TDM Response Option Generator is shown in Figure 5.3. Inputs to the generator include the modified baseline activity-travel characteristics, TDM characteristics provided by user, and the socio-economic characteristics of both household and individual. Characteristics of the TDM can be easily modified via a windows-based graphical user-interface. This property facilitates convenient and expeditious analysis of different TDM scenarios and levels.

Figure 5.3: TDM Response Option Generator



The TDM Response Option Generator employs a neural network being trained with inputs of both revealed-preference and stated-preference data. A neural network is an assembly of artificial neurons that are usually arranged in layers. Input variables, for example, socio-economic characteristics and the modified baseline activity-travel pattern etc., serve as input neurons. A weighted set of these inputs is then transmitted to the next layer, and the process is continued until the output layer is obtained. Output neurons indicate which outcome -- in this case a TDM response option -- is likely. Training the neural network involves the estimation of weights such that the neural network will provide an appropriate output in response to a certain set of inputs.

The neural network developed for the AMOS model system is based on the theory of Connectionism. Theory of Connectionism postulates that humans process information by breaking it down into smaller inter-connected elements. The strengths of these connections are defined by the weights, estimated during the training of the neural network.

Various response options are being considered in this version of AMOS. These include:

- No change in travel behavior
- Change departure time for work trip
- Switch work trip mode to transit
- Switch work trip mode to car/van pool
- Switch work trip mode to bicycle
- Switch work trip mode to walk
- Work at home

An individual may respond in any one of these seven ways, given changes being brought by the introduction of a TDM option. Given the input variables, training the neural network will yield probabilities that the individual would choose each of these response options. Based on these probabilities, a particular response option is chosen via a Monte Carlo simulation. The chosen response option serves as a key input to the Activity-Travel Pattern Modifier.

5.3 Activity-Travel Pattern Modifier

The Activity-Travel Pattern Modifier generates feasible alternative activity-travel patterns that an individual may adopt as a consequence of the response option chosen in the TDM Response Option Generator. The modifier consists of a complex algorithm that can re-sequence and re-schedule activities, break and make trip chains, and change travel modes and activity locations. The structure of the modifier is shown in Figure 5.4 and its various aspects are discussed in the following sections.

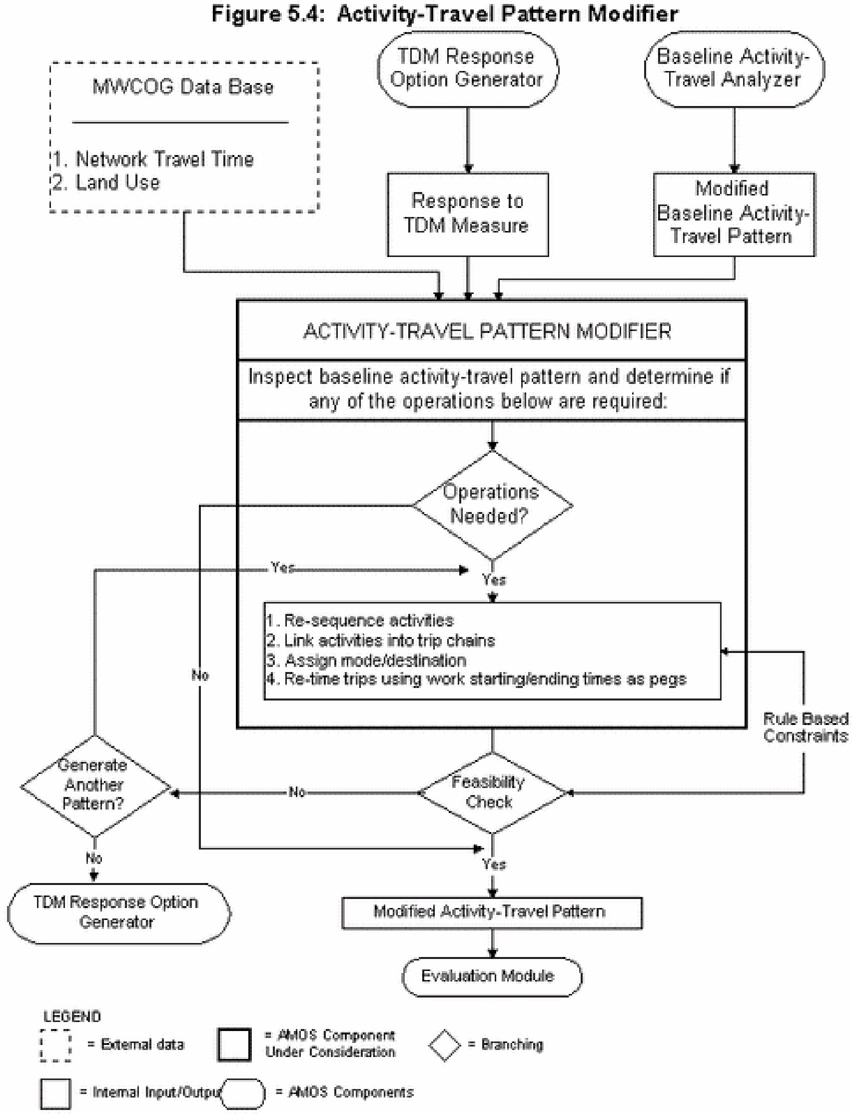
5.3.1 Approach

Figure 5.4 illustrates the basic approach followed by The Activity-Travel Pattern Modifier. Its inputs include the baseline activity-travel pattern and socio-economic characteristics of the individual, his or her behavioral response to a TDM option, and secondary data bases including network data and land-use information.

The Activity-Travel Pattern Modifier inspects the baseline activity-travel pattern and determines whether any modifications are needed. For example, if an individual is found to travel by auto only during off-peak periods and the implemented TDM measure is peak-hour congestion pricing, then modifications to the baseline activity-travel pattern are not necessary. On the other hand, if modifications are deemed necessary, then the modifier will re-sequence and re-schedule activities, adjust travel modes and destinations, and establish new trip chains as appropriate.

These modifications will result in the formation of an alternative activity-travel pattern. The pattern is then sent through a series of logical consistency and feasibility checks against a set of rule-based constraints. If the alternative pattern does not pass the feasibility check, the pattern is rejected and the modifier will search for a new pattern. If an alternative pattern passes the feasibility check, it will be sent to the next AMOS component for evaluation.

Figure 5.4: Activity-Travel Pattern Modifier



5.3.2 Activity-Trip Re-sequencing Algorithm

The activity-trip re-sequencing algorithm generates alternative activity-travel patterns using a set of heuristic rules and constraints within which travelers make decisions. The modifier implements a different algorithm for each possible behavioral response to a TDM measure. Due to the complex nature of activity-travel behavior and its underlying relationships, simplifying assumptions have been adopted in the development of the first versions of these algorithms. These assumptions are described as follows:

- Activity and task allocation among household members is not considered. Only the activity-travel pattern of one individual in a household is analyzed, independent of activity-travel behavior exhibited by other household members.
- Out-of-home activity durations for various purposes are kept a constant before and after the introduction of the TDM measures. However, in-home activity duration and travel times may vary.
- The frequency with which various out-of-home activities are pursued is also kept a constant before and after the introduction of the TDM measures. However, trip frequencies may vary as trip linking patterns may be modified.
- The activity-trip re-sequencing algorithms do not consider multi-day activity-trip engagement. Only one-day activity-travel itineraries are adjusted, independent of activity-travel itineraries on any other day.
- The algorithms deal only with activity-travel pattern modifications for commuters.

As such, the algorithms currently operate on a one-day baseline activity-travel pattern of one commuter in a household, while holding the frequency and duration of out-of-home activities fixed. However, the algorithms do allow for the modification of several activity-travel attributes including:

- Travel mode
- Trip destinations (activity locations)
- Trip timing (activity scheduling)
- Trip chaining (activity sequencing)

There may be many possible ways in which these attributes may be modified. However, the search for alternative feasible patterns is made efficient in AMOS through the introduction of a series of logical rule-based conditions. The following is a listing of the main rules and constraints to which all modifications must adhere:

<u>Spatio-Temporal Constraints</u>

- *Activity Duration:* Activity duration for purpose m, Am   0, for all m = 1, ..., p.
- *Trip Duration:* Trip duration for a specific-purpose activity m, Tm   em, for all m = 1, ..., p, where e is the lower bound for trip duration. Also, em = f(m, c) where m is a vector of modal attributes and c is a vector of network attributes for the trip.
- *Temporal Continuity:* BT(n+1) = ETn + An, where BT(n+1) represents the beginning time of trip (n+1). ETn represents the ending time of trip n, and An must be equal or greater than zero.
- *Spatial Continuity:* The destination place of trip (n) becomes the origin place of trip (n+1). That is, D(n)   O(n+1) .

<u>Physiological Constraints</u>

- Total time spent in-home (or its equivalent), Ah d, where d is the lower bound (minimum) of the time needed for a person to fulfill physiological needs including sleep, preparing and/or eating meals, personal and household care, etc. This lower bound will differ from individual to individual; i.e., d = f(z, x) where z is a vector of employment characteristics and x is a vector of household characteristics.
- In addition, certain specific activities related to satisfying the biological needs of the human body may have lower bounds. Activities mentioned above, namely, sleep, eating meal, and personal care are likely to have lower bounds. This may not apply to everyone under all circumstances. In general, Ai di, where i represents a subsistence activity.

Assumptions regarding subsistence activities are expressed as follows:

- A set of personal care and hygiene activities should precede the journey to work.
- Eating meal activities generally occur during the day.
- Sleeping usually occurs at night under a roof.

As an initial effort in the AMOS implementation, scheduling these basic subsistence activities in any modified patterns is being kept as similar to the baseline patterns as possible.

<u>Coupling Constraints</u>

Institutional: Work Related

- *Spatial Fixity of Travel and Activities:* Work place is predetermined for those who always work at the same place or fixed in real time for construction workers, on-site service personnel, etc.
- *Temporal Fixity of Travel:* The beginning and end-times of a commute trip should fall within certain time bands. For example, ET(w,min) ET(w) ET(w,max) where ET(w) represents the ending time of a trip to work. ET(wmin) and ET(wmax) are the minimum and maximum ending time of a trip. Then, the time interval within which the work trip begin time BT(w) must satisfy BT(w,min) BT(w) BT(w,max), where BT(w,min) and BT(w,max) refer to the minimum and maximum trip begin time. In addition, BT(w,min) = ET(w,min) - T(w,max) and BT(w,max) = ET(w,max) - T(w,min). T(w) represents travel time to work. T(w,min) and T(w,max) are the minimum and maximum travel time to work. T(w) is a function of modal attributes, network attributes, and the individual's travel pattern. A stop on the way to work can well increase the value of T(w).

Both of the above apply to work-related activities and trips.

- *Temporal fixity of activities:* Work and work-related activities must be accomplished within certain time intervals. The degree of their flexibility is a function of employment, personal, and household characteristics. So, BA(w,min) BA(w) BA(w,max) where BA(w) represents the beginning time of work activity. BA(w,min) and BA(w,max) are the minimum and maximum beginning time of the work-related activities. Similarly EA(w,min) EA(w) EA(w,max) must be held also. EA(w) represents the ending time of work activity. EA(w,min) and EA(w,max) are the minimum and maximum beginning time of the work-related activities. These constraints apply for each piece of work activity. It is important to note that temporal fixity of travel is closely related to the temporal fixity of activities. For example, BT(w,max) = BA(w,max) - T(w,min).

- Non-work activities can be performed before work, after work, or within small time windows during work (e.g., lunch breaks) subject to certain institutional constraints. These constraints are defined below.

Institutional: Non-Work Related

- There are many operational formulas that may apply here. A few examples include: OPENTnw BAnw CLOSETnw. The beginning time of an out-of-home and non-work activity BAnw is usually governed by the opening and closing times of the store, business and gym expressed as OPENTnw and CLOSETnw.
- EAnw < BA(w,max) or BAnw > EA(w,min) A non-work activity must end before the latest required work start time. Or alternatively, a non-work activity can begin only after the earliest possible work end time. These formulas can be further enhanced by including travel times in the relationships. These relationships hold for any intermediate time window available for non work activities during work hours.
- Both personal business and shopping trip destinations and time of the day may change subject to satisfying interrelated spatial and temporal constraints.
- All school trips and child serve-passenger trips are constrained like work trips. They have fixed destinations and fixed time intervals within which arrival and departure must occur. Most of the formulas applicable to work and non-work activities apply to these trips.

<u>Household Role-Based Constraints</u>

- A person may be constrained to arrive at home by a certain time to take care of household duties. The existence and nature of this constraint is a function of household and personal demographic and socio-economic characteristics. Generally, ET(h,max) BA(h,max) , where ET(h,max) represents the latest allowable ending time of a trip to home and BA(h,max) represents the latest allowable beginning time of in-home activity. BA(h,max) = f(z, x), where z is a vector of employment characteristics and x is a vector of household characteristics.
- Household members may prefer to pursue certain activities jointly, eating meals in the evening. This certainly places constraints on household members' arrival time at home in the evening and consequently the departure time from work.

<u>Modal Constraints</u>

- A vehicle must be available for an auto driver trip. Then, HHCARS > 0 where HHCARS represents household car ownership. Also, a vehicle must be available at the time and location where the trip originates.

- Modal continuity must be maintained. The mode of trip (n+1) is the same as mode for trip (n) unless the purpose of trip (n) is home, change mode, or serve-passenger. Use of a company car is permitted during work hours.
- No intermediate stops are only allowed for carpool commute trips except for dropping off and picking up carpool members.
- Transit trips are constrained by transit operating hours, schedules, and routes.
- Walking and bicycle trips or access are constrained by bicycle availability, safety considerations, and distance.

Activity Constraints

- Activity duration will have both lower bounds and upper bounds. Then, A(i,min)   Ai   A(i,max) where Ai represents the activity duration for activity type i. A(i,min) and A(i,max) are the minimum and maximum duration time for activity type i, respectively.
- The sum of all activity durations and any individual activity durations must be less than or equal to 24 hour. This rule can be expressed as: A(i,max)   24 hours and SAi = 24 hours.
- Mandatory activities including going to work and attending classes are pursued first. Flexible activities such as personal business and subsistence shopping are performed afterwards. Discretionary activities including convenience shopping, recreation, and entertainment are pursued at last. Trade-offs among time spent at various activities are reflected in the modified activity/travel patterns.
- Certain preferences may govern the time-of-day during which certain activities are pursued. For example, leisure activities such dining and going out to a movie usually occur in the evening.

Value of Time

- Marginal utilities of travel vary across modes, people, and environmental scenarios.
- Route choice preferences vary across individuals with different socio-economic characteristics and different perceptions.

The activity-trip re-sequencing algorithm uses these rules and constraints in generating alternative activity-travel patterns.

5.3.3 Simulation of Trip Timing and Mode

Attributes of trips in the new activity-travel patterns generated by the activity-trip re-sequencing algorithm are determined by using a series of models. Discrete choice models have been incorporated to determine modes used for various trips. Interdependency among trips, for example, the mode used for trip *n-1* must also be used for trip *n*, is explicitly accounted for in the rule-based constraints. Trip departure times are also determined within the rule-based constraints while recognizing the need for temporal continuity and temporal fixity, for example, work trips may be fixed with respect to their ending times. If a trip departure time is flexible, for example, departure time of a trip after a home sojourn, probabilistic rules are applied to logically infer the likely departure time. This determination can be made using travel time from the network file given information on the trip origin, destination, and mode.

In addition, there may be situations where the trip destination may be chosen. For example, if a person switches from SOV to transit, it is likely that any activities done on the way to work could now be undertaken at alternate locations. A location/destination choice model has not yet been incorporated into the activity-trip sequencing to account for this possibility. At this time, destination locations are kept fixed when generating alternative activity-travel patterns. However, future enhancements of the AMOS model system will incorporate a location/destination choice model that uses elaborate land-use data to develop attractiveness and accessibility measures of various destination opportunities.

5.3.4 Feasibility and Consistency Check

The alternative activity-travel pattern generated by the activity trip re-sequencing algorithm is finally checked for its feasibility and logical consistency. Many of the rules and constraints defined previously in Section 5.3.2 are used to perform this check. If a pattern is found to violate a rule, The Activity-Travel Pattern Modifier discards the pattern and loops back to the activity trip re-sequencing algorithm to generate another pattern. If no other feasible pattern can be generated, then another TDM response option is generated and activity-travel pattern modification is attempted again.

If an alternative activity-travel pattern passes the feasibility check, then it is sent for further processing. The modified activity-travel pattern is assembled and sent to the next component of AMOS, namely, the Evaluation Module and Acceptance Routine.

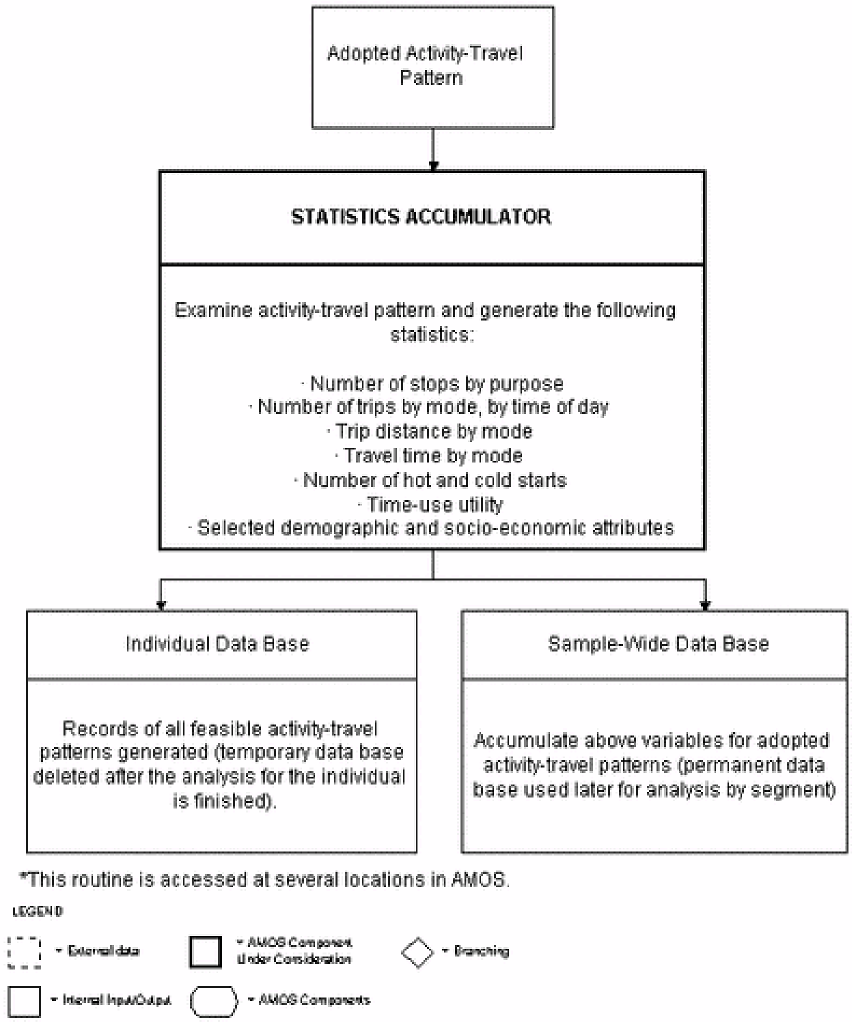
5.4 Evaluation Module and Acceptance Routines

This component evaluates the utility associated with alternative activity-travel patterns generated by the Activity-Travel Pattern Modifier. It assesses whether a certain alternative activity-travel pattern is acceptable and whether the search for a new pattern should be continued.

5.5 Statistics Accumulator

The Statistics Accumulator constitutes the final output and reporting device of the AMOS model system. Its structure is shown in Figure 5.5. An accepted activity-travel pattern from the previous component serves as input to the statistics accumulator. The accumulator examines the activity-travel pattern and interfaces with a statistical routine to compute various descriptive and frequency summaries for an individual's daily travel pattern. These measures include the type of activity, trip frequencies by purpose, trip frequencies by mode, activity and trip frequencies by time of day, vehicle miles traveled, travel times, number of hot and cold starts, time-use utility, and selected demographic and socio-economic characteristics.

Figure 5.5: Statistics Accumulator*



The Statistics Accumulator first records an individual data base that contains records of all feasible activity-travel patterns generated for that individual. This component is accessed at several locations in the AMOS model system and therefore must keep a record of all feasible activity-travel patterns generated for an individual. After the analysis of an individual is completed, only the final adopted activity-travel pattern is retained in the permanent database. Then the Statistics Accumulator accumulates various statistics of the adopted activity-travel patterns of the entire sample into a permanent database. This database lends itself further to regional forecasting and policy analysis.

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Chapter 6: Application to the Washington, D.C. Area

As probably the first implementation of an activity-based policy analysis tool in the world, AMOS is applied to the Washington, D.C. area for the Metropolitan Washington Council of Governments

(MWCOG), the MPO for that area. The application involved an elaborate survey effort (which shall be referred to as the AMOS Survey) involving the collection of both revealed-preference and stated-preference data. This survey provided the necessary information for training the neural network in the TDM Response Option Generator module of AMOS. Once the neural network training was completed, MWCOG's household travel survey data (trip diary data) provided the baseline travel patterns to which AMOS could be applied. This section describes the AMOS survey in elaborate detail, presents the results of neural network training and sensitivity analysis, then provides sample results of the application of AMOS to MWCOG's household travel survey data.

6.1 AMOS Survey

The objective of the AMOS survey was to develop a data set that can be used to model individual and household responses to various TDM measures. The survey introduces two innovative approaches to examine individuals' and households' travel behavior in response to changes in the travel environment -- a time-use (or activity-based) travel survey and a stated-preference (SP) approach.

6.1.1 Approach

The AMOS survey is a time-use (or activity-based) travel survey that explicitly posits travel behavior as a demand derived from individuals' demand to conduct various activities (and hence, to use time) at different times and locations. Hence, a complete activity-travel diary was collected for the respondent. The second innovative feature of the survey was the stated-preference approach that was employed to gather data on the response to the introduction of TDM measures. Stated-preference approaches involve asking respondents to express their preferences or responses to hypothetical scenarios that have been characterized in terms of attributes (in this case, changes in the travel environment). In this survey, respondents were asked to identify how they would respond to a change in the travel environment created by specific TDM measures. Obviously, stated-preferences are relied upon where there is no pre-existing data. As such, the SP approach is subject to the limitations of an imagined response as opposed to actual revealed-preference (RP) data. In order to control for these types of limitations every means is employed in this effort to increase the realism of the hypothetical situation to which the respondent is exposed. This was accomplished primarily by: (1) explicitly exploring the impacts of the proposed TDM measure on the respondent's own activity-travel pattern recorded on and reported for the prior day (e.g., in terms of its impact on trip attributes -- time, costs, mode, etc.), (2) checking their response against the potential constraints of their activity-travel pattern (e.g., a parent's obligations to drop off a child at day care and arrive at work by a certain hour), and (3) customizing TDM parameters to best represent the respondents commute situation.

Together these approaches provide the basis for exploring trade-offs people may make between in-home and out-of-home activities (e.g., rather than eating breakfast at home, a commuter may leave home early and eat on the road or at work to avoid peak period), re-scheduling (e.g., combining or deferring) activities throughout the day, and the occurrence of constraints that bind an individual to a particular activity-travel pattern (e.g., child care). If an activity-based survey was conducted for an entire household over the course of a week, the basis for exploring trade-offs in activities between family members and over time could be examined. However, this was not possible due to resource limitations.

Based on these objectives, the survey acquired the following information for a sample of households:

- general household socioeconomic characteristics (number of persons, car ownership, etc.);
- characteristics of household occupants (age, sex, employment status, work location, etc.);
- for a single selected individual in the household, information on his/her time-use and travel was collected both in-home and out-of-home and included an activity-trip diary on a particular weekday;
- for the same selected individual, a set of stated-preference responses to a selected set of hypothetical TDM policies were gathered.

6.1.2 Sample Design

The target population consisted of adults who commuted regularly (3 times per week or more) to school or work in the MWCOG jurisdiction. While it was recognized that a significant proportion of the market response to TDM measures would also come from non-commuters, higher probabilities are placed on commuters.

The sampling frame for this survey was three dimensional: households were selected at random, persons to be interviewed were selected at random from the commuters in the household, and activity/travel days were selected at random for persons in the sample. Travel days were assigned throughout the survey so that an approximately equal number of activity/travel days were assigned for each weekday (Monday through Friday excluding holidays). The representative sample of numbers was secured for both listed and unlisted telephone numbers in the MWCOG region.

Because the respondent universe was likely to be very diverse in behavior and attitudes and because hypothetical TDM scenarios had to be customized for each individual's activity and travel pattern, complex skipping patterns were required in the survey questionnaire to collect the desired information in an effective manner. Hence, an on-line computer aided telephone interviewing (CATI) approach was selected which was able to automatically control all skipping patterns with complete reliability and no time delays.

6.1.3 TDM Measures Considered in AMOS Survey

Following are the TDM measures that were selected in conjunction with a working group consisting of representatives from MWCOG, FHWA and EPA for the AMOS survey. The selection of these TDM measures was a function both of those proposed in the MWCOG region, as well as those that provided a number of analytical challenges.

TDM #1:	**Parking Pricing:**

	incremental parking surcharge at work place
	-- $1 to $3 per day in suburbs
	-- $3 to $8 per day in DC and downtowns
	walking time trade-offs: 10 minutes, 15 minutes and 20 minutes
TDM #2:	**Improved Bicycle/Pedestrian Facilities:**
	well-marked and well-lighted bicycle paths and a secure place to park a bike wherever a person went
TDM #3:	**TDM #1 & TDM #2**
TDM #4:	**Parking Pricing & Employer-Supplied Commuter Voucher**
	-- $40 to $80 per month for both
TDM #5:	**Congestion Pricing**
	--10% to 30% time savings and $.15 to $.50 charge per mile
TDM #6:	**TDM #4 & TDM #5**

TDM #1, the parking charge, was complicated by two factors. First, parking charges vary over the MWCOG region. Second, there is a considerable amount of free parking even in the central business districts as well as the outer suburbs. Considering these, the level of parking pricing is expressed in terms of surcharges. For the customization of SP questions, MWCOG provided a detailed map of average daily parking costs by area. Rather than trying to get too specific about the location of the respondent's workplace, the survey obtained the city where the person worked. According to MWCOG, average daily parking costs range roughly between $1 and $3 in the suburbs (i.e., inside the "Beltway"), and between $4 and $7.50 in the central areas. For each respondent, a level of parking pricing was chosen at random from the appropriate range.

TDM #2, improved bicycle/pedestrian facilities, is described as continuous, well-marked and well-lighted network of bicycle and pedestrian paths and a secure place to park a bike wherever a person went.

TDM #1, and TDM #2, were combined as a separate TDM scenario to explore the potential for synergistic rather than merely additive effects.

TDM #4 provided an employer-supplied commuter voucher and a supplementary parking charge over and above what the commuter currently paid at the time of the survey. The MWCOG region has considered a combination of $60 monthly benefit and $60 supplementary monthly parking charge, which would result in a zero net cost to single-occupant vehicle (SOV) users. MWCOG's proposed charges were used as guidelines for those combinations developed for the AMOS survey.

TDM #5 was a congestion pricing measure. MWCOG reported their congested hours (facilities operating at level of service E or F) had been from about 6:00 am to 9:30 am and about 4:00 pm to 7:30 pm. The AMOS survey simplified this by making the congestion applicable from 6:00 am to 9:00

am and from 4:00 pm to 7:00 pm. Any driver whose trip fell wholly or partly within these periods was charged the full congestion price.

Potential time savings have been speculated at 10% to 30% for congestion pricing of $0.15 to $0.35 per mile by MWCOG. The AMOS survey used an upper limit of $0.50 per mile. The congestion price was applied to the entire trip distance, not just the portion on the freeways. The scenario thus represents an area-wide pricing scheme. In the survey time savings of 10% to 30% of total travel times were applied to respondents' actual commute times while avoiding combinations of high congestion pricing and low time savings, or low congestion prices with high time savings.

Once again, TDM #4 and TDM #5 were combined into a new scenario in TDM #6 to explore the potential for synergistic effects when TDM measures are combined.

6.1.4 Survey Design

The following topics were covered in the survey questionnaire:

- Commute characteristics including use of alternative travel modes
- Work schedules (last week)
- Stops made on the way to/from work (last week)
- Trips made while at work (last week)
- One-day time use and travel data for the assigned activity travel day
- Parking cost and walking distance trade-offs
- Responses to SP questions for hypothetical TDM scenarios:
- "What would you do if (a description of one TDM was provided that included the impacts on the trip attributes for the commuters' activity travel pattern from the previous day)?"
- The respondent was not prompted with a list of possible changes unless necessary. The eight responses that were pre-coded included:
  1. Changed departure time to work/school
  2. Walk to work/school
  3. Bicycle to work/school
  2. Carpool to work/school
  4. Transit to work/school
  3. Work at home
  4. Do nothing different
  5. Other (not specified)

If relevant, the respondent was asked a series of questions that were tied to his initial response, such as:
- for change to transit: "how would you perform chauffeuring and other stops on the way to/from work?"
- for change in departure time: "when would you have left for work?"
- for many responses: would this have changed any other activities that you did?
- Household and person demographics and socio-economics.

A complete copy of the survey instrument is included in appendix B.

6.1.5 Survey Administration

The AMOS survey was a multi-phase CATI survey with mail-out instruments conducted, as follows:

- **Phase 1 --initial CATI:** screening, commute characteristics, work schedules, demographics, assign travel dates, etc.
- **Phase 2 -- mail-out:** memory joggers to record travel itinerary
- **Phase 3 -- second CATI:** time-use and travel survey, stated-preference TDM questions customized to each individual's commute situation

The initial contact with the household was used to gather household occupant information, to recruit a selected individual as the commuter to provide follow-on response in Phases 2 and 3 of the survey, and to assign a day for recording his/her activities and travel diary. In the second phase, a "memory jogger" was mailed to the selected individual for him/her to record their activities and trips on the assigned day. In the third phase, the activity travel information was retrieved and the stated-preference portion of the survey was administered, on the day following the assigned travel day.

The AMOS survey employed a number of techniques to insure that unbiased data was collected and to optimize the response rates, as follows:

- A combined random digit dialing and reverse directory were used to efficiently obtain a sample of both listed and unlisted households;
- Introductory letters describing the survey were sent prior to the initial household telephone contact on the survey contractor's letterhead to listed households;
- The sample was based on the proportion of population from counties within MWCOG's modeled region including the District of Columbia, Virginia and Maryland;
- The initial CATIs were conducted from 11/19/94 to 12/31/94 with travel dates assigned from 11/28/94 to 12/16/94.

The final sample consisted of 656 fully completed survey instruments (i.e., completed through the CATI-2). The activity travel diaries for the completed CATI-2 surveys were evenly distributed across the five day work week.

Table 6.1 shows the response rates obtained in the conduct of this survey. Of the final 656 completed responses, 112 of them, or 17%, were from unlisted numbers. This ratio of listed to unlisted completed CATI-2 surveys is comparable to the actual proportion of listed to unlisted phones numbers in the MWCOG region. The low response rate for the unlisted phone numbers may make this an unrepresentative sample of that population. The response rates for the listed phone number were significantly higher, i.e., 34% of all live calls to listed phone numbers completed the entire survey compared to a completion rate of 10% for unlisted numbers. This difference is likely due to a number of factors including that people who don't list their phone numbers use this as a means to screen out certain types of interactions such as surveys, as well as the potential increase in credibility that the introductory letter provided that was sent to listed phone numbers whose addresses were available.

Table 6.1: AMOS Survey Completion Rates

	Listed with Letters	**Unlisted**	**Total Sample**
Total Attempted Numbers			
2,972			
2,970			
5,942			
Live/Answered Calls	1,583	1,081	2,664
No. Completed CATI-1	949 (60%)	334 (31%)	1283 (48%)
No. Qualified and Agreed	748	255	1,003
No. Completed CATI-2	544	112	656
as % of Qualified	72%	44%	65%
as % of Live Calls	34%	10%	25%

6.2 AMOS Survey Sample Profile

Table 6.2 shows average household characteristics for the respondent sample of 656 households. The average household size is 2.7, while the average number of commuters per household is 1.7. On average, there are 2 vehicles and 1.4 bicycles per household. 90% of the households have at least one vehicle per commuter. A little over one-half of the households may be considered to fall within the middle income class. About one-fifth of the households have at least one child less than five years of age.

Table 6.2: Average Household Characteristics

(N=656 households)

Characteristic	**Average Value**
Household Size	2.7
No. of Commuters	1.7
No. of Vehicles	2.0
No. of Bicycles	1.4
% #Vehicles Commuters	90%
% Income $30K - $75K	53%
% Child < 5 years	20%

Table 6.3 provides descriptive statistics on the survey respondents who provided detailed revealed and stated-preference activity-travel data.

Almost all of the respondents are licensed and employed. Nearly 58% of the respondents are males. About 70% of the respondents indicated driving alone (SOV) as their usual mode of transport to work (used 3 or more days per week). Average commute distance for the sample is 15.2 miles while the average commute time (measured as direct home-to-work travel time) is found to be 31.7 minutes. Quite a few of the respondents indicated that they trip chained at least one day in the previous week (either during the journey to work or from work). About 13% of the respondents stopped on the way to or from work to serve/pick up a child on at least one day. Nearly one-half of the respondents indicated that they stopped on the way home from work for an activity other than serving a child. As such, it is possible that the implementation of TDM strategies may entail rescheduling of trips and the formation or breaking up of trip chains.

6.3 Analysis of Stated Responses to TDM Strategies

As mentioned in Section 6.1, the respondents were presented with six hypothetical customized TDM scenarios and asked how they would respond to them. Their responses were coded into 8 possible categories. Table 6.4 shows the distribution of responses for the various TDM strategies.

Table 6.3: Respondent Characteristics
(N=656 Respondents)

Characteristic	**Average Value**
% 30 - 49 years age	60%
% Drivers License	98%
% Male	58%
% Employed (outside home)	99%
Modal Shares: Work Trip%	
Drive Alone (SOV)%	70%
Car/Van Pool%	16%
Transit (Bus + Rail)%	10%
Bike + Walk	3%
Commute Distance (miles)%	
< 5 miles%	15.222%
5-25 miles	61%
Home-Work Travel Time (min.)% .	
<10 min.%	31.712%

10-30 min	48%
Trip Chaining Patterns (1+ days)	
Home-Work: Serve Child	13%
Home-Work: Other Activity	28%
Work-Home: Serve Child	14%
Work-Home: Other Activity	49%
At Work: All Activities	40%

6.3.1 Distributions of Stated Responses

An examination of the response distributions indicates that about 60-80% of the sample would not change their baseline activity-travel pattern even after the introduction of a TDM strategy. Interestingly, combinations of TDM strategies do not seem to provide cumulative impacts. Congestion pricing yields the largest percent change (nearly 40%). In general, the indications provided by the table are as anticipated. Parking pricing strategies have little impact on departure time, but substantial impact on mode switching. Congestion pricing appears to have a substantial effect on both departure time and mode to work. Improved bicycle and pedestrian facilities (TDM#2) was met with 11% of the sample indicating a switch to bicycle. Interesting results were obtained when these response distributions were cross-tabulated against various socio-demographic and commute characteristics. Sections 6.3.2 and 6.3.3 provide a sample of such cross-tabulations in an effort to explore factors that contribute to variations in stated choices across different population segments.

Table 6.4: TDM Strategy Response Distributions
(N=656 Respondents)

Response	TDM #1	TDM #2	TDM #3	TDM #4	TDM #5	TDM #6
No Change	70%	82%	75%	71%	61%	62%
Change Departure Time to Work	1%	0%	0%	1%	20%	12%
Switch to Transit	11%	3%	5%	10%	8%	10%
Switch to Car/Vanpool	10%	3%	5%	9%	4%	6%
Switch to Bicycle	1%	11%	12%	6%	4%	5%
Switch to Walk	2%	1%	1%	1%	1%	1%
Work at Home	2%	0%	1%	1%	1%	1%
Other	4%	1%	1%	2%	2%	3%
TDM#1: Parking Pricing TDM#2: Bike/Ped Improvements TDM#3: TDM#1 + TDM#2 TDM#4: Parking Pricing+Empl Voucher						

TDM#5: Congestion Pricing TDM#6: TDM#4 + TDM#5

Statistical tests were performed to examine the null hypothesis of equality of response distributions across the TDM measures. The response distribution to TDM#1 was found to be significantly different (at the 0.05 level) from that to TDM#2. The c2 test statistic was found to be 22.8 with 7 degrees of freedom. Similarly, the response distribution to TDM#1 was found to be different from that to TDM#3, the combination TDM strategy. The response distribution to TDM#1 was found to be significantly different from that of TDM#5, but not significantly different from that of TDM#4. This seems to indicate that the effect of the employer benefit/voucher program was not significant. It was also found that, when compared against the combined TDM strategy TDM#6, both TDM#4 and TDM#5 response distributions were not statistically different. Table 6.5 provides selected c2 test statistics comparing various response distributions.

Table 6.5: Statistical Tests of Similarity of Response Distributions

TDM Distributions Compared	c2 Test - Statistic	Degrees of Freedom	Significance Level (p value)
TDM #1 vs. TDM #2	22.8	7	0.0019
TDM #1 vs. TDM #3	16.86	7	0.0183
TDM #2 vs. TDM #3	2.35	6	0.8848
TDM #1 vs. TDM #4	5.01	7	0.6585
TDM #1 vs. TDM #5	24.0	7	0.0011
TDM #4 vs. TDM #5	20.5	7	0.0046
TDM #4 vs. TDM #6	10.80	7	0.1474
TDM #5 vs. TDM #6	2.94	7	0.8908

As shown above, the response distribution to TDM #3 is significantly different from that to TDM #1. There appear to be synergy effects produced by combining parking pricing and bike/pedestrian facility improvement. A further inspection of the distributions (Table 6.4), however, indicates that this is not the case. In response to parking pricing alone (TDM #1), 70% of the respondents indicated they would make no change while 30% indicated some adjustments. When presented with the synergy scenario of parking pricing combined with bike/pedestrian facility improvement (TDM #3), the fraction of the respondents indicating behavioral changes decreased to 25%. Since the latter synergy scenario represents a larger magnitude of change in the travel environment than does the former, it should have produced a larger fraction of respondents indicating behavioral changes.

This inconsistent result is due to a total of 76 respondents (12.0%) who responded to TDM #1 with behavioral changes while indicating “no change” to TDM #3. Although this inconsistency is much less frequent between the responses to TDM #2 and TDM #3 (19 respondents, or 3.0%), the results cast serious doubt on the validity of the response to the portion of the SP survey that concerns TDM #3. It is possible that this particular synergy combination was not presented to respondents in a well understandable manner. It is however unlikely that respondent fatigue or the length of the interview was the problem because the second synergy combination, TDM #6, yielded consistent results. In any event, the responses to TDM #3 are not used in the analyses presented in the rest of this report due to the inconsistencies in the data.

6.3.2 Responses to Congestion Pricing (TDM #5)

As shown in Table 6.4, there are six TDM response distributions. Cross-classifying these response distributions against a host of socio-demographic variables would potentially yield 30 to 40 tables. As such, for purposes of brevity, only cross-classification tables for the response distribution of TDM #5, Congestion Pricing and TDM #2, Bike/Pedestrian Facility Improvement, are presented in this section and in Section 6.3.3. Many of the findings from this analysis are also found to be applicable to response distributions for other TDM strategies as well.

Table 6.6 shows the response distribution for congestion pricing by usual work mode. The usual work mode is defined as that mode used 3 or more days per week. The transit category includes both bus and metro users. From the table, it can be seen that the TDM strategy has the largest impact on SOV commuters; this result is as anticipated.

Table 6.6: Congestion Pricing Response Distribution by Work Mode

TDM Response Option	SOV (N=460)	Car/Vanpool (N=103)	Transit (N=66)
No Change	57%	74%	83%
Change Departure Time to Work	24%	11%	7%
Switch to Transit	7%	6%	n/a
Switch to Car/Van Pool	4%	n/a	2%
Switch to Bicycle	4%	4%	6%
Switch to Walk	0%	2%	2%
Work at Home	1%	2%	0%
Other	2%	2%	0%
c2 test-statistic = 35.515; d.f. = 14; p=0.0012			

Approximately one-quarter of SOV users would change their departure time to avoid congestion pricing. About 15% would change their commute mode. In other words, SOV users appear to be more amenable to changing their departure time rather than their mode of travel. As car/van pool users would share the costs of congestion pricing, the 11% change in departure time and 12% mode switch is understandable. However, nearly three-quarters do not see the need to change their behavior. As far as transit commuters are concerned, 17% are found to indicate that they would change their behavior. Further investigations into the characteristics of this subsample showed that they were those who used SOV as their transit access mode. As their access trip would be subject to congestion pricing, they presumably felt the need to change their behavior. The c2 test shows that the response distributions differ significantly across mode groups at the 95% confidence level.

Table 6.7 shows the response distribution by commute distance.

Table 6.7: Congestion Pricing Response Distribution by Commute Distance

Commute Distance	Change Mode	Change Departure Time
< 5 miles (N=142)	18%	11%
5 - 15 miles (N=266)	18%	23%
15 - 25 miles (N=120)	15%	26%
25 - 50 miles (N=97)	17%	19%
> 50 miles (N=8)	0%	13%
c2 test-statistic = 15.102; d.f. = 4; p=0.0045		

Except for the very short distance commuters (<5 miles), all others seem to indicate a greater willingness to change departure time than mode to work. Very short distance commuters may be able to switch modes relatively easily when compared with longer distance commuters. Commuters whose distance to work lies between 5 and 25 miles appear more inclined to change departure time than mode. As the commute distance increases beyond 25 miles, the willingness to change departure time reduces. Nobody with a commute distance greater than 50 miles was willing to change mode; possibly very long commutes are not flexible with respect to mode shifts. In general, commute distance is found to significantly affect individual's response options; the c2 test-statistic is found to be significant at the 0.05 level.

Table 6.8 shows the variation in response distribution by the need for trip chaining on the way from home-to-work. Of the 656 respondents, 226 indicated that they had stopped on at least one day the previous week on the way from home-to-work. These commuters are found to be more resistant to changing their mode when compared with those who did not stop at all the previous week. However, they are almost equally inclined to change their departure time. It appears that trip chaining acts as a deterrent to mode switching, but not to departure time shifts. Approximately one-fifth of the sample responded with a change in departure time whether or not they trip chained at least one day the previous week. However, with regard to mode shifts, 20% of those who did not trip chain at all indicated a willingness to change mode. The corresponding percentage for those who trip chained at least one day the previous week is 11%. Trip chaining is found to be significantly related to the response distribution at a p-value of 0.0628. If SOV commuters are isolated in the case of Table 6.8, then the percent of those with no change becomes 53% and those who change departure time increases slightly to 24%, while all other commuter categories show little change, consistent with the above discussion.

Table 6.8: Congestion Pricing Response Distribution by Trip Chaining

TDM Response Option	Stops on 0 Days(N=430)	Stops on 1+ Days(N=226)
No Change	57%	67%
Change Departure Time to Work	19%	20%
Switch to Transit	9%	5%
Switch to Car/Van Pool	5%	3%
Switch to Bicycle	5%	2%
Switch to Walk	1%	1%
Work at Home	1%	0%
Other	2%	1%
c2 test-statistic = 13.406; d.f. = 7; p=0.0628		

Finally Table 6.9 explores the influence of gender and household role on TDM response distributions. The gender role is defined by the gender (male or female) of the respondent coupled with the presence or absence of at least one stop to serve a child the previous week.

Table 6.9: Congestion Pricing Response Distribution by Gender Role

TDM Response Option	Change Mode	Change Departure Time
MALE	18%	22%
Serve-Child Stop (N=35)	6%	29%
No Stop (N=347)	19%	21%
FEMALE	15%	16%
Serve-Child Stop (N=47)	9%	13%
No Stop (N=227)	17%	17%

In general, a larger percentage of males are willing to change their behavior. Forty percent of males would change either their mode or departure time, while the corresponding percentage for females is only 31%. Also, the presence of a stop to serve a child appears to reduce the flexibility of changing behavior for both males and females. Only 35% of males with a serve-child stop are willing to change their behavior, while 40% of those with no stop are willing to change. Similarly, for females, the corresponding percentages are 22% and 34%. Interestingly, both of these percentages are lower for females indicating their possibly greater household roles, and consequent reduced flexibility.

The analysis presented here is quite preliminary in nature and emphasizes bivariate relationships. In order to model the stated responses more accurately, it would be necessary to conduct a rigorous multivariate analysis using appropriate discrete choice modeling methods. Such models are currently under development and will be available for dissemination in the near future. However, the tabulations in this section provide some preliminary insights into the types of variables that influence TDM response distributions. Notably, it is found that trip chaining deters mode change, but not departure time changes. Also, females with a serve-child stop show the lowest propensity to change their commute behavior. Broadly, these findings point to the need for including household role and life-cycle variables as well as trip chaining characteristics in discrete choice modeling efforts.

6.3.3 Responses to Bike/Pedestrian Facility Improvement (TDM #2)

Responses to TDM #2, Bike/Pedestrian Facility Improvement, are analyzed in this section. As one may expect, the distribution of responses is strongly associated with commute distance (Table 6.10). Quite notably over a quarter of respondents whose commute distances were 1.5 miles or less indicated that they would switch to cycling or walking to work if TDM #2 were implemented. This percentage drops rapidly when commute distance exceeds 10 miles and declines to 3%.

Table 6.10: Bike/Pedestrian Facility Improvement Response Distribution by Commute Distance

Commute Distance	Switch to Bike/Walk (N = 69)	Other Changes (N = 46)	No Change (N = 520)	Total (N = 635)
≤ 1.5 miles (N = 47)	25.5%	8.5%	66.0%	100%
1.5 - 5 miles (N = 87)	19.5%	9.2%	71.3%	100%
5 - 10 miles (N = 139)	12.9%	7.9%	79.1%	100%
10 - 20 miles (N = 200)	8.0%	6.5%	85.5%	100%
20 - 30 miles (N = 102)	3.9%	5.9%	90.2%	100%
> 30 miles (N = 60)	3.3%	6.7%	90.0%	100%
Total	10.9%	7.2%	81.9%	100%
2 test statistic = 30.6; d.f. = 10, p = 0.0007				

As expected, younger commuters are more likely to respond to TDM #2 by switching to cycling or walking to commute (Table 6.11). It can be also seen that male commuters are more likely to take advantage of improved bike/pedestrian facilities (Table 6.12). Although these tendencies are clear in the tables, they are not statistically significant, presumably because the tables are dominated by respondents in the "no change" category.

Table 6.11: Bike/Pedestrian Facility Improvement Response Distribution by Age

Age	Switch to Bike/Walk (N = 69)	Other Changes (N = 46)	No Change (N = 518)	Total (N = 633)
19 - 29 (N = 94)	12.8%	10.6%	76.6%	100%
30 - 39 (N = 210)	13.3%	6.2%	80.5%	100%

40 - 49 (N = 176)	9.1%	9.7%	81.2%	100%
50 - 59 (N = 118)	9.3%	3.4%	87.3%	100%
≥ 60 (N = 35)	5.7%	5.7%	88.6%	100%
Total	10.9%	7.3%	81,8%	100%
2 test statistic = 9.84; d.f. = 8, p = 0.276				

Table 6.12: Bike/Pedestrian Facility Improvement Response Distribution by Sex

Sex	Switch to Bike/Walk (N = 69)	Other Changes (N = 46)	No Change (N = 520)	Total (N = 635)
Male (N = 372)	12.1%	7.5%	80.4%	100%
Female (N = 263)	9.1%	6.8%	84.0%	100%
Total	10.9%	7.2%	81.9%	100%
2 test statistic = 1.602; d.f. = 2, p = 0.449				

Responses to TDM #2 is only weakly associated with the presence of stops made during commute trips. Table 6.13 shows the distribution of responses by the presence of stops on the way to or from work to drop off or pick up a child. Only 2.5% of the respondents who made such stops at all during the last week indicated they would make some behavioral adjustments other than switching to cycling or walking to work, while 87.5% of them indicated “no change.” With respect to the switch to the bicycle or walk mode, however, practically the same fraction (10.0%) of these respondents chose to switch as those who did not stop to pick up or drop off children (11.0%). The association, however, is not statistically significant at the 10% level.

Table 6.13: Bike/Pedestrian Facility Improvement Response Distribution by Number of Serve-Child Stops During Commute Trips

Serve-Child Stops	Switch to Bike/Walk (N = 69)	Other Changes (N = 46)	No Change (N = 520)	Total (N = 635)
None (N = 555)	11.0%	7.9%	81.1%	100%
On 1+ Day (N = 80)	10.0%	2.5%	87.5%	100%
Total	10.9%	7.2%	81.9%	100%
2 test statistic = 3.26; d.f. = 2, p = 0.1961				

Contrary to this result, those respondents who made stops during their commute trips for purposes other than dropping off or picking up children are more likely to switch to the bicycle or walk mode than those who did not make such stops (**Table 6.14**). The fraction of respondents who indicated “no change" is very similar between the two groups, while those making such stops tended not to make other changes. The association, however is statistically not significant.

Table 6.14: Bike/Pedestrian Facility Improvement Response Distribution by Number of Other Stops During Commute Trips

Stops Other than to Serve Child	Switch to Bike/Walk (N = 69)	Other Changes (N = 46)	No Change (N = 520)	Total (N = 635)
None (N = 459)	10.0%	8.3%	81.7%	100%
On 1+ Day (N = 176)	13.1%	4.5%	82.4%	100%
Total	10.9%	7.2%	81.9%	100%
2 test statistic = 3.54; d.f. = 2, p = 0.1702				

The analysis here indicates that commute distance is the primary factor that affects commuters responses to bike/pedestrian facility improvement as a TDM strategy. Age and sex are also associated with the intention to switch to the bicycle or walk mode. Overall, however, statistical indications are weak. The dominance of commute distance as a factor contributing to commuters intended reaction to this TDM strategy implies that this measure must be carefully implemented while considering the distribution of residence and work locations and targeting those neighborhoods where residence-job proximity exists.

6.4 Implementation of TDM Response Option Generator

The AMOS survey data described in the previous sections was used to develop and implement the TDM response option generator. This section describes the neural network methodology, neural network "training" procedures, and provides results of a sensitivity analysis performed on the AMOS survey sample.

6.4.1 Development of Neural Networks

The TDM response option generator consists of a neural network that is trained, using results of the AMOS survey, to recognize a pattern of inputs and provide an appropriate output. In this application inputs consist of baseline travel patterns, land-use and socio-economic data, travel supply data, and TDM characteristics. The output comprises a set of behavioral responses of an individual to the TDM under investigation. This section is aimed at providing a brief overview of neural networks followed by a discussion of the neural network currently being implemented in AMOS.

A neural network may be considered a general-purpose function estimator or pattern recognizer. A neural network is an assembly of artificial neurons that is intended to mimic the learning behavior of the human mind. These neurons are usually arranged in several layers, namely an input layer, an output layer, and quite often, one or more intermediate hidden layers. Neurons in the input layer accept inputs and re-transmit them to each neuron in the next layer. If one or more hidden layers is included, each neuron in a hidden layer accepts a weighted set of inputs from the previous layer and transmits a signal to all neurons in the next layer. Finally, neurons in the output layer accept inputs from the last hidden layer and produce the output of the neural network.

A neuron is the basic building block of the neural network. Each neuron receives an activation, from which it produces an output defined by its activation function. The activation of a neuron is simply a weighted sum of its inputs. The output signal of a neuron is determined as follows:

$$S_{ni} = f_{ni}(x_{ni})$$

where S_{ni}, f_{ni}, and x_{ni} are the output signal, the activation function, and the activation of the i-th neuron in layer *n*. The activation, x_{ni}, is given by,

where is the output signal of the j-th neuron in layer *n-1* and is the weight applied to the signal from the j-th neuron in layer *n-1*. The weights are the quantities that determine the performance of a neural network. Training a neural network consists of adjusting the weights so that the desired outputs, associated with different patterns of inputs, are achieved.

Neural networks present certain key advantages that make their adoption in AMOS appealing. Neural networks are general purpose function estimators that have been demonstrated to be able to replicate a wide variety of functions with rather small numbers of neurons (say, 50 to 100). Thus neural networks could be used to implement general purpose choice functions for individuals responses to transportation policies. The neural network could represent non-linear relationships that are not easily embodied in current choice models. Conceivably, neural networks could also be trained to generate a sequence of activities (rather than just a basic behavioral response) given a set of input data. In addition, neural networks could be used as pattern recognizers to classify various sequences of activities. More recent advances in neural network applications have seen the combining of neural networks with fuzzy set theory and fuzzy logic to develop neural networks that embody relationships difficult to quantify or establish deterministically.

6.4.2 Results of Neural Network Training Using AMOS Survey Data

The trained neural network is applied to trip diary data and other information available in the 1994 MWCOG Household Travel Survey (described later in Section 6.5). This calls for the judicious selection of input and output nodes for defining the neural network, as the neural network must be trained using a set of variables that is available in both the AMOS survey database and the MWCOG survey database.

The two databases were compared and variables common to both were identified. This exercise yielded various alternative neural network structures. At this time, the neural network that utilizes the most information available in the databases and provides the best results (in terms of predictive accuracy) is found to be one that uses 36 input nodes and 8 output nodes. The 36 input nodes are:

- Parking pricing level for TDM #1
- Employer benefit for TDM #4
- Parking charge (per month) for TDM #4
- Congestion pricing for TDM #5
- Travel time reduction for TDM #5
- Respondent age 5-15 years; Dummy=1 if yes, =0 otherwise
- Respondent age >15 years; Dummy=1 if yes, =0 otherwise
- Respondent age unknown; Dummy=1 if yes, =0 otherwise
- Sex of respondent; =1 if male, =0 otherwise
- Midpoint of household income category in the range $0 to $150,000
- Household income > $150,000? =1 if yes, =0 otherwise
- Household income unknown? =1 if yes, =0 otherwise
- Number of vehicles owned by household in the range 0 to 8
- Number of vehicles in household > 8? =1 if yes, =0 otherwise
- Number of vehicles in household unknown? =1 if yes, =0 otherwise
- Number of persons in household who commute regularly; range 0 to 8
- Number of commuters in household > 8? =1 if yes, =0 otherwise
- Number of persons in household more than 5 years of age; range 0 to 14
- Number of persons more than 5 years > 14? =1 if yes, =0 otherwise
- Number of persons more than 5 years unknown? =1 if yes, =0 otherwise
- Number of persons 5 years of age or less; range 0 to maximum value
- Residence is a single family unit? =1 if yes, =0 otherwise
- Residence is a multi-family unit? =1 if yes, =0 otherwise
- Residence is of other type? =1 if yes, =0 otherwise
- Commute distance in miles; range 0 to 240 miles
- Commute distance unknown? =1 if yes, =0 otherwise
- Work mode on travel day is SOV? =1 if yes, =0 otherwise
- Work mode on travel day is car/vanpool? =1 if yes, =0 otherwise
- Work mode on travel day is bicycle or walk? =1 if yes, =0 otherwise
- Work mode on travel day is bus, rail, train? =1 if yes, =0 otherwise
- Worked at home on travel day? =1 if yes, =0 otherwise
- Number of stops to serve child on way from home to work
- Number of stops for any other purpose on way from home to work
- Number of stops to serve child on way from work to home
- Number of stops for any other purpose on way from work to home
- Number of car trips while at work

Each variable above constitutes one input node. It can be seen that the inputs to the neural network include socio-economic characteristics, demographic characteristics, commute characteristics, work mode information, and trip chaining (stop) patterns.

As noted earlier in Section 6.3.1, survey responses to TDM #3, the synergy combination of parking pricing and bicycle/pedestrian facility improvement, are not consistent with those to TDM #1, parking pricing. Furthermore, TDM #2, bicycle/pedestrian facility improvement, is qualitatively quite different from the rest of the TDM strategies considered in the study. Consequently, it was decided to develop a separate model for TDM #2 (see Section 6.4.3). The neural network with the above input nodes thus addresses TDM #1, #4, #5 and #6. The above set of input nodes reflects this.

The method of backpropogation is used to adjust the weights associated with the links in the network so that the predictive accuracy of the network is maximized. The predictive accuracy is measured in terms of the percentage of cases whose output nodes are correctly classified when compared against their stated response. The neural network consists of 8 output nodes, one output node for each response option. When the training is complete, a certain output node (corresponding to one behavioral response option) is activated for each respondent. If this activation coincides with their stated response (in the survey), then the case is deemed correctly classified.

Three alternative neural network configurations have been trained and their predictive accuracy compared. The first neural network structure has one hidden layer with 29 hidden nodes. The second structure has two hidden layers with one layer having 29 nodes and the other having 28 hidden nodes. A third structure has three hidden nodes having 12, 10, and 8 hidden nodes respectively. Although the three networks offered similar predictive accuracies, the network with two hidden layers is chosen for further analysis considering complexity and predictive sensitivity.

6.4.3 Conversion of Activation Levels to Probability Measures

The output signals at the eight output neurons of the neural network indicate the "activation levels" of the respective neurons. In the context of this study, the activation level of an output neuron is associated with the likelihood that the TDM response option corresponding to the output neuron will be chosen by an individual. Activation levels are, however, not probabilities, despite the fact that they lie in the range between 0 and 1. The response option generator of AMOS requires the probability associated with each response option be determined for each individual and for each TDM measure such that response options can be properly generated in the micro-simulation. This calls for the conversion of activation levels to proper probability measures.

A new approach is developed in this project to meet the requirement of converting neuron activation levels to probability measures. The approach is based on the principle of maximum likelihood, and statistically estimates a conversion function such that the neural network best replicates the observed responses in the training data set.

Let Sj be the activation level of the j-th output neuron, which represents the j-th response option; and let Pj be the probability that the j-th response option will be chosen. Let the conversion function for the j-th option be Gj. Then, for the eight response options described in Section 6.3,

Pj = Gj(S1, S2, .., S8), j = 1, 2, .., 8

where Gj is at this point an unknown function. The objective here is to determine Gj such that resulting Pj's will best agree with observed response options in the training data set (in this case the options selected by the survey respondents).

The following two alternative functional forms are examined in the study:

Pj = (Sj) /   , j = 1, 2, .., 8

and

Pj =   /   , j = 1, 2, ..., 8,

where is a parameter whose value is to be determined. By evaluating the performance of these two alternative functional forms using the training data set, it was determined that the latter function produces better likelihood function values (a likelihood function value is computed as the product of the predicted choice probabilities (Pj's) for those response options that were selected by the respondents in the survey). The optimum value of was statistically determined to be 3.135. This value is used in the sensitivity analysis presented later in this section, and also in the micro-simulations for the policy analysis of Section 7.

6.4.4 Model for TDM #2

As noted earlier TDM #2, bike/pedestrian facility improvement, is qualitatively different from the other TDM strategies considered in this study. The survey responses indicate that this measure is effective for a smaller fraction of commuters for whom riding a bicycle or walking is a realistic commuting mode. For these reasons, responses to TDM #2 are modeled separately.

As the distribution of responses indicates (Table 6.4), responses to this scenario are concentrated on a fewer response options. The input-output relationship is simpler here because the modeling effort here is concerned with only one TDM strategy. Considering these factors, decision was made to model responses to TDM #2 using the multinomial logit model, which requires far less time for model development.

Based on the analysis presented in Section 6.3.3, a range of explanatory variables were examined. The final model selected is presented in **Table 6.15**. Responses are grouped into three categories' no change; switch to bicycle or walk; and others. The model's explanatory power is, unfortunately, limited. Although the overall chi-square statistic of 610.4 (df = 9) is highly significant, this is largely due to the uneven distribution of responses. Once the alternative-specific constant terms account for this unevenness, the remaining variations in responses that are explained by the model are small. In fact the chi-square statistic associated with the variations explained by the explanatory variables is 23.3 (df = 7).

Table 6.15: Multinomial Logit Model of Response to TDM #2

	No Coef.	Change t	Bike Coef.	Walk t	Others Coef.	Others t
Household Income (in $10,000)	0.388	1.18				
Female & picks up child during commute	0.147	0.36				
Makes stops during commute	0.134	0.61				
Constant	1.478	3.64				
Commute distance (10 mi.)			-0.547	-3.53		
Age between 19 and 29			0.306	0.77		
Age between 30 and 39			0.510	1.72		
Male			0.465	1.56		
Constant					-0.636	-1.81
N	476		41		65	
L(0) = -640.5, L(C) = -347.0, L(_\f "Symbol" \s 10) = -335.3						

6.4.5 Sensitivity Analysis

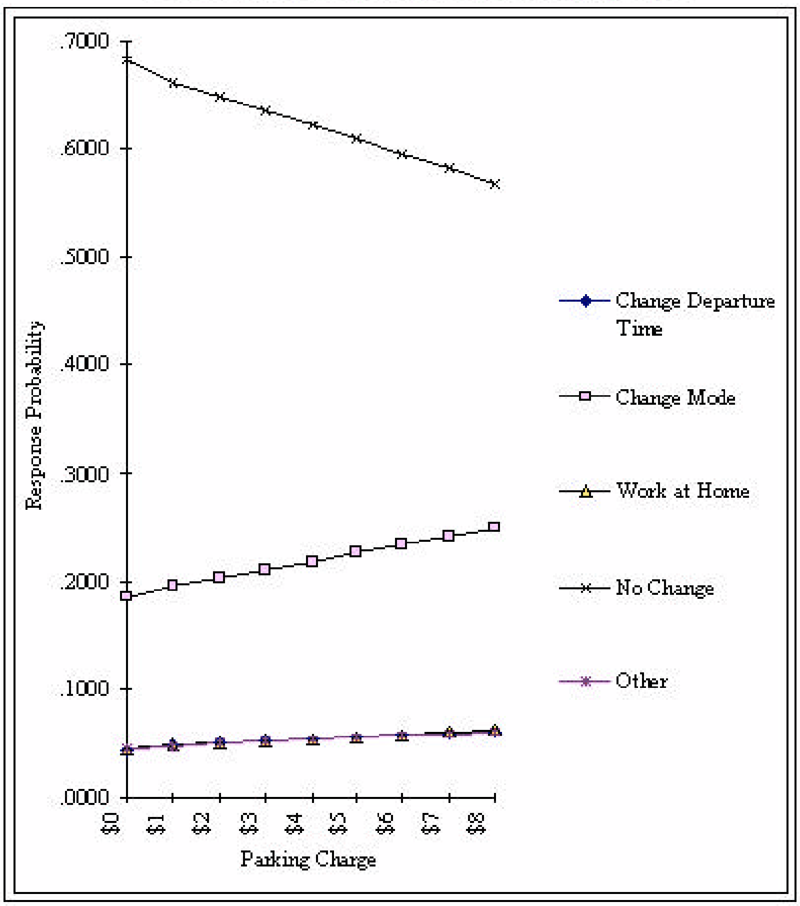
The sensitivity of behavioral responses to TDM measures is examined in this section by conducting a sensitivity analysis. The neural network is applied to the sample respondents of the survey. In the sensitivity analysis, a parameter characterizing a TDM measure is incrementally changed. The analysis is performed as follows: the 36 input variables (see Section 6.4.2) are prepared to represent the characteristics of the respondent, his/her household and travel pattern, as well as the TDM measure; output neuron activation levels are evaluated by the neural network and converted to probabilities; sample-wide averages of response probabilities are computed; and behavioral sensitivity to the TDM measure is assessed in terms of the sample-wide average probabilities of the respective response options, in particular, "No Change."

Parking Pricing (TDM #1)

The level of parking surcharge is varied from $0 (no charge) to $8 per day (the differential pricing between downtown areas and suburbs is not applied in this sensitivity analysis). Figure 6.1 shows averages of response option choice probabilities as calculated by the neural network and the conversion function described above. All respondents, including non-SOV commuters, are included in this analysis as the neural network is specified to include all types of commuters.

At the pricing level of $0, the neural network indicates that on average 68.1% of individuals will make "no change." The probability decreases by 16.6% to 0.568 with a parking charge of $8. Theoretically, one may argue that the probability of "no change" with no parking charge should be 1 as no charge implies no TDM. On the other hand, one may argue that behavioral responses are always probabilistic and cannot have a 100% probability associated with them, and that the neural network is providing probabilities that are associated with the randomness in responses even at the pricing level of $0.

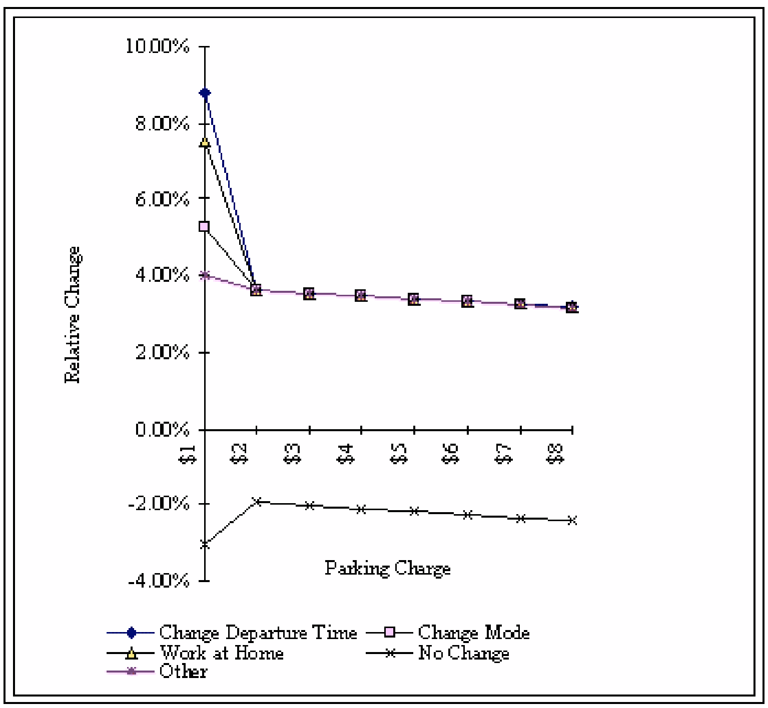
Figure 6.1. Sensitivity of Neural-Network-Based TDM Response Probabilities to Parking Charge Level



Changing commute mode is the second most frequent response next to "no change." The neural network indicates the probability of this option at no parking change to be 0.185 (again, one may take on the view that this probability at no TDM should be 0). This increases by 34.5% to 0.249 at $8. With the charge increasing from $0 to $1, the probability increases from 0.185 to 0.196, a marginal increase of 5.56% in relative terms. The choice probability continues to increase while the relative rate of increase declines as the parking charge increases. The relative increase is 3.28% with the parking change increase from $7 to $8.

Other response options, “change departure time,” “work at home,” and “other,” have similar initial and final probabilities. Their initial probabilities at $0 are 0.0434, 0.0448 and 0.0453, and the final probabilities at $8 are 0.0606, 0.0617 and 0.0601, respectively. The relative increases in choice probabilities that correspond to a charge increase from $0 to $1 are 9.63%, 8.15% and 4.17% for these three response options, respectively (Figure 6.2). Corresponding values for a charge increase from $1 to $2 are 3.76%, 3.75% and 3.75% for the three options respectively. The relative increase become uniform rapidly across the response options. For a change increase from $7 and $8, the relative increase is 3.29% for the three response options.

Figure 6.2. Relative Change in TDM Response Probabilities



Comparing the above neural network results and tabulations of survey responses presented earlier (e.g., Table 6.4) reveals that the results obtained from the neural network runs do not necessarily agree with the distributions obtained from the survey. This is in part due to the fact that different levels of TDM parameters are applied to different respondents in the survey, while in the sensitivity analysis one single parameter value is applied to all respondents at a time. Yet there are cases where critical discrepancies exist. For example, the average probability for “no change” obtained by the neural network with a parking charge of $0 (no TDM), 0.681, is less than the relative frequency of 70%, obtained from the survey for parking charge (TDM #1) with randomized levels of parking charges ranging from $1 to $8. Because the neural network uses for its computation the very sample of respondents which came from the survey, theoretically speaking the neural network result with no charge should not exceed that from the survey for this option of “no change.” Likewise, the neural-network-based probabilities of the response options, “change departure time” and “work at home” at a parking charge of $0, both exceed those obtained from the survey (0.0434 vs. 1% for the former option and 0.0448 vs. 2% for the latter). This of course should not happen from theoretical points of view. These inconsistencies presumably stem from the fact that the neural network used here is formulated for multiple TDM measures (TDM #1, #4, #5 and #6). It is anticipated that this problem will be resolved by developing a neural network which is dedicated for each TDM measure.

6.5 Implementation of AMOS with MWCOG Databases

This section discusses the implementation of AMOS for the MWCOG. First, a brief overview of how various MWCOG databases are used within AMOS is provided. This is followed by a description of the MWCOG survey sub-sample extracted for AMOS implementation.

6.5.1 MWCOG Data File Access

AMOS is being implemented in the MWCOG study area using the MWCOG traffic analysis zone (TAZ) system and zone-to-zone network skim tree travel time matrices by travel mode. AMOS therefore has the level of geographical resolution that equals that of the MWCOG's TAZ system. Network skim data are available for: drive alone or low-occupancy vehicles (SOV), high-occupancy vehicles, public transit with walk access, and public transit with auto access. The travel times for bicycle and walk modes were not contained in the original MWCOG network file; therefore, travel times for these modes were derived based on assumed average travel speeds by these modes. The implementation effort thus utilizes as much spatial and modal information as available from the MWCOG data base. The spatial and temporal resolution of micro-simulation results can be refined in the future by adopting the entire data base available from the 1994 MWCOG survey, and further by generating synthetic households distributed over the study area.

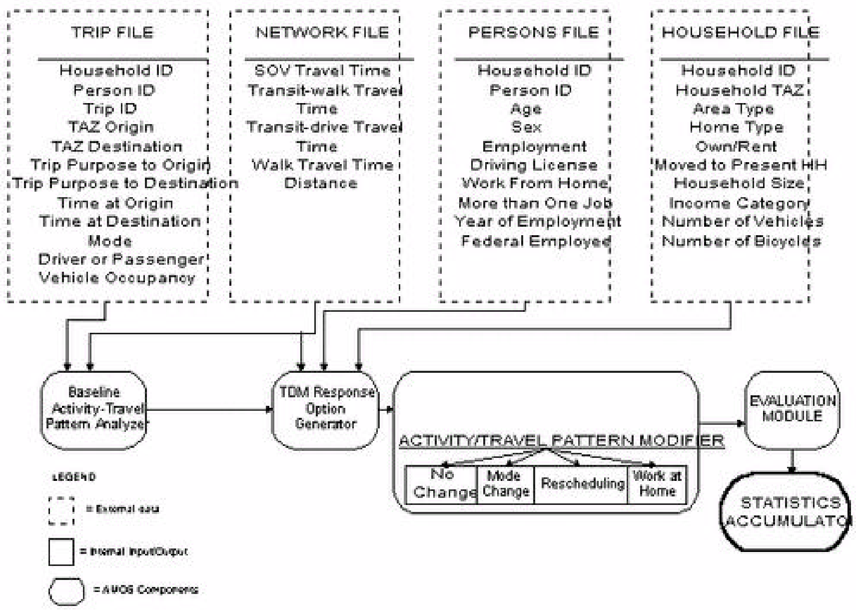
The limited size of the sample of households at 158 and related commute trips at 98 has not allowed a rigorous evaluation of TCMs as anticipated. When combined with the fact that limited resources constrained the scope of the AMOS survey to the collection of data essential in determining the necessary commuter attributes and basic TDM responsiveness, several AMOS research issues remain unresolved. Despite efforts to proceed with the originally intended analyses to fully validate the usefulness of AMOS as a practical tool for public policy analysts and transportation planners, the results have proven to be deficient in some instances. For instance, limited AMOS survey scope and MWCOG sample trip data has:

- Not allowed meaningful measurement of distributive effects across travel market segments and socioeconomic groups.
- Prevented implementation of meaningful analyses of air emissions from personal vehicles.

Four MWCOG data files are used in the implementation. Figure 6.3 indicates the files, their contents, and where in the AMOS prototype the data are used.

These files are accessed in the Baseline Activity-Travel Pattern Analyzer, TDM Response Option Generator, and Activity-Travel Pattern Modifier.

Figure 6.3: MWCOG Data Flow



File Access in Baseline Activity-Travel Pattern Analyzer: Daily trip records from the 1994 MWCOG survey are read person by person in this module. As noted earlier, the Analyzer checks the consistency and completeness of the trip records and determines whether or not the person falls in the target group of analysis. The network file is accessed to supplement, when possible, missing travel time information.

File Access in TDM Response Option Generator: The person and household files are accessed in Generator to prepare the set of input variables that feed into the neural network. Along with this, the Generator accesses the file prepared by the Analyzer that contains indicators of activity-travel pattern characteristics.

File Access in Activity-Travel Pattern Modifier: The trip file and network file are accessed by the Modifier. Travel time information from the network file is used when a mode change takes place, or trips with new origin and destination emerge due to re-sequencing and re-linking of activities ("re-linking" refers to the re-grouping of trips into home-based trip chains while retaining the same sequence of out-of-home activities. Re-sequencing, on the other hand, implies changing the sequence of out-of-home activities). For example, consider the sequence of stops, h - i - h - j - h, where h denotes the home base and i and j are non-home destinations. In this case, destinations i and j are visited in two separate trip chains each containing one stop. Suppose this is re-linked as h - i - j - h. Namely, i and j are now visited in one trip chain which contains two stops. In this case, the trip between i and j is a trip with a new combination of origin and destination.

The modifier goes through the trip records for each sample person and changes their attributes as necessary. With re-sequencing and re-linking, the number of trips itself may change. In any case, the same set of information as in the original MWCOG trip file is available in the modified trip records produced by the modifier as its output.

6.5.2 Initial AMOS Assumptions

In addition to the above procedures, there are many assumptions introduced into the prototype, especially in the Modifier. Many of them are initial simplifying assumptions which will be eventually eliminated as AMOS becomes more complete. Some arise from the fact that AMOS is at this stage conceived as a short-term policy analysis tool. Yet others represent theoretical relationships that are believed to exist in activity-travel behavior. These assumptions are summarized in Table 6.16. In addition, the various constraints summarized in Section 5 are also incorporated into the prototype.

Table 6.16: List of Initial Assumptions in the AMOS Prototype

Initial Assumptions • The activity-travel pattern of one person can be analyzed at a time while ignoring inter-personal interaction. • The activity-travel pattern over one day can be analyzed at a time while ignoring activity scheduling over a longer time span. • Out-of-home activity durations are fixed. • The number of out-of-home stops is fixed (no new activities, or foregone activities). • No intermediate stops along commuter trips can be made when a person rideshares to commutes. • When out-of-home activities engaged before (after) work are re-sequenced, they will be placed before (after) work. • Destination locations are fixed. • HOV travel time equals SOV travel time unless otherwise specified by TDM scenarios.
Coupling Constraints • Work starting and ending times are fixed. • Store houses are 10:00 AM to 9:00 PM for comparison shopping and all day for grocery shopping. • Business hours for offices and businesses are 9:00 AM to 5:00 PM.
Short-Term Policy Analysis • Home and work locations are fixed. • Household vehicle ownership is fixed. • No change in work schedule policies.

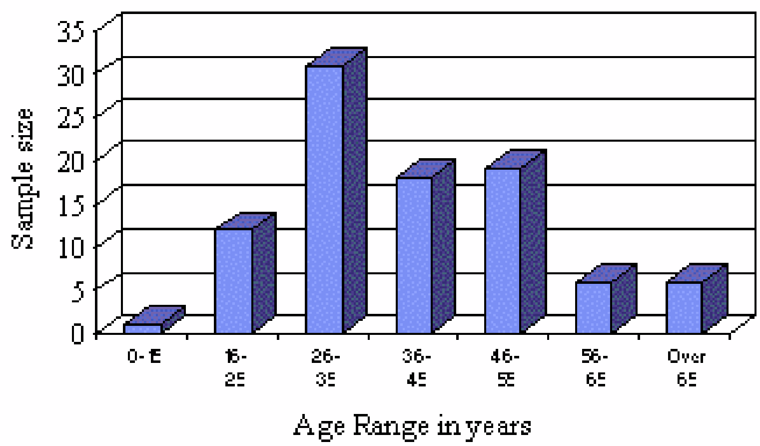
6.5.3 Overview of MWCOG Survey Sample

MWCOG provided the RDC, Inc. research team with a small sample of 89 households from the 1994 MWCOG Household Travel Survey. For these 89 households, trip information is geo-coded by TAZ (transportation analysis zone). In addition, information is available for 191 persons and 686 trips reported by the respondents in the trip diaries.

Detailed household, person, travel, and commute characteristics are provided for this sample in RDC, Inc. (1995b). It was found that 158 persons (of the 191) reported at least one trip on the travel diary day. Of these 158 persons, 98 reported at least one work trip. The sub-sample of 98 commuters was extracted for conducting a TDM response analysis. This is because the current AMOS prototype is applicable only to commuters. As such, a data set for these 98 commuters consisting of 36 variables (each one corresponding to an input node of the neural network) was prepared.

A few person-based descriptive statistics are provided below for the 36 variables used in the neural network analysis. The age distribution of the sample is shown in Figure 6.4.

Figure 6.4
Age Distribution in Sample



Only one person is less than 15 years of age. Five cases had missing age information. As this sample consists of only commuters, the age distribution is as expected. Almost 90% of the sample is drawn from the 16 to 65 year age groups. The average age for the sample is found to be about 38 years. As far as the sex ratio is concerned, the 98 commuters were distributed as 56 males and 42 females.

Figure 6.5 shows the distribution of household vehicle ownership for the 98 commuters. More than 50% of the sample resides in households with 2 vehicles. Only two persons reside in a household that owns no vehicle. An almost equal number of persons reside in households with one and three vehicles. However, it should be noted that there are more households that own one vehicle than those that own three vehicles.

Figure 6.6 shows the distribution of the sample by income category.

Figure 6.5
Distribution of Vehicle Ownership

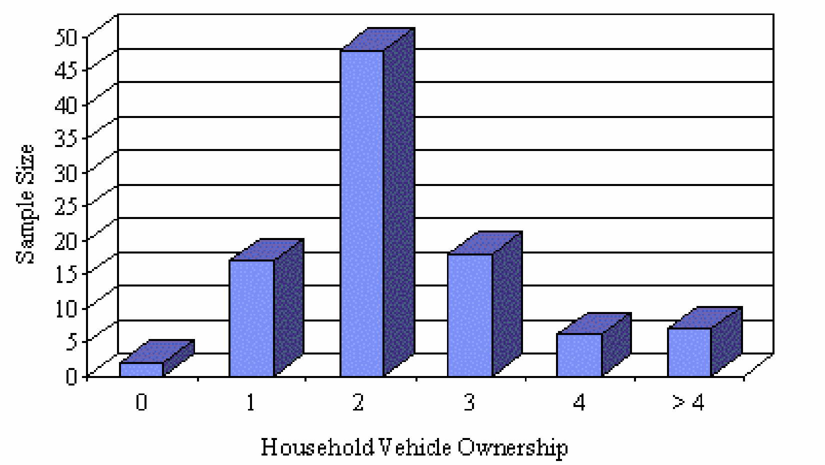
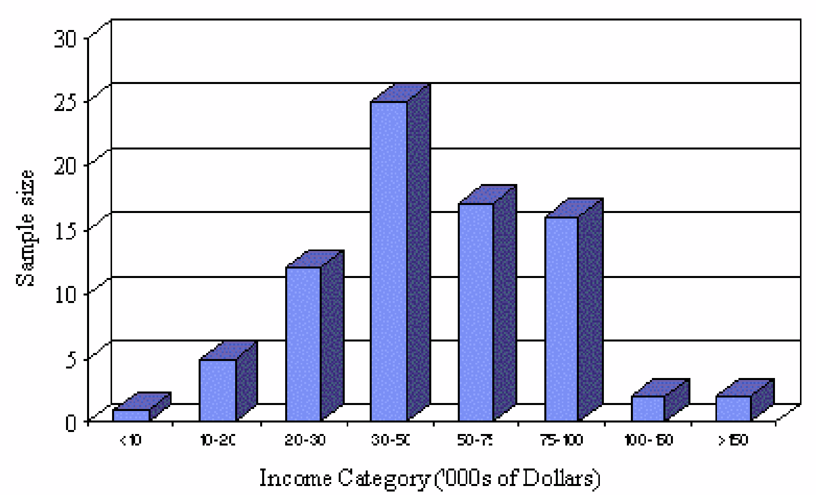
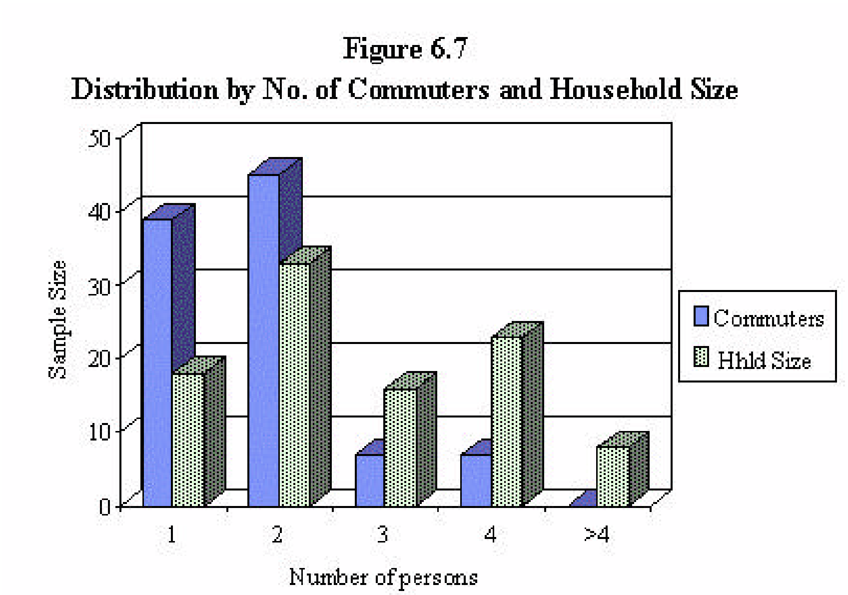


Figure 6.6
Income Distribution in Sample

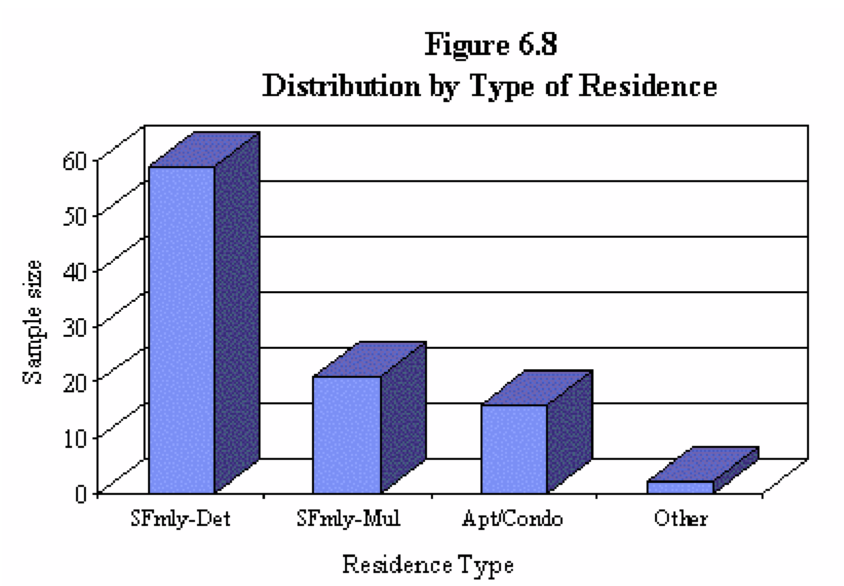


As expected the income variable had a substantial amount of missing information. Eighteen persons reside in households that refused to provide income data. The figure below represents the distribution for the remaining 80 commuters. Only one household (having two persons) reports an income over $150,000.

An examination of the distribution of the number of commuters in the household shows that they are predominantly one- or two-worker households (Figure 6.7). On the other hand, the household size distribution is found to be more uniform signifying the potential presence of young non-commuters in the households.



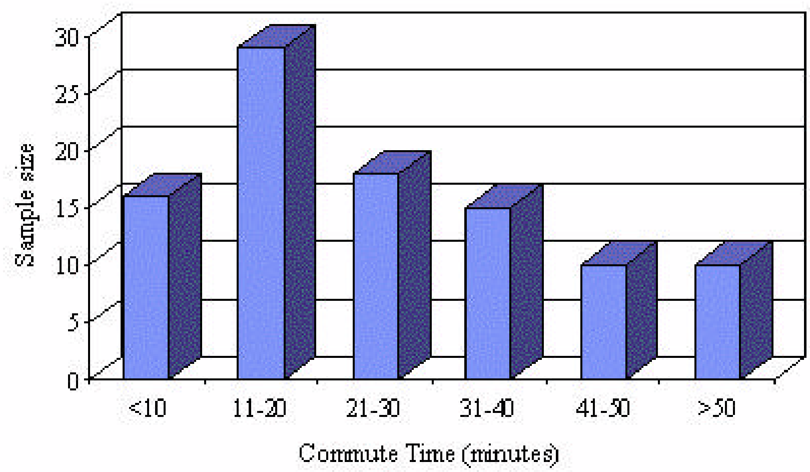
The distribution by type of residence is shown in Figure 6.8.



Of the 98 commuters, 80 live in Single Family dwelling units while 16 reside in apartments or condominiums.

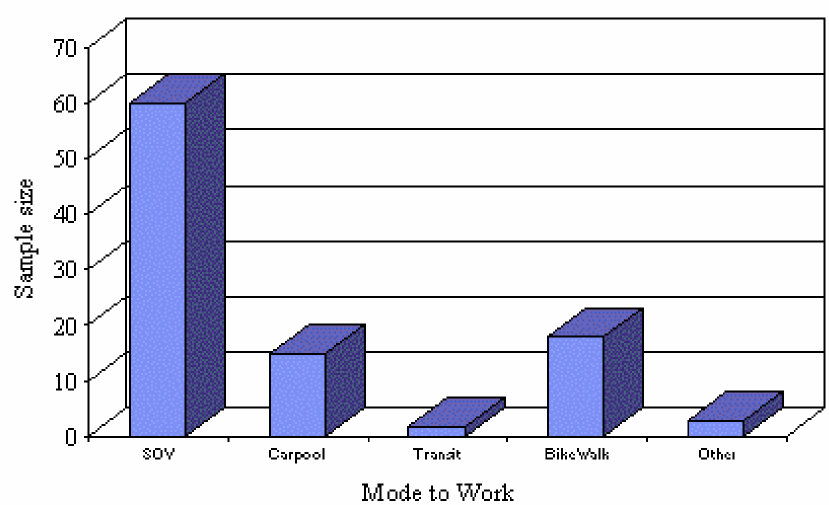
Figure 6.9 shows the distribution of commute times for the 98 commuters. The commute time is measured here by the time taken to reach the work destination. As such, time spent at stops on the way to work may be included for those who trip chain on the journey to work. The mean commute time for the sample is found to be about 30 minutes with the distribution slightly skewed in favor of travel times below the mean value.

Figure 6.9
Distribution of Commute Travel Times



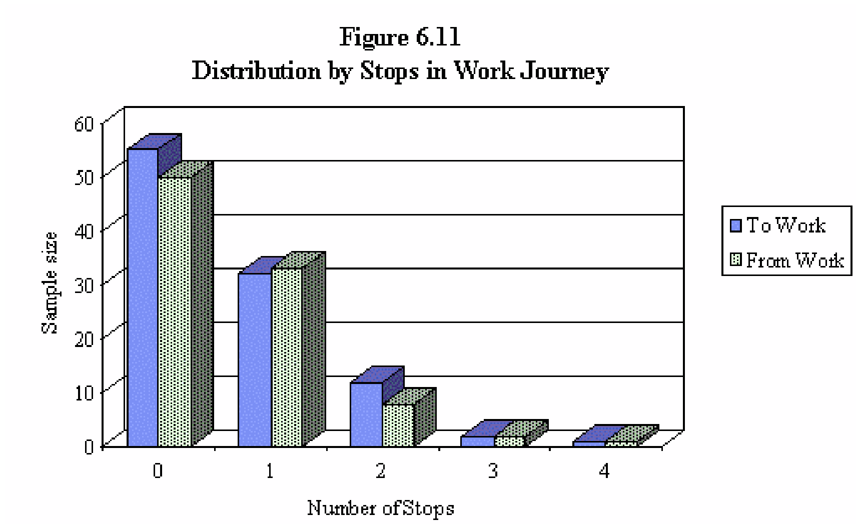
The next figure (Figure 6.10) shows the distribution of the sample by work mode.

Figure 6.10
Distribution by Mode to Work



About 60% of the sample commutes by SOV, while about 15% commutes by car or van pool modes. Interestingly, the percentage of commuters using walk mode at 17% is second only to SOV. In this commuter sample, only 2% of the sample uses any form of transit.

Finally, Figure 6.11 provides an indication of the level of trip chaining that is undertaken as part of the journey to or from work.



The number of persons making stops on the way to work and the number making stops on the way back from work are shown in the figure. The distributions are rather similar; noteworthy is the fact that about 45% of the sample makes at least one stop either on the way to or from work.

This section is intended to provide information regarding the sample of commuters being used to predict TDM response distributions in the MWCOG region. As the MWCOG survey sample size is too small to develop weights, sample-based results will be pivoted off of regional control totals to obtain first-cut region wide estimates of TDM response distributions and TDM impacts.

6.6 Examples of AMOS Application to Commuters in MWCOG Sample

The TDM response option generator provides a first level basic response that an individual may exhibit when a TDM is introduced. However, this response, by itself, does not provide the necessary information for computing changes in travel characteristics such as trip frequencies by mode and purpose, cold and hot starts, travel durations, vehicle miles traveled, etc. In order to obtain such statistics, the basic response option must be used further to deduce secondary and tertiary changes that may be brought about in an individuals' activity-travel pattern.

The activity-travel pattern modifier uses a rule-based algorithm to determine alternative, but feasible activity-travel patterns that an individual may adopt in the new travel environment. In applying AMOS to the MWCOG survey sample, the activity-travel pattern modifier was applied to the 98 commuters' baseline travel patterns to obtain modified activity-travel patterns that may occur as a consequence of the basic response.

This section summarizes results for five representative cases drawn from the sample. For each case, the baseline travel pattern and the basic response option for TDM #5 (Congestion Pricing with Travel Time Reduction), the modified activity-travel pattern, and the changes in travel indicators are discussed.

6.6.1 Baseline Characteristics and TDM Response Option

The five cases chosen for presentation in this report are all commuters who differ in their socio-economic characteristics, trip chaining and stop patterns, and commute lengths. This section first describes baseline characteristics and then provides the basic TDM response option that was produced by the TDM response option generator for each of the five cases. For purposes of this analysis, the AM peak period is defined as 7 am to 9 am and the PM peak period as 4 pm to 6 pm.

<u>Case 1</u>: The baseline travel characteristics of the first case are shown in Table 6.17.

Table 6.17: Baseline Travel Pattern for Case 1
Household ID: 10094324; Person ID: 2

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	1236	1238	Home	Work	8:45	9:01	Walk	Not Appl
2	1238	1236	Work	Home	9:45	10:01	Walk	Not Appl
3	1236	1236	Home	Recreatn	10:15	10:30	Auto	Passenger
4	1236	1246	Recreatn	Shop	13:00	13:15	Auto	Passenger
5	1246	1236	Shop	Home	14:15	14:30	Auto	Passenger
6	1236	1236	Home	Work	17:00	17:10	Walk	Not Appl
7	1236	1236	Work	Home	18:15	18:25	Walk	Not Appl

Summary Characteristics

Age: 79	Auto Psgr Trips:	3	Work Trips:	2	Peak Trips:
Sex: Male	Walk Trips:	4	Home Trips:	3	Total Trips:
Commute Mode: Walk					

Case 1 is a 79 year old male who walks 16 minutes (one-way) to work. He also makes three trips as an auto passenger. Even though some of his trips are in the peak period, he is not affected by the congestion pricing as he does not use the automobile during those periods.

<u>Case 2</u>: The baseline travel characteristics of the second case are shown in Table 6.18. The person is a 33 year old female who uses the bus and walk modes to get to work. She makes four trips during the peak periods, three by walk and one by bus. Congestion pricing does not affect this person also, as she does not commute by automobile.

Table 6.18: Baseline Travel Pattern for Case 2
Household ID: 10168870; Person ID: 1

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	651	652	Home	Chng Mod	6:45	6:55	Bus	Not Appl
2	652	24	Chng Mod	Work	7:25	7:35	Walk	Not Appl
3	24	24	Work	Chng Mod	15:55	16:05	Walk	Not Appl
4	24	164	Chng Mod	Chng Mod	16:15	16:20	Walk	Not Appl
5	164	651	Chng Mod	Home	16:20	16:55	Bus	Not Appl

Summary Characteristics

Age: 33	Auto Psgr Trips:	0	Work Trips:	1	Peak Trip Legs: 4
Sex: Female	Walk Trips:	3	Home Trips:	1	Total Trip Legs: 5
Commute Mode: Bus/Walk					

Case 3: The baseline travel characteristics of the third case are shown in **Table 6.19**.

Table 6.19: Baseline Travel Pattern for Case 3
Household ID: 10004125; Person ID: 2

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	1193	1219	Home	Work	7:00	7:20	Auto	Driver
2	1219	1193	Work	Home	15:42	16:08	Auto	Driver

Summary Characteristics

Age: 51	Auto Drvr Trips:	2	Work Trips:	1	Peak Trips:	2
Sex: Female	Commute Mode:	Auto Driver	Home Trips:	1	Total Trips:	2

Case 3 is a 51 year old female who makes a total of two trips. The morning trip occurs during the AM peak period. The person commutes by driving alone to work and is therefore affected by the congestion pricing.

Case 4: The baseline travel characteristics of the fourth case are shown in Table 6.20. Case 4 is a 38 year old male who also commutes by driving alone to work during the peak periods. He makes three trips as the driver and another three trips as a passenger.

Table 6.20: Baseline Travel Pattern for Case 4
Household ID: 10196665; Person ID: 2

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	217	7	Home	Work	8:18	8:38	Auto	Driver
2	7	217	Work	Home	17:30	17:50	Auto	Driver
3	217	209	Home	Social	18:50	19:00	Auto	Passenger
4	209	217	Social	Home	21:45	21:55	Auto	Passenger
5	217	110	Home	Chld Care	22:00	22:12	Auto	Passenger
6	110	217	Chld Care	Home	22:13	22:25	Auto	Driver

Summary Characteristics

Age: 38	Auto Psgr Trips:	3	Work Trips:	1	Peak Trips:	
Sex: Male	Auto Drvr Trips:	3	Home Trips:	3	Total Trips:	
Commute Mode: Auto Driver						

Case 5: The baseline travel characteristics of the fifth case are shown in Table 6.21. Finally, case 5 pertains to that of a 70 year old male who makes only two trips. This person does not work full time; he commutes by automobile, but during off-peak periods only. As such, this person is not affected by the congestion pricing.

Table 6.21: Baseline Travel Pattern for Case 5
Household ID: 10007300; Person ID: 2

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	338	11	Home	Work	10:00	10:25	Auto	Passenger
2	11	338	Work	Home	13:15	13:45	Auto	Driver

Summary Characteristics

Age: 70	Auto Drvr Trips: 1	Work Trips:	1	Peak Trips:	0
Sex: Male	Auto Psgr Trips: 1	Home Trips:	1	Total Trips:	2
Commute Mode: Auto Driver					

Given these baseline travel characteristics and other input nodes, the TDM response option generator predicted the TDM response option that would be chosen by each of these cases. The results are presented in Table 6.22.

Table 6.22: Predicted TDM Response Option for Five Cases

Case No.	Household ID	Person ID	TDM Response	Remarks
1	10094324	2	No Change	Commute mode is walk.

2	10168870	1	No Change	Commute mode is bus/walk.
3	10004125	2	Change Dep Time	Commute mode is auto driver with work trip in peak period.
4	10196665	2	Change Dep Time	Commute mode is auto driver with work trip in peak period.
5	10007300	2	No Change	Commute mode is auto driver but no trip is in peak period.

Among the five cases, two respond with a change in their travel behavior. Cases 3 and 4 commute by automobile as a driver during the peak period. As congestion pricing is levied during that time, the predicted response of change departure time is consistent with the TDM under investigation. Cases 1 and 2 commute by walk and bus (alternative modes) and are therefore not affected by congestion pricing; similarly case 5, though commuting by automobile, does so during the off-peak period. As such, cases 1, 2, and 5 are predicted to exhibit no change in their travel choices.

6.6.2 Modified Activity-Travel Patterns

After obtaining the basic TDM response, a modified activity-travel pattern that incorporates possible secondary and tertiary changes can be generated. This is done by the activity-travel pattern modifier; the modified patterns are then evaluated using a time-use utility measure to identify the alternative pattern that is most likely to be adopted by the traveler. This section provides a description of the modified travel patterns.

Case 1: The modified travel pattern for the first case is shown in Table 6.23.

Table 6.23: Modified Travel Pattern for Case 1
Household ID: 10094324; Person ID: 2

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	1236	1238	Home	Work	8:45	9:01	Walk	Not Appl
2	1238	1236	Work	Home	9:45	10:01	Walk	Not Appl
3	1236	1236	Home	Recreatn	10:15	10:30	Auto	Passenger
4	1236	1246	Recreatn	Shop	13:00	13:15	Auto	Passenger
5	1246	1236	Shop	Home	14:15	14:30	Auto	Passenger
6	1236	1236	Home	Work	17:00	17:10	Walk	Not Appl
7	1236	1236	Work	Home	18:15	18:25	Walk	Not Appl

Summary Characteristics

Age: 79	Auto Psgr Trips:	3	Work Trips:	2	Peak Trips:	2

Sex: Male	Walk Trips:	4	Home Trips:	3	Total Trips:	7
Commute Mode: Walk						

The modified pattern is consistent with the TDM response option generated for this person. This person shows no change in travel behavior even after the introduction of congestion pricing. This is because he is not affected by the congestion pricing as his commute mode is walk.

Case 2: The modified travel characteristics of the second case are shown in Table 6.24. Congestion pricing does not affect this person also, as she does not commute by automobile. As such, the modified travel pattern provided by the activity-travel pattern modifier is the same as the baseline pattern.

Table 6.24: Modified Travel Pattern for Case 2
Household ID: 10168870; Person ID: 1

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	651	652	Home	ChngMod	6:45	6:55	Bus	Not Appl
2	652	24	Chng Mod	Work	7:25	7:35	Walk	Not Appl
3	24	24	Work	Chng Mod	15:55	16:05	Walk	Not Appl
4	24	164	Chng Mod	Chng Mod	16:15	16:20	Walk	Not Appl
5	164	651	Chng Mod	Home	16:20	16:55	Bus	Not Appl

Summary Characteristics

Age: 33	Auto Psgr Trips:	0	Work Trips:	1	Peak Trips:
Sex: Female	Walk Trips:	3	Home Trips:	1	Total Trips:
Commute Mode: Bus/Walk					

Case 3: The modified travel characteristics of the third case are shown in Table 6.25. In this case, the person is affected by the TDM. As the person travels during the peak periods, the person is subject to congestion pricing. As a result, the activity-travel pattern modifier provided an alternative pattern where the person reaches the work place before the onset of the peak period (7-9 am). As the person now reaches work 20 minutes earlier than in the baseline pattern, the person also leaves work 20 minutes earlier and arrives home 20 minutes earlier. As such, the total in-home time is not changed. Moreover, the PM peak period is also avoided. For this person, while total trip generation remains constant, the peak period trip generation drops from 2 to 0.

Table 6.25: Modified Travel Pattern for Case 3
Household ID: 10004125; Person ID: 2

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger

1	1193	1219	Home	Work	6:40	7:00	Auto	Driver
2	1219	1193	Work	Home	15:22	15:48	Auto	Driver

Summary Characteristics

Age: 51	Auto Drvr Trips:	2	Work Trips:	1	Peak Trips:	
Sex: Female	Commute Mode:	Auto Driver	Home Trips:	1	Total Trips:	2

Case 4: The modified travel characteristics of the fourth case are shown in **Table 6.26**.

Table 6.26: Modified Travel Pattern for Case 4
Household ID: 10196665; Person ID: 2

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
1	217	7	Home	Work	9:00	9:20	Auto	Driver
2	7	217	Work	Home	18:12	18:32	Auto	Driver
3	217	209	Home	Social	19:32	19:42	Auto	Passenger
4	209	217	Social	Home	22:27	22:37	Auto	Passenger
5	217	110	Home	ChldCare	22:42	22:54	Auto	Passenger
6	110	217	ChldCare	Home	22:55	23:07	Auto	Driver

Summary Characteristics

Age: 38	Auto Psgr Trips:	3	Work Trips:	1	Peak Trips:
Sex: Male	Auto Drvr Trips:	3	Home Trips:	3	Total Trips:
Commute Mode: Auto Driver					

In this case, the person made two peak period trips in the baseline travel pattern. The person was subject to congestion pricing both during the AM and PM peak periods. The activity-travel pattern modifier shifted both of these trips to avoid the peak periods. The trip to work in the morning now commences at 9:00 am instead of 8:18 am; and the trip from work commences at 6:12 pm instead of 5:30 pm. Here again, peak period trip generation is completely eliminated as a result of the TDM.

Case 5: The modified travel characteristics of the fifth case are shown in Table 6.27. As this person commutes only during off-peak periods, he is not affected by the congestion pricing. The TDM response option generator predicted that he would not change his behavior; accordingly, the activity-travel pattern modifier provided a modified travel pattern that is the same as the baseline pattern.

Table 6.27: Modified Travel Pattern for Case 5
Household ID: 10007300; Person ID: 2

	Origin	Destn	Origin	Destn	Depart	Arrive		Driver/

Trip No.	TAZ	TAZ	Locn	Locn	Time	Time	Mode	Passenger
1	338	11	Home	Work	10:00	10:25	Auto	Passenger
2	11	338	Work	Home	13:15	13:45	Auto	Driver

Summary Characteristics

Age: 70	Auto Drvr Trips: 1	Work Trips:	1	Peak Trips:	0
Sex: Male	Auto Psgr Trips: 1	Home Trips:	1	Total Trips:	2
Commute Mode: Auto Driver					

This section has provided an illustration of how the activity-travel pattern modifier, in conjunction with the TDM response option generator, provides alternative activity-travel patterns that will be adopted as a result of a change in the travel environment. The modified patterns can be compared against the baseline patterns to obtain measures of changes in travel characteristics. The next section briefly describes such a comparison.

6.6.3 Changes in Travel Characteristics

Finally, the adopted modified activity-travel patterns together with the baseline travel patterns can be used to compute changes in travel indicators as a result of the introduction of a certain TDM. In this section, changes in travel characteristics exhibited by each of the five cases as a result of the modification in travel patterns are computed and presented. The statistics provided in this section may be regarded as one among the primary outputs of AMOS, namely, impacts of TDM measures on travel demand.

For the sample cases considered here, Table 6.28 shows the changes in peak period trip generation by time of day and the aggregate change over all five cases.

Table 6.28. Changes in Travel Characteristics for Five Cases

Case No.	Baseline AM Peak Trips	Modified AM Peak Trips	Baseline PM Peak Trips	Modified PM Peak Trips	Total Baseline Peak Trips	Total Modified Peak Trips	Change in Total Peak Trips
1	1	1	1	1	2	2	0
2	1	1	3	3	4	4	0
3	1	0	1	0	2	0	-2
4	1	0	1	0	2	0	-2
5	0	0	0	0	0	0	0
Total	4	2	6	4	10	6	-4

From the table, it can be seen that AMOS provides both a disaggregate and aggregate level output of TDM impacts. While the baseline patterns included a total of 10 peak period trips for all five cases, the modified patterns included only 6 thus reflecting a 40% reduction in peak period trip generation as a result of congestion pricing. The negative sign in the last column (depicting change) signifies the realization of a decrease in the travel indicator.

Similarly, AMOS can also provide disaggregate and aggregate measures of changes in other travel indicators, such as trip frequencies by purpose, trip frequencies by mode, and vehicle miles traveled, that are brought about by a TDM strategy or TDM.

This section illustrates how AMOS may be applied to individual trip records to predict changes in travel demand that may occur as a result of a TDM strategy. As a first attempt at performing a TDM policy analysis, AMOS was applied to commuters in the 1994 MWCOG household survey sub-sample and estimates of TDM impacts on sample-wide travel demand indicators were obtained. The next section describes the methodology and results obtained from the policy analysis which was aimed at evaluating the potential effectiveness of TDM strategies in the Washington, D.C., metropolitan area.

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Chapter 7: Policy Analysis

As an application example of the AMOS prototype described in Section 6, impacts of alternative TDM measures on commuters' daily travel patterns are evaluated in this section. The data base of this analysis comprises commuters from a set of sample households available from a home interview survey conducted by the MWCOG in 1994 and the MWCOG network travel time data files. As noted in Section 6.5, trip diaries are available for this exercise from only a very small number of households from the MWCOG survey data. Furthermore, only a subset of the available diaries can be used in the analysis because the prototype is specified only for commuters and because of missing information (e.g., household income). Consequently the number of commuter diaries in the data file is extremely limited. Considering potential magnitudes of sampling errors associated with such a small sample, it is decided not to produce any estimates of regional impacts of alternative TDM measures. For the same reason, the results presented in this report should not be considered to represent an assessment of the relative merits of the respective TDM measures. Rather, the results presented in this section should be taken as numerical examples which illustrate how the activity-based policy tool applies to various TDM measures and how it evaluates the impact of each TDM measure on daily travel patterns in their entirety. For the same reason of the limited sample size, no analysis is performed by commuter segments at this stage.

7.1 Evaluation Measures

The examples in Section 6.6 showed in detail how a commuter's daily itinerary is reconstructed based on the TDM response option predicted to be adopted by the commuter. Changes in daily travel patterns are aggregated and sample-wide mean values are obtained for the following:

- total number of trips per day, by mode and by purpose,
- total travel time by mode,
- overall modal split,
- number of peak trips by mode and by purpose,
- peak-period travel time,
- peak-period modal split,
- average number of trips per person,
- fraction of hot starts by time of day, and
- time utility of in-home activities.

7.2. Micro-Simulation Procedure

The AMOS prototype is applied to the subsample of commuters from the MWCOG survey data to illustrate how AMOS can be applied to various TDM measures. The first step of micro-simulation is to specify the parameters that characterize the TDM strategy being analyzed. For TDM #1, #4, #5 and #6, they are:

- surcharge for parking per day (in $, TDM #1)
- parking charge per month, and amount of monthly transportation voucher (in $, TDM #4 and #6)
- congestion charge per mile (in $), and peak travel time reduction (in %, TDM #5 and #6).

Given the values of relevant parameters, the neural network is run, using also a data file that contains variables that define the sample commuters' demographic, socio-economic, and travel characteristics. This neural network run results in a set of activation levels at the output neurons for each sample commuter. These are then converted to probabilistic measures using the method described in Section 6.4.2.

A uniformly distributed random number is then generated to produce a response option for each sample commuter. A random number refers to a number whose values cannot be predetermined, and which assumes a certain value according to a prespecified statistical distribution. A uniformly distributed random number lies between 0 and 1, and assumes any value between 0 and 1 with the same probability. For example, it may take on a value of 0.154 or 0.673 with exactly the same probability. Therefore if you draw uniform random numbers 100 times, then their values will be greater than 0.5 on average 50% of the time. In this application a uniform random number is drawn and a response option is selected as follows.

Suppose the neural network run indicates that a commuter's choice probabilities are as shown in the left column of numbers below. These probabilities are converted to cumulative probabilities as shown on the right column.

Probabilities				

no change		0.71		0.71
change departure time	0.11		0.82	
switch to transit	0.06		0.88	
switch to car/vanpool	0.04		0.92	
switch to bicycle	0.05		0.97	
switch to walk		0.02		0.99
work at home		0.01		1.00

In this illustration, a uniform random number is then drawn and that response option, whose cumulative probability value is larger than, and closest to, the value of the random number. For example, suppose the random number drawn is 0.76. Then "change departure time" will be selected. Likewise a random number value of 0.95 would produce "switch to bicycle" and 0.45 "no change." This procedure will generate response options according to the choice probabilities determined by the neural network.

Given a response option thus selected, the sample commuter's daily itinerary will be adjusted by the modifier.

In this simulation experiment, the evaluation routine comprises a simple rule that when the total travel time increases more than 60 minutes then the modified travel pattern is regarded as infeasible. This is largely to focus the effort on developing more realistic modifier routines.

The simulation is repeated for the same TDM strategy by generating different sets of random numbers, which will probabilistically generate different sets of response options from the sample of commuters. Summary statistics are generated by the reporting routine, and presented in the next section.

7.3 Results of AMOS Prototype Simulation Runs

The TDM strategies and parameter values examined here are summarized as follows:

- TDM #1, parking pricing: parking surcharge of $8.00 per day,
- TDM #4, parking pricing with employer-paid voucher: parking charge of $80 per month and a commuter voucher of $60,
- TDM #5, congestion pricing: congestion charge of $0.50 per mile, travel time reduction by 30%, and
- TDM #6, a synergy combination of TDM #4 and TDM #5: parking charge of $80 per month, commuter voucher of $60, and congestion charge of $0.50 per mile.

In the rest of this section, the baseline case is first examined, then simulation results are reviewed for each of these TDM strategies. A total of 20 simulation runs were performed for each TDM measure.

7.3.1 Baseline Case

The distribution of trip purposes (work vs. non-work), travel mode (auto-driver, auto-passenger, other), mean trip duration by mode, percent of hot starts, average number of trips per person, and in-home time utility are summarized in Table 7.1 for AM peak, PM peak and off-peak periods. Slightly over 60% of the trips are work trips (including trips from work to home), with higher fractions during the morning and afternoon peaks. Overall over three-quarters of the trips are made by auto. The large fraction of trips by "other" mode in the afternoon peak period represents walk trips made in this period by this sample of commuters.

Table 7.1: Baseline Travel Characteristics

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	60.4%	75.7%	68.6%	49.0%
Non-Work	39.6%	24.3%	31.4%	51.0%
TRAVEL MODE				
Auto - Driver	59.6%	76.8%	54.0%	57.1%
Auto - Passenger	17.9%	12.2%	19.6%	21.1%
Other	22.5%	11.0%	27.5%	21.8%
TRIP DURATION (min.)				
Total	23.7	32.5	27.3	17.1
Auto-Driver	23.8	30.8	29.7	30.0
Auto-Passenger	29.1	44.5	47.8	18.3
Other	19.2	31.0	30.8	18.6
HOT STARTS (%)	14.3%	12.5%	1.%	21.6%
PERCENT OF TRIPS	100%	29.3%	21.8%	48.9%
TRIPS PER PERSON	3.33			
IN-HOME TIME UTILITY	2.59			

7.3.2 Parking Pricing (TDM #1)

Results of simulation runs with TDM #1, parking pricing with a surcharge of $8 a day, are summarized in Table 7.2. The most notable change is in modal split. The fraction of auto driver trips decreased from 59.6% in the baseline case to 55.2%, while auto passenger trips increased from 17.9% to 20.5%. Similar shifts can be observed for both peak and off-peak periods.

Table 7.2: AMOS Simulation Results: Parking Pricing (TDM #1)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				

Work	61.2%	73.1%	66.2%	52.3%
Non-Work	38.8%	26.9%	33.8%	47.7%
TRAVEL MODE				
Auto - Driver	55.2%	68.8%	47.3%	51.1%
Auto - Passenger	20.5%	17.2%	16.9%	24.0%
Other	24.3%	14.0%	35.8%	24.9%
TRIP DURATION (min.)				
Total	24.0	33.0	26.4	17.9
Auto-Driver	26.4	34.9	30.8	18.1
Auto-Passenger	26.1	36.4	39.4	17.7
Other	16.8	19.2	14.5	17.6
HOT STARTS (%)	11.1%	13.3%	2.0%	13.9%
PERCENT OF TRIPS	100%	28.0%	22.3%	49.7%
TRIPS PER PERSON	3.43			
IN-HOME TIME UTILITY	2.73			

The overall average trip duration (in min.) shows virtually no changes between the two cases. Importantly, the mean driver trip duration increased from 23.8 min. to 26.4 min. This suggests that long-distance commuters tended to remain solo drivers while shorter distance travelers adopted other options. Mean passenger trip durations, on the other hand, decreased with the TDM. The differences are more noticeable for both morning and afternoon peak periods; the mean morning peak duration decreased from 44.5 min. to 36.4 min., and the afternoon peak duration from 47.8 min. to 39.4 min. It appears that long distance commuters who shared ride tended to switch to other options with the parking pricing.

The distribution of trips across morning peak, afternoon peak and off-peak shows only minor changes. The fraction of morning peak trips decreased slightly from 29.3% to 28.0%, while that of afternoon peak trips increased from 21.8% to 22.3%.

The fraction of total hot starts shows a decrease. This is due to a decrease in the off-peak period. There are slightly more hot starts during the morning and afternoon peak periods, presumably reflecting more frequent linked trips in these periods with the implementation of the TDM measure.

The average number of trips per person increased slightly from 3.33 to 3.43. This reflects activity-based re-linking following a commute mode choice, a measure of the impact of the TDM measure on the quality of life of affected individuals, shows an increase from 2.59 to 2.73. This is probably due to stops at home that were introduced after the above re-linking of activities. This may over-represent the impact of the TDM measure on time utility, and constitutes an area where the current prototype needs improvement.

7.3.3 Parking Pricing and Commuter Voucher (TDM #4)

The results with parking pricing ($80 a month) with employer-supplied commuter voucher (worth also $80 a month) are very similar to those of TDM #2, parking pricing with a surcharge of $8 per day (Table 7.3). The fraction of driver trips is slightly lower (47.3% vs. 45.8%), and that of other trips lower (35.8% vs. 37.5%) during the afternoon peak with TDM #4. Whether these differences are due to the commuter voucher is difficult to determine. Also noticeable is the slight shift in trip timing; the fraction of trips during off-peak periods increased from 49.6% with TDM #1 to 50.6% with TDM #4, and those during morning and afternoon peaks decreased slightly.

Table 7.3: AMOS Simulation Results: Parking Pricing with Employer-Supplied Commuter Voucher (TDM #4)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	60.7%	74.0%	65.0%	51.6%
Non-Work	39.3%	26.0%	35.0%	48.4%
TRAVEL MODE				
Auto - Driver	55.3%	68.8%	45.8%	51.6%
Auto - Passenger	20.0%	16.2%	16.7%	23.5%
Other	24.7%	14.9%	37.5%	24.6%
TRIP DURATION (min.)				
Total	24.1	33.2	26.8	17.9
Auto-Driver	26.3	34.9	31.2	18.3
Auto-Passenger	26.5	38.0	41.5	17.6
Other	17.0	19.8	14.9	17.5
HOT STARTS (%)	10.6%	12.9%	0.8%	13.5%
PERCENT OF TRIPS	100%	27.7%	21.6%	50.7%
TRIPS PER PERSON	3.46			
IN-HOME TIME UTILITY	2.78			

7.3.4 Congestion Pricing (TDM #5) and Synergy Combination (TDM #6)

The results with congestion pricing at a level of $0.50 per mile with 30% reduction in travel time, are again similar to those of the previous two TDM scenarios (Table 7.4). The fraction of auto trips is the highest with this TDM, but no discernible differences exist for the morning peak period. During the afternoon peak period, TDM #6 has the largest fraction of other trips. These differences, however, are probably due to the randomness associated with Monte Carlo simulation, and are unlikely to represent differential effects of these TDM scenarios. The synergy combination Table 7.5 (TDM #6), produced virtually the same results as TDM #5, and very similar results as TDM #4.

Table 7.4: AMOS Simulation Results: Congestion Pricing (TDM #5)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	60.8%	74.0%	66.1%	51.2%
Non-Work	39.2%	26.0%	33.9%	48.8%
TRAVEL MODE				
Auto - Driver	55.8%	68.8%	46.3%	52.7%
Auto - Passenger	19.8%	16.9%	15.7%	23.1%
Other	24.4%	14.3%	38.0%	24.2%
TRIP DURATION (min.)				
Total	23.9	32.8	26.7	17.8
Auto-Driver	25.8	34.4	31.0	17.7
Auto-Passenger	26.7	37.3	43.2	17.7
Other	17.0	19.6	14.7	17.8
HOT STARTS (%)	10.8%	13.0%	1.7%	13.5%
PERCENT OF TRIPS	100%	27.7%	21.8%	50.5%
TRIPS PER PERSON	3.47			
IN-HOME TIME UTILITY	2.77			

Table 7.5: AMOS Simulation Results: Synergy Combination of Parking Pricing and Congestion Pricing (TDM #6)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	60.8%	74.0%	65.0%	51.8%
Non-Work	39.2%	26.0%	35.0%	48.2%
TRAVEL MODE				
Auto - Driver	54.7%	67.5%	45.0%	51.8%
Auto - Passenger	20.1%	16.9%	16.7%	23.4%
Other	25.2%	15.6%	38.3%	24.8%
TRIP DURATION (min.)				
Total	24.1	33.2	26.6	18.1
Auto-Driver	26.7	35.8	31.3	18.7

Auto-Passenger	26.4	37.3	41.5	17.6
Other	16.6	18.0	14.7	17.3
HOT STARTS (%)	10.8%	13.0%	1.7%	13.5%
PERCENT OF TRIPS	100%	27.7%	21.6%	50.7%
TRIPS PER PERSON	3.47			
IN-HOME TIME UTILITY	2.77			

7.3.5 Discussion

The exercise here has shown that AMOS is capable of practically producing travel forecasts while simulating daily travel patterns. It has also demonstrated that the TDM measures considered here do have certain impacts on travel demand. From model development viewpoints, results are very encouraging as they show that activity-based models can be implemented in a metropolitan region and can produce forecasts for policy analysis.

From transportation policy viewpoints the results, however, may seem less encouraging because the effects of the TDM scenarios examined here are small, and because there are no discernible differences among the impacts of the respective TDM scenarios. These results may be simply due to the small sample used in the exercise; the sample to contain a set of commuters in similar travel environments who tended to behave in similar ways. In fact the small fraction of auto trips during the afternoon peak period in the sample is suggestive of such sampling error.

It is also conceivable that the commuters in the sample had very limited alternative commute options and were able to respond within very narrow ranges to whatever TDM scenarios were being implemented. Whether this observation can be generalized or not needs to be determined in the future by the analysis of a full data set.

Another possibility is that the Response Option Generator has not been fine-tuned enough to be able to detect possibly minute differences in commuters' responses to different TDM measures. In particular, the results suggest that a neural network be developed for each TDM measure separately (in the current prototype, the neural network is designed to be able to handle all TDM scenarios examined here). This is another area where the current AMOS prototype can be improved.

The invariance in simulation results across the TDM scenarios may also be due to the fact that destination choice has not been implemented in the current AMOS prototype. In addition, the simplistic evaluation and acceptance rules adopted in the prototype may have resulted in premature search termination for each commuter, possibly leading to the acceptance of the baseline patterns with a higher probability than it should receive.

As noted earlier, this exercise has been made for illustrative purposes and the size of the sample used here, and some of the simplifying assumptions existent in the prototype, warrant neither generalization of the results obtained here nor general assessment of the relative effectiveness of the TDM scenarios examined here.

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Chapter 8: Conclusions and Recommendations

This project represents the first implementation of a full-fledged activity-based model system for transportation planning and policy analysis. Despite the theoretical arguments that warrant their practical applications, activity-based approaches remained within the domain of academia for nearly two decades. The development of AMOS and its implementation in the Washington, D.C., metropolitan area, therefore, represent a significant step forward in transportation planning and policy analysis. The development is especially significant considering the importance of travel demand management in the current planning contexts set forth by the Clean Air Act Amendments and Intermodal Surface Transportation Efficiency Act.

In the project, a micro-simulation model system which produces travel demand forecasts based on principles of activity-based analysis has been constructed and applied to selected set of TDM measures using a sample of trip diaries from the 1994 MWCOG survey. Because of the simplifying assumptions adopted in the current prototype and the small sample used in the TDM evaluation exercise, the results obtained in the study are unfortunately difficult to validate or generalize. Despite these limitations, the study is nonetheless believed to have contributed significantly to the field of transportation planning by demonstrating that activity-based approaches are potential methods for demand forecasting and policy analysis. The achievements of this effort can be summarized as follows.

- The project has demonstrated that the activity-based model system can be implemented in a metropolitan area using data available from a typical MPO, such as trip diary data, network travel time data, and land-use inventory data (the only additional data needed for AMOS implementation are small to medium-scale stated-preference survey results from the area which are used to customize a component of AMOS to the area residents' responsiveness to TDM measures).

- The TDM evaluation exercise has offered evidence that travel demand forecasts can be developed while treating the daily travel pattern in its entirety, without breaking it into individual trips and thereby compromising the interdependencies and continuities that exist across the series of trips made by a traveler.

- This also implies that practical capabilities have been developed to assess TDM impacts more cohesively while accounting for secondary and tertiary changes in a traveler's daily travel pattern that are brought about as results of a primary change in response to a TDM measure (for example, if an SOV commuter, who stops on the way to and from work to drop off and pick up a child at day-care, switches to carpooling in response to congestion pricing (primary change), then new, two round-trip SOV trips may be made between the home and day-care to drop off and pick up the child).

- The AMOS survey designed in this project has shown that the stated-preference questions developed in this project have produced credible results (except for the case of a particular synergy combination of two TDM measures), and that the survey can be applied to obtain information vital for the assessment of potential effectiveness of alternative TDM measures.

- The AMOS survey data produced rich statistical results that have revealed the characteristics of responses commuters would show when faced with TDM measures; for example, female commuters who make stops on the way to or from work tend not change their travel in response to a TDM measure.

The numerical examples using the sample of MWCOG trip diary data have shown the AMOS prototype is capable of producing aggregate statistics of travel demand at levels that are comparable to the conventional trip-based model systems (except that the current version of AMOS operate with static zone-to-zone travel time matrices rather than internally conducting network assignment).

It is worthy to note that the development of the AMOS prototype incorporates a number of theoretical concepts, such as "adaptation behavior" and "time-space constraints," into a practical model system which fully utilizes the data that are maintained by a typical MPO.

It is also worthy to note that the survey conducted in this project collected a wide range of information that was needed to develop the prototype. In the future when AMOS is more fully developed, then the contents of the survey can be substantially reduced. Therefore,

- In the future, AMOS can be implemented in a metropolitan area using the data bases maintained by the area MPO and a low-cost, small-sample survey that can be readily administered. Furthermore, this survey is not required if customizing a component of AMOS to the area to reflect its residents' TDM responsiveness, is not desired.

It is noted that fully developing AMOS, however, will require a significant amount of data. This is further discussed below as one of the recommendations.

It is believed that AMOS will be in the near future a useful short-term policy analysis tool for MPOs that seek the most effective set of transportation policy measures. At this point, however, the AMOS prototype contains several areas that need improvement. For example, as noted in Section 7, a component, the Response Option Generator, may not have been fine-tuned enough to be able to detect possible differences in commuters' responses to different TDM measures, and the search termination rule adopted is overly simplistic Considerations of the needs for new transportation policy tools and the current state of development of AMOS have led to the following recommendations.

The recommendations following suggest possible courses of action to support the expeditious transfer of AMOS to MPOs and other interested parties, recognize the continuing programmatic obligations imposed on MPOs as defined by federal law and implementing regulations, and ensure that AMOS becomes a valuable tool for a large number of diverse MPOs and other stakeholder organizations:

Enhance AMOS Performance. This category is defined to comprise all actions which enhance the productivity of the *existing* version of AMOS:

- *Quality and Accuracy* -- Focus on refinement and replacement of *current* analytical techniques used in AMOS including, but not limited to re-training neural networks, incorporating destination choice components, and enhancing the realism of each model development. These actions are short-term, since they are improvements in current methodology relying for the part on current data.

- *Cost Reduction and Control Measures* -- The value to achieving acceptability of AMOS by MPOs is enormous in an era of either limited or declining budgets. One large cost element in implementing AMOS is the activity-based survey data that it requires. It is believed that there are approaches which require investigation including, but not limited to, regional transfers of existing survey data, and synthetic households.

- *Data Collection* -- Cost reduction at MPO levels can be achieved by developing a robust model system that can be implemented to any locale with minimum modifications and therefore with less implementation costs. The AMOS survey in the MWCOG survey area contained a substantial amount of questions that probed into commuters' activity scheduling, work schedules, and various types of constraints governing their travel behavior. Development of a generalized model system calls for staging an extensive data collection effort in multiple urban areas. Furthermore, the AMOS survey in the MWCOG area was limited to commuters; no information is obtained about the travel behavior and TDM adaptation behavior by non-commuters. It is believed that such data collection efforts will be most effective when they are tied to the implementation of TDM measures and take on a form of before-and-after panel study.

Increase AMOS Applicability. This category is defined to comprise all actions which increase the applicability (or scope) of AMOS, and could easily necessitate the creation of a new version. One clear way to expedite the transfer of AMOS to interested parties is to modify AMOS so that it is applicable to a greater variety of MPO situations, thereby increasing the number of MPOs who would find it to be a useful tool:

- *Case Studies* **--** This report marks the completion of the testing of the AMOS prototype for the metropolitan Washington, D.C., area. It is recognized that the extent of AMOS "acceptability" depends in part on the number and character of demonstrations. It is recommended that three or more case studies be conducted in metropolitan areas that are widely different in geographical location and other attributes.

- *Adaptability* -- It is suggested that efforts be made to increase the scope of AMOS to address a greater number of policy issues including more TDM measures, and a more rigorous treatment of land-use, air quality, energy use, advanced transportation technologies, and alternative transportation fuels. In this manner AMOS becomes more adaptable to a wide variety of MPO situations.

Improve AMOS Usability. This category is defined to comprise all actions which enhance the usability of the *existing* version of AMOS. The following represent areas for improving the usability of AMOS:

- *User Interface Enhancements* -- For the immediate future, it is suggested that substantive value could be achieved in ensuring AMOS is user-friendly, including development of: Enhanced Graphic User Interface (GUI), and computer files comprising a "User's Manual" and a "User's Tutorial." Field research is important to determine what is needed by and helpful to MPO and other key end-users.

- *Technical Support* -- Opportunities exist to provide on-going AMOS technical support and related information to MPOs and other parties-of-interest through Internet. These services would provide immediate answers to questions like `What is AMOS?', `Who can use it?', `How is it accessed?' and other basic information. The technical support to AMOS *users* should be provided to quickly respond and help solve situational and generic problems in its use.

Disseminate AMOS Information. This category is defined to comprise all actions which disseminate information on AMOS to MPO and other potential users.

- *MPO Dissemination* -- There are several kinds of activities which would support the objective of familiarizing representatives of MPO and other organizations (e.g., environmental groups) with AMOS including, but not limited to, regional short courses, individual briefings, and Internet access.

- *General Communications* -- There are activities essential to making the transportation stakeholders aware of AMOS. These activities include, but are not limited to, preparation of selected publications such as AMOS pamphlets, manuals, conference papers, and targeted presentations and briefings.

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Appendix A: Selection of TCMs

A.1 Overview

A key step in the study was the selection of the Transportation Control Measures (TCMs) that were used in the implementation of AMOS for the MWCOG regions. The specific TCMs selected dictated the data requirements for the AMOS survey (See Section 6) and some design elements of the AMOS prototype. The effectiveness of the TCM selection process was crucial, since it had to address factors that influence travel behavior; ensure reasonable inclusion of these factors in the selection of candidate

TCMs; ensure that the AMOS survey strategy collected data essential in an acceptable testing of the selected TCMs, and allowed reasonable specification of the evaluation measures for the TCMs.

Twenty eight TCMs were selected for detailed evaluation in this research project by representatives of FHWA, the U.S. EPA, and MWCOG's Travel Forecasting and Traffic Mitigation Subcommittees. Based on a ranking of the 28 TCM candidates, six TCMs each were then selected for inclusion in this AMOS research project.

TCM Set 1:
- Regional voucher program
- Congestion pricing
- Combination of regional voucher program and congestion pricing

TCM Set 2:
- Bicycle/pedestrian measures
- Employee parking space tax
- Combination of bicycle/pedestrian measures and parking space tax.

The research objective of this project is to prototype and demonstrate the effectiveness of an activity-based approach to travel demand modeling in a real-world context. Hence, the TCMs to be evaluated in this research project were selected to meet either of the following criteria:

1. The measures can be analyzed with both four-step and activity-based modeling approaches, but the activity-based approach performs significantly better.
2. The measures can be analyzed poorly or not at all with the four-step approach, but can be analyzed well with the activity-based approach.

Exhibit 1 compares and contrasts the analysis capabilities of the four-step and activity-based approaches for the TCMs that we propose to analyze. The table reflects the following practice in the four-step process, which is typical of that used in the U.S. Trip generation depends on population and land-use activity only, and is insensitive to price. Trip distribution depends on estimated trip generation and highway travel times only. Mode choice can include characteristics of the traveler in addition to modal costs and levels of service. Trip timing is simulated by estimating the time distribution of trips by trip type, either from national or regional averages, or from a regional household travel survey. Non-motorized modes are usually ignored entirely, although some agencies have models that do a "pre-mode split" to separate out bicycle and pedestrian trips prior to trip distribution and mode choice; these pre-mode split models typically depend only on socioeconomic characteristics of the traveler, and are insensitive to modal attributes.

Exhibit 1: Comparison of Analysis Capabilities: Four-Step and Activity-Based Approaches

TCM Measure	Four-Step	Activity-Based
1. Set 1		

1.1 Regional voucher program	Modeled through effects on mode choice as addition to auto travel cost. Ignores effects on trip generation, distribution, timing.	Captures effects on trip generation, trip timing, distribution, mode choice.
1.2 Congestion pricing	Same as 1.1.	Same as 1.1.
1.3 Combination of regional voucher and congestion pricing	Same as 1.1. Assumes policies are additive; cannot estimate interaction effects.	Same as 1.1. Can capture interaction effects between policies.
2. Set 2		
2.1 Bicycle/pedestrian measures	Bicycle and pedestrian modes typically ignored by most four-step modeling approaches.	Same as 1.1.
2.2 Employee parking space tax	Modeled through effects on mode choice as addition to auto travel cost. Ignores effects on trip generation, distribution, timing.	Same as 1.1.
2.3 Bicycle/pedestrian measures and employee parking space tax	Can only look at effects of parking space tax; ignores effects of bicycle/pedestrian measures. Cannot capture interaction effects.	Same as 1.3.

The following factors were considered critical during the comparison between the four-step and activity-based approaches:

- Travel costs enter the four-step process only through the mode choice model. The activity-based model can estimate the effects of travel costs on all aspects of travel, including trip generation, trip distribution, and trip timing.

- Bicycle and pedestrian modes are usually ignored within the four-step process. Four-step approaches that include these modes are insensitive either to level of service characteristics of these modes or cannot reflect attributes such as safety and security associated with separated bikeways and secure bike parking facilities.

The four-step process assumes an additive effect of combined measures. The activity-based approach can account for interaction effects.

A.2 Discussion of the Individual TCM Options

The selection of the 6 TCMs was made based on an assessment of the 28 candidate TCMs as related to implementation feasibility using a stated-preference survey and consistency with objectives of this research project. The 28 candidate TCMs fall into 6 basic categories which are discussed in the following sections. Exhibit 2 summarizes the 28 candidate TCMs their respective ranking.

A.2.1 VMT or Gas Tax

The gas tax measure has a short-term versus a long-term response consisting of reducing VMT via shorter trips and changing modes in the former case, while individuals may switch to more fuel efficient vehicles in the latter case. A vehicle choice model is required to address the vehicle switching issues, however this is beyond the scope of the current project.

While neither measure targets specific uses of the vehicle, which are issues that we hope to explore in AMOS' development, both measures are feasible to assess within the current survey effort given the limitation described above for gas taxes. Should these measures be selected, setting the fees to recover local general funds spent on road construction (i.e., shortfalls of revenues from local gas taxes and user fees) is complicated by the fact that local property taxes are transferred to state and federal road projects. This suggests that a more complete analysis would be required to determine the net subsidy of all road construction funded by local government. Instead of entering into this more complex analysis at this point, we suggest that a range of fee values is selected for exploring the sensitivity of vehicle use to the cost per mile.

A.2.2 Parking Pricing

This topic covers a combination of policies that include cash-out subsidy, regional voucher programs, and employee parking space taxes.

Cash-out Policy

A cash-out policy requires an employer to calculate the subsidy given to employees who park at the work place for free or at reduced rates. The employer must subsidize transit or HOV users at the same rate. This policy presents several problems for analysis. It is difficult to estimate out-of-pocket costs that an employer subsidizes based on the full cost of a parking space at the place of employment, less the amount that the employer pays. This subsidy can be estimated only on an aggregate basis irrespective of the type of parking structure and other anomalies that affect parking prices in any given locale. From the point of view of the survey, it is not possible to determine the amount of the parking subsidy prior to the time of the survey. Hence, we will not test a cash-out policy.

Regional Voucher Program

A regional voucher program requires that employers give employees a fixed travel allowance (e.g., $60 per month); SOV users who park at the work place are charged an amount equal to the travel allowance. SOV users would see no net change in their benefits; HOV users would gain in an amount that depended on vehicle occupancy, assuming that parking costs were shared; others would receive the full travel allowance.

This policy is much easier to collect information on because it is not necessary to estimate the amount of the current effective subsidy. Hence, it is the most likely candidate TCM measure for inclusion in the project.

This policy has the disadvantage that it may not appear sensible to those who currently park at the work place: the employer is simultaneously giving them a travel allowance and taking it away. A possible variation on this policy is to charge an amount for parking that is *higher* than the travel allowance, requiring those who park to pay something. The amount to be charged would depend on the area within the region (e.g., Washington CBD, outer suburbs, etc.). For areas where there is currently no parking charge, the required payment would be in the form of a parking space tax.

This variation is conceptually as straightforward to include in the model as is the regular regional voucher program. It would, however, require some extra effort in survey design because the amount of the subsidy, and the amount charged for parking, would have to depend on the location of the work place.

Employee Parking Space Tax

If the Employee Parking Space Tax is framed as a pass-through fee to employees, then it represents another variation on the cash-out subsidy or regional voucher program, except that it would appear as a disincentive; as discussed above. As such, there is no reason that it cannot be addressed in the SP survey.

A.2.3 Congestion Pricing

This measure provides the opportunity to develop a central feature that the activity-time framework offers, and is feasible within the current scope of work. Traveler response to peak period pricing that can be captured include changing departure times, changing sequence of activities and trips, changing activities and trips, and changing modes. We believe that for simplicity of analysis (and to conform with economic rationality), congestion pricing should be assumed to apply to *all* roadways, not just limited-access facilities. This is within the scope of current technology; for example, the DRIVE program in Europe includes a demonstration of technology for collecting road user charges.

A.2.4 Region-Wide HOV Network

As currently proposed by the Washington COG, this measure would entail building a system of HOV lanes throughout the region. Analyzing this measure would require that we estimate for each traveler the portion of each trip that is currently on a highway that would be included in the HOV network. While it is possible to develop a method that provides travel times by origin-destination pairs matched for the HOV network, this would require a commitment of an estimated two to three person weeks on the part of COG staff or an alternate to develop. It would also be necessary to determine whether a traveler who currently does not use these highways would be diverted to use the HOV facilities, which is at the frontier of current research in route choice and beyond the current state of practice in network modeling. Hence, this measure would be conceptually difficult to collect stated-preference data on and model. We do not propose to include it in the list of TCMs for implementation.

A.2.5 Bicycle/Pedestrian Measures

Bicycle/Pedestrian Measures can be framed at two levels, only one of which is feasible to analyze within the current scope of effort. A number of key factors can contribute to a bicycle/pedestrian strategy including: (1) a safe and continuous network of bicycle and pedestrian pathways; (2) safe parking at transit and metro stations, as well as park and ride lots; (3) amenities to facilitate the use of these modes such as showers at the place of work; and (4) urban redesign factors (e.g., high density development, retail center development, traffic calming). The first three factors can be combined into a "bicycle/pedestrian" scenario that can be credibly explored using stated-preference (SP) questions within the current scope of effort. The development of a "bicycle/pedestrian" capability into the current research effort would capitalize on the capabilities of AMOS that are largely unmet by other modeling approaches.

It seems to us that whether cycling is a practical thing to do is rather easy for people to judge and there will not be too many people in the gray zone. The SP approach would consist of describing the scenario to the interviewee and asking questions like, "Would you consider riding to the rail station, then taking the rail to work?". But we want to add that practically nobody used the bicycle as a feeder mode to rail 20 years ago in Japan; now there are more bicycles around every rail station than there are parking spaces. Who knows whether the same change won't take place in the US before too long?

Extending the bicycle/pedestrian scenario to include urban redesign implies a departure from current conditions that strains the validity of the SP approach. It constitutes an additional "urban redesign" scenario that requires a complete evaluation in and of itself. Presenting a land-use scenario in a stated-preference (SP) format pushes the edge of making the questions as "real" as possible to the interviewee. The SP method depends on the customization of questions to real-world conditions (i.e., the "realness") for the validity of its results. There are tow different approaches to achieving this. The first consists of designing detailed pair-wise trade-offs between key site design criteria and presenting these choices in graphical form to the interviewee. Unfortunately, the cost of this type of customized graphics approach is prohibitive within the scope of the current survey budget. The second approach to modeling a complex land-use scenario would be to build AMOS using actual micro-level land-use data. While Montgomery County does have this type of data, the project would be required to implement AMOS at two different levels of aggregation, i.e., one for Montgomery County and another for the MWCOG regions in their entirety. Again, the scope of the existing budget cannot bear this expense.

Exhibit 2: Detailed Assessment of MWCOG Proposed TCMs

TCMs	Source	4 Step	Amos	Data Sources	Segment	Synergies	Rank
Pricing Measures							
Gas Tax Increase: $.25/gal for 10	COG 12	1	4	HH survey	4	A-5, B,	4

years (M-10), auto insurance						C, & D	
VMT Tax: $.05/mi for > 10,000 mi/credit LEVs (M-15)	COG 14						
VDRPT 1	1	4	HH survey	4	A-5, B, C, & D	4	
Pollution Fee: $500/yr/gas vehicle (M-9)	VDRPT 1	0	4	HH survey	4	A-5, B, C, & D	4
Regional Voucher Program: $60/mo to all employees & $60/mo parking charge (M-42)	VDRPT 2	0	4	HH survey	3	A-5, C, D	5
Transit Incentives: $1/trip or ½ fare Metro feeders (M-8,14)	VDRPT 5	3	5	HH survey mode choice data	3	A, B, C, D	3
Congestion Pricing on LOV: $.20/mi < 3 occupants (M-11)	FED	1*	5*	HH survey	4	D, esp D-2	5
B. Parking Measures							
1. Build Park-n-Ride Lots (M-39)	COG 1 VDRPT 6	0	3	HH survey	4	A-5	2
2. Cash-out Subsidy for Transit/HOV: match subsidy for employer parking benefits to HOV/transit users (M-7)	EPA/COG	2	5	HH survey	3	A, C, D	5
3. Employee Parking Space Tax: suburb-$14/mo,$25/mo-metro (M-12,13)	EPA	2	5	HH survey	3	C, D	4
C. Bike/Ped Scenario							
1 Bicycle Element of Long Range Plan (M-37): to be specified	COG 6 VDRPT 4			HH survey			
1 Bicycle Racks & Lockers at All Transit Stations (M-29)	COG 7	0	3	HH survey	2	A, B, D & E	5
1 Pedestrian Facilities Near Rail Stations: within 1 mile (M-28)	COG 8	0	3	HH survey	2	A, B, D & E	5
1 Bike Incentives: cash-out or subsidy for bike-related fees	COG 23/ WABA	0	3	HH survey	1	A, B, D & E	2
1 Bike Employee Trip Reduction Programs	COG 24/ WABA	1	3	HH survey	2	A, B, D & E	4

1 Bike Parking at Public Facilities	COG 26/ WABA	0	3	HH survey	1	A, B, D & E	5
Scenario Background: maps & traffic engineering for bikes	COG 21 & 28/WABA	0	1	HH survey	3	A, B, D & E	1
Scenario Background: site planning & land-use measures	EDF/						
WABA	0	3	HH survey	4	A, B, D & E	1	
ETR/ECO/Telecommute							
Trip Reduction Incentives Program (ETR)	COG 4 VDRPT 3	0	5	HH survey	4	A & B	
Revised Employee Commute Options (ECO): support alternatives to SOV, alternative work schedules, incentives	COG 5 VDRPT 3	0	5	HH survey	4	A & B	4
Integrated Ridesharing (M-47):							
- ride finders							
- guaranteed ride home	COG 11	1					
1	4						
5	HH survey	4	A & B	3			
4							
Financial Incentives for Telecommuting Program: for employer programs (M-46)	COG 19 VDRPT 7	0	5	HH survey	3	A & B	3
Telecommuting Centers in Outlying Areas (M-58)	COG 20 VDRPT 7	0	5	HH survey	3	A & B	2
Land-Use Measures							
to be specified		0	3	HH survey Land-use data	5	A, B, C, D	0
Network-based Measures							
Highway Ramp Metering (M-31)	COG 4	2	3				
Increase Frequency of Existing Transit Service (M-25)	COG 5	3	5	HH survey mode choice data			46

Increase Frequency of Commuter Rail Service (M-26)	COG 6	3	5	HH survey mode choice data			4
Timed Transfer with Extensive Suburban Coverage (M-27)	COG 7	3	4	HH survey mode choice data			4
Speed Limit Adherence (M-24)	COG 9						
Flashing Yellow Signals (M-30)	COG 10	0	0				
Control Extended Idling (M-56)	COG 13						
Marketing &Outreach							
Bike Marketing, Outreach, and Education Programs	COG 22	0	2	HH survey			1
Bike Site Planning Programs for Developers	COG 25	0	3	HH survey			1
Bike Public Participation and Planning Programs	COG 27	0	1	HH survey			1

Notes: (1) SCALE: 1 to 5 indicates lowest to highest, as follows:

(a) *4 step and AMOS*: ability to evaluate the impacts of the TCM within either model,
(b) *Segment*: preliminary estimate of the relative size of the market segment impacted by the TCM,
(c) *Synergies*: cross-references the TCMs in the matrix that this TCM has potential synergies with,
(d) *Rank*: overall assessment of the value of evaluating this TCM within the current scope of work.
(2) Sources refer to documents provided by Virginia Department of Rail and Public Transit (VDRPT) on behalf of the Washington COG, the Washington Area Bicycling Association (WABA), the Environmental Defense Fund (EDF), and the Washington COG (COG).
(3) An asterisk (*) indicates that a complete analysis depends relatively more predominantly on network assignment.

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Appendix B: AMOS Survey Instrument

Appendix B is not available at this time.

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Appendix C: AMOS Survey Databases

PART 1: DEMOGRAPHICS AND STATED PREFERENCES
FILENAME: AMOSVER1.DAT
Number of Cases = 656

This data file contains information on person and household demographics as well as the stated responses of individuals to various TDM scenarios. This file was created by combining the following raw data files provided to RDC, Inc. by Strategic Consulting Research, Inc., the contracting firm that administered the survey and assembled the data bases:

AMOS1.XLS
AMOS2.XLS
AMOS3.XLS
PARK.XLS
CODES.XLS
TCM1.XLS
TCM2.XLS
TCM3.XLS
TCM4.XLS
TCM5.XLS
TCM6.XLS

The file format with variable definitions and codes is provided first, followed by general notes and descriptions of derived variables (not saved in the original data bases) if any.

VARIABLE DESCRIPTIONS

Variable No. Name	Variable Definition	Question in AMOS CATI Instrument
1 HHID	Household ID Code	
2 COMMUTER	No of persons in hhld who commute at least once per week	CATI-1:Q3
3 RES_TYPE	Type of Residence	CATI-1:Q15
4 TENURE	Number of years at current address	CATI-1:Q16
5 OWNRENT	Own or rent home?	CATI-1:Q17
6 HHLDSIZE	Household size	CATI-1:Q18
7 GT5YRS	No of persons greater than 5 years of age	CATI-1:Q19
8 NVEHICLE	No of vehicles owned, leased, etc.	CATI-1:Q21
9 NBICYCLE	No of bicycles in household	CATI-1:Q26
10 MARKET_D	Distance to nearest market	CATI-1:Q27

11 MARKET_U	Units of distance to market	CATI-1:Q28
12 BUSDIST	Distance to nearest bus stop	CATI-1:Q29
13 BUSUNIT	Units of measurement (miles/blocks)	CATI-1:Q30
14 METRDIST	Distance to nearest metro/rail stop	CATI-1:Q31
15 METRUNIT	Units of measurement (miles/blocks)	CATI-1:Q32
16 PARKDIST	Distance to nearest park	CATI-1:Q33
17 PARKUNIT	Units of distance to nearest park	CATI-1:Q34
18 SIDEWALK	Are there sidewalks near home?	CATI-1:Q35
19 BIKEPATH	Are there bikepaths near home?	CATI-1:Q36
20 INCOME	Household Income	CATI-1:Q37
21 PRKCHRG	Parking cost per month	CATI-1:Q88
22 FREEPAID	Employer paid or free parking	CATI-1:Q90
23 T_ACCESS	Transit access mode	CATI-1:Q91
24 T_EGRESS	Transit egress mode	CATI-1:Q92
25 AGECATEG	Age category of respondent	CATI-1:Q38
26 GENDER	Gender of respondent	CATI-1:Q39
27 LICENSE	Is respondent licensed to drive?	CATI-1:Q41
28 EMPLOY	Employment status of respondent	CATI-1:Q42
29 WRKPLACE	Place of work (outside/inside home)	CATI-1:Q44
30 JOB2	Do you have second job?	CATI-1:Q46
31 JOB2PLC	Place of second job	CATI-1:Q47
32 HMWKDIST	Distance from home to work place	CATI-1:Q58
33 HMWKUNIT	Units of measurement (miles/blocks)	CATI-1:Q59
34 WKHMDIST	Distance from work to home place	CATI-1:Q61
35 WKHMUNIT	Units of measurement (miles/blocks)	CATI-1:Q62
36 HMWKTIME	Travel time from home to work (min)	CATI-1:Q161
37 NDAYSOV	No of days last week by SOV	CATI-1:Q64
38 NDAYDRIV	No of days last week by Drive with Passengers	CATI-1:Q65
39 DRIVHHLD	Are passengers hhld members?	CATI-1:Q66
40 NDAYRIDE	No of days last week by Riding with Someone	CATI-1:Q67
41 RIDEHHLD	Are passengers hhld members?	CATI-1:Q68
42 NDAYBUS	No of days last week by Bus/No Rail	CATI-1:Q69
43 NDAYMETR	No of days last week by Metro/Rail	CATI-1:Q70
44 NDAYTRN	No of days last week by Train	CATI-1:Q71

45 NDAYMOP	No of days last week by Motorcycle/Moped	CATI-1:Q72
46 NDAYBIKE	No of days last week by bicycle only	CATI-1:Q73
47 NDAYWALK	No of days last week by walking only	CATI-1:Q74
48 NDAYHOME	No of days last week working at home	CATI-1:Q74-2/167
49 AVLSOV	Is SOV available?	CATI-1:Q76
50 AVLDRIV	Is Drive with passengers available?	CATI-1:Q77
51 AVLRIDE	Is Ride with someone available?	CATI-1:Q79
52 AVLBUS	Is Bus/No Rail available?	CATI-1:Q81
53 AVLMETR	Is Metro/Rail available?	CATI-1:Q82
54 AVLTRN	Is Train available?	CATI-1:Q83
55 AVLMOP	Is Motorcycle/Moped available?	CATI-1:Q84
56 AVLBIKE	Is Bicycle Only available?	CATI-1:Q85
57 AVLWALK	Is Walking Only available?	CATI-1:Q86
58 WK_AR_HR	Work arrival time (hour)	CATI-1:Q93
59 WK_AR_MN	Work arrival time (minutes)	CATI-1:Q93
60 EARLY_AR	Flexibility to arrive early (minutes)	CATI-1:Q96
61 LATE_AR	Flexibility to arrive late (minutes)	CATI-1:Q97
62 WK_LV_HR	Work leave time (hour)	CATI-1:Q98
63 WK_LV_MN	Work leave time (minutes)	CATI-1:Q98
64 EARLY_LV	Flexibility to leave work early (minutes)	CATI-1:Q101
65 LATE_LV	Flexibility to leave work late (minutes)	CATI-1:Q102
66 HW_CHILD	No of days dropped child at daycare/school on way from home to work	CATI-1:Q104
67 HW_NOTCH	No of days stopped on way from home to work other than pickup/drop child	CATI-1:Q105
68 HW_WKREL	No of days stopped on way from home to work for work related activity	CATI-1:Q107
69 HW_SHOP	No of days stopped on way from home to work for grocery or other shopping Q109	CATI-1:Q108+
70 HW_PNBSN	No of days stopped on way from home to work for personal business	CATI-1:Q110
71 HW_SRVPS	No of days stopped on way from home to work to serve passenger other than child	CATI-1:Q113
72 HW_RECR	No of days stopped on way from home to work for recreational activity	CATI-1:Q112
73 HW_OTHER	No of days stopped on way from home to work	CATI-1:Q111+

	for eat, gas, other activities Q114+Q115	
74 WH_CHILD	No of days stopped on way from work to home to pickup/drop child at school/daycare	CATI-1:Q117
75 WH_NOTCH	No of days stopped on way from work to home other than pickup/drop child	CATI-1:Q118
76 WH_WKREL	No of days stopped on way from work to home for work related activity	CATI-1:Q120
77 WH_SHOP	No of days stopped on way from work to home for grocery and other shopping Q122	CATI-1:Q121+
78 WH_PNBSN	No of days stopped on way from work to home for personal business	CATI-1:Q123
79 WH_SRVPS	No of days stopped on way from work to home to serve passenger other than child	CATI-1:Q126
80 WH_RECR	No of days stopped on way from work to home for social recreational activity	CATI-1:Q125
81 WH_OTHER	No of days stopped on way from work to home for eat, gas, other activities Q127+Q128	CATI-1:Q124+
82 AW_TRIP	No of days made car trip while at work	CATI-1:Q129.2/163
83 AW_WKREL	No of days made work-related trip while at work	CATI-1:Q131
84 AW_SHOP	No of days made shopping trip while at work	CATI-1:Q132+Q133
85 AW_PNBSN	No of days made personal business trip while at work	CATI-1:Q134
86 AW_RECR	No of days made recreational trip while at work	CATI-1:Q136
87 AW_SRVPS	No of days made serve passenger trip (other than child)while at work	CATI-1:Q137
88 AW_CHILD	No of days made trip to serve child (other than school/daycare) while at work	CATI-1:Q137.2/Q166
89 AW_EAT	No of days made eat meal trip while at work	CATI-1:Q135
90 CCAR_USE	Company car available/use?	CATI-1:Q140+Q141
91 WALKTM1	Walking time for parking tax scenario(minutes)	CATI-2:Q37
92 WALKTM2	Walking time for parking tax scenario(minutes)	CATI-2:Q38
93 TAXQ37	Parking tax for scenario Q37 ($)	CATI-2:Q37
94 TXQ38	Parking tax for scenario Q38 ($)	CATI-2:Q38
95 TXQ39_60	Parking tax for TCM1 - Q39/60	
96 BEN_PARK	Level of Employer Benefit/Parking	CATI-2:Q61/Q66
97 PAY_TIME	Level of Congestion Pricing/Travel time Reduction	CATI-2:Q63/66

98 RUR_CITY	Rural or City?	
99 PRKRES37	Response to park/walk tradeoff	CATI-2:Q37
100 PRKRES38 Response to park/walk tradeoff	CATI-2:Q38	
101 TCMRES1	Response to TCM1:Parking tax	CATI-2:Q39
102 TCMRES2	Response to TCM2:Improved Bicycle Facilities	CATI-2:Q59
103 TCMRES3	Response to TCM3:TCM1+TCM2	CATI-2:Q60
104 TCMRES4	Response to TCM4:Employer Benefit+Prking Tax	CATI-2:Q61
105 TCMRES5	Response to TCM5:Congestion Pricing+ Travel Time Benefits	CATI-2:Q63
106 TCMRES6	Response to TCM6:TCM4+TCM5	CATI-2:Q66

VARIABLE CODES

Variable No. Name	**Coding Scheme**
3 RES_TYPE	1=Single Family Detached House
	2=Single Family Attached House
	3=Apartment or Condominium
	4=Mobile Home
	5=Hotel or Motel Unit
	6=Group Quarters Unit
	7=Other
5 OWNRENT	1=Own
	2=Rent
	3=Don't Know
	4=Refused
11 MARKET_U	1=Miles
	2=Blocks
	3=Don't Know
	4=Refused
13 BUSUNIT	1=Miles
	2=Blocks
	3=Don't Know
	4=Refused

15 METRUNIT	1=Miles
	2=Blocks
	3=Don’t Know
	4=Refused
17 PARKUNIT	1=Miles
	2=Blocks
	3=Don’t Know
	4=Refused
18 SIDEWALK	1=Yes (sidewalk present)
	2=No (sidewalk absent)
	3=Don’t Know
19 BIKEPATH	1=Yes (bikepath present)
	2=No (bikepath absent)
	3=Don’t Know
20 INCOME	1=Less than $5,000
	2=$5,000 - $10,000
	3=$10,001 - $20,000
	4=$20,001 - $30,000
	5=$30,001 - $50,000
	6=$50,001 - $75,000
	7=$75,001 - $100,000
	8=$100,001 - $125,000
	9=$125,001 - $150,000
	10=Over $150,000
	11=Don’t Know
	12=Refused
22 FREEPAID	1=Free to park at workplace
	2=Employer pays for parking
23 T_ACCESS	1=Walk only
	2=Drive alone
	3=Drive with others
	4=Get ride from somebody
	5=Bicycle
	6=Other

24 T_EGRESS	1=Walk only
	2=Drive alone
	3=Drive with others
	4=Get ride from somebody
	5=Bicycle
	6=Other
25 AGECATEG	1=5-10 years
	2=11-15 years
	3=16-18 years
	4=19-29 years
	5=30-39 years
	6=40-49 years
	7=50-59 years
	8=Greater than or equal to 60 years
	9=Don't know
	10=Refused
26 GENDER	1=Male
	2=Female
27 LICENSE	1=Person drives
	2=Peson does not drive
	3=Refused
28 EMPLOY	1=Employed full time (30+ hours per week)
	2=Employed part time (<30 hours per week)
	3=Student only
	4=Student & work part time
	5=Student & work full time
	6=Seeking work
	7=Retired
	8=Homemaker
	9=Disabled
	10=Volunteer
	11=Other
29 WRKPLACE	1=Works mainly at home
	2=Works at another place

30 JOB2	1=Has second job
	2=Does not have second job
31 JOB2PLC	1=Second job is at home
	2=Second job is at another place
33 HMWKUNIT	1=Miles
	2=Blocks
	3=Don’t Know
	4=Refused
35 WKHMUNIT	1=Miles
	2=Blocks
	3=Don’t Know
	4=Refused
39 DRIVHHLD	1=Vehicle occupants are household members
	2=Not household members
	3=Some are household members
	4=Don’t know
41 RIDEHHLD	1=Vehicle occupants are household members
	2=Not household members
	3=Some are household members
	4=Don’t know
49 AVLSOV	1=Yes, it is available
	2=Not available
	3=Don’t Know
50 AVLDRIV	1=Yes, it is available
	2=Not available
	3=Don’t Know
51 AVLRIDE	1=Yes, it is available
	2=Not available
	3=Don’t Know
52 AVLBUS	1=Yes, it is available
	2=Not available
	3=Don’t Know
53 AVLMETR	1=Yes, it is available
	2=Not available

	3=Don't Know
54 AVLTRN	1=Yes, it is available
	2=Not available
	3=Don't Know
55 AVLMOP	1=Yes, it is available
	2=Not available
	3=Don't Know
56 AVLBIKE	1=Yes, it is available
	2=Not available
	3=Don't Know
57 AVLWALK	1=Yes, it is available
	2=Not available
	3=Don't Know
58 WK_AR_HR	-5=Variable (any hour)
59 WK_AR_MN	-5=Variable (any minute)
60 EARLY_AR	-5=Varable (any number of minutes)
61 LATE_AR	-5=Varable (any number of minutes)
62 WK_LV_HR	-5=Variable (any hour)
63 WK_LV_MN	-5=Variable (any minute)
64 EARLY_LV	-5=Varable (any number of minutes)
65 LATE_LV	-5=Varable (any number of minutes)
90 CCAR_USE	0=No company car
	1=Company car available for work purposes only
	2=Company car available for home-to-work journey
	3=Other
98 RUR_CITY	1=City (urban)
	2=Rural
99 PRKRES37	1=Pay parking tax
	2=Not pay parking tax, would rather walk
100 PRKRES38	1=Pay parking tax
	2=Not pay parking tax, would rather walk
101 TCMRES1	1=Change departure time to work
	2=Switch work mode to Walk
	3=Switch work mode to Bicycle

	4=Switch work mode to Car/Van Pool
	5=Switch work mode to Transit
	6=Switch to Working at Home
	7=No change in behavior
	8=Other
	9=Refused
102 TCMRES2	1=Change departure time to work
	2=Switch work mode to Walk
	3=Switch work mode to Bicycle
	4=Switch work mode to Car/Van Pool
	5=Switch work mode to Transit
	6=Switch to Working at Home
	7=No change in behavior
	8=Other
	9=Refused
103 TCMRES3	1=Change departure time to work
	2=Switch work mode to Walk
	3=Switch work mode to Bicycle
	4=Switch work mode to Car/Van Pool
	5=Switch work mode to Transit
	6=Switch to Working at Home
	7=No change in behavior
	8=Other
	9=Refused
104 TCMRES4	1=Change departure time to work
	2=Switch work mode to Walk
	3=Switch work mode to Bicycle
	4=Switch work mode to Car/Van Pool
	5=Switch work mode to Transit
	6=Switch to Working at Home
	7=No change in behavior
	8=Other
	9=Refused
105 TCMRES5	1=Change departure time to work

	2=Switch work mode to Walk
	3=Switch work mode to Bicycle
	4=Switch work mode to Car/Van Pool
	5=Switch work mode to Transit
	6=Switch to Working at Home
	7=No change in behavior
	8=Other
	9=Refused
106 TCMRES6	1=Change departure time to work
	2=Switch work mode to Walk
	3=Switch work mode to Bicycle
	4=Switch work mode to Car/Van Pool
	5=Switch work mode to Transit
	6=Switch to Working at Home
	7=No change in behavior
	8=Other
	9=Refused

NOTE

Negative values for any data field are defined as follows, unless otherwise specified above:
-1 = REFUSED
-2 = DONT KNOW
-3 = SKIPPED (NOT APPLICABLE)
-4 = NOT APPLICABLE
-5 = ANY HOUR (OR MINUTE), i.e., flexible hours
-6 = VARIES

DATA FILE FORMAT

Variable No. Name	Record No.	Column		Input Format
		Beg	End	
1 HHID	1	1	8	F8.2
2 COMMUTER	1	9	16	F8.2
3 RES_TYPE	1	17	24	F8.2
4 TENURE	1	25	32	F8.2

5 OWNRENT	1	33	40	F8.2
6 HHLDSIZE	1	41	48	F8.2
7 GT5YRS	1	49	56	F8.2
8 NVEHICLE	1	57	64	F8.2
9 NBICYCLE	1	65	72	F8.2
10 MARKET_D	1	73	80	F8.2
11 MARKET_U	2	1	8	F8.2
12 BUSDIST	2	9	16	F8.2
13 BUSUNIT	2	17	24	F8.2
14 METRDIST	2	25	32	F8.2
15 METRUNIT	2	33	40	F8.2
16 PARKDIST	2	41	48	F8.2
17 PARKUNIT	2	49	56	F8.2
18 SIDEWALK	2	57	64	F8.2
19 BIKEPATH	2	65	72	F8.2
20 INCOME	2	73	80	F8.2
21 PRKCHRG	3	1	8	F8.2
22 FREEPAID	3	9	16	F8.2
23 T_ACCESS	3	17	24	F8.2
24 T_EGRESS	3	25	32	F8.2
25 AGECATEG	3	33	40	F8.2
26 GENDER	3	41	48	F8.2
27 LICENSE	3	49	56	F8.2
28 EMPLOY	3	57	64	F8.2
29 WRKPLACE	3	65	72	F8.2
30 JOB2	3	73	80	F8.2
31 JOB2PLC	4	1	8	F8.2
32 HMWKDIST	4	9	16	F8.2
33 HMWKUNIT	4	17	24	F8.2
34 WKHMDIST	4	25	32	F8.2
35 WKHMUNIT	4	33	40	F8.2
36 HMWKTIME	4	41	48	F8.2
37 NDAYSOV	4	49	56	F8.2
38 NDAYDRIV	4	57	64	F8.2

39 DRIVHHLD	4	65	72	F8.2
40 NDAYRIDE	4	73	80	F8.2
41 RIDEHHLD	5	1	8	F8.2
42 NDAYBUS	5	9	16	F8.2
43 NDAYMETR	5	17	24	F8.2
44 NDAYTRN	5	25	32	F8.2
45 NDAYMOP	5	33	40	F8.2
46 NDAYBIKE	5	41	48	F8.2
47 NDAYWALK	5	49	56	F8.2
48 NDAYHOME	5	57	64	F8.2
49 AVLSOV	5	65	72	F8.2
50 AVLDRIV	5	73	80	F8.2
51 AVLRIDE	6	1	8	F8.2
52 AVLBUS	6	9	16	F8.2
53 AVLMETR	6	17	24	F8.2
54 AVLTRN	6	25	32	F8.2
55 AVLMOP	6	33	40	F8.2
56 AVLBIKE	6	41	48	F8.2
57 AVLWALK	6	49	56	F8.2
58 WK_AR_HR	6	57	64	F8.2
59 WK_AR_MN	6	65	72	F8.2
60 EARLY_AR	6	73	80	F8.2
61 LATE_AR	7	1	8	F8.2
62 WK_LV_HR	7	9	16	F8.2
63 WK_LV_MN	7	17	24	F8.2
64 EARLY_LV	7	25	32	F8.2
65 LATE_LV	7	33	40	F8.2
66 HW_CHILD	7	41	48	F8.2
67 HW_NOTCH	7	49	56	F8.2
68 HW_WKREL	7	57	64	F8.2
69 HW_SHOP	7	65	72	F8.2
70 HW_PNBSN	7	73	80	F8.2
71 HW_SRVPS	8	1	8	F8.2
72 HW_RECR	8	9	16	F8.2

73 HW_OTHER	8	17	24	F8.2
74 WH_CHILD	8	25	32	F8.2
75 WH_NOTCH	8	33	40	F8.2
76 WH_WKREL	8	41	48	F8.2
77 WH_SHOP	8	49	56	F8.2
78 WH_PNBSN	8	57	64	F8.2
79 WH_SRVPS	8	65	72	F8.2
80 WH_RECR	8	73	80	F8.2
81 WH_OTHER	9	1	8	F8.2
82 AW_TRIP	9	9	16	F8.2
83 AW_WKREL	9	17	24	F8.2
84 AW_SHOP	9	25	32	F8.2
85 AW_PNBSN	9	33	40	F8.2
86 AW_RECR	9	41	48	F8.2
87 AW_SRVPS	9	49	56	F8.2
88 AW_CHILD	9	57	64	F8.2
89 AW_EAT	9	65	72	F8.2
90 CCAR_USE	9	73	80	F8.2
91 WALKTM1	10	1	8	F8.2
92 WALKTM2	10	9	16	F8.2
93 TAXQ37	10	17	24	F8.2
94 TXQ38	10	25	32	F8.2
95 TXQ39_60	10	33	40	F8.2
96 BEN_PARK	10	41	48	F8.2
97 PAY_TIME	10	49	56	F8.2
98 RUR_CITY	10	57	64	F8.2
99 PRKRES37	10	65	72	F8.2
100 PRKRES38	10	73	80	F8.2
101 TCMRES1	11	1	8	F8.2
102 TCMRES2	11	9	16	F8.2
103 TCMRES3	11	17	24	F8.2
104 TCMRES4	11	25	32	F8.2
105 TCMRES5	11	33	40	F8.2
106 TCMRES6	11	41	48	F8.2

DERIVED VARIABLES

BENEFIT = EMPLOYER BENEFIT MEASURED IN DOLLARS PER MONTH.
PARKFEE = ADDITIONAL PARKING CHARGE IN DOLLARS PER MONTH.
CONG_PRC = CONGESTION PRICING MEASURED IN CENTS PER MILE.
TT_SAVE = TRAVEL TIME SAVINGS MEASURED IN PERCENT, i.e., 10%, 20%, 30%.
COM_DIST = HOME-TO-WORK COMMUTE DISTANCE

DERIVATION:
IF (BEN_PARK EQ 1) THEN (BENEFIT = 40. PARKFEE = 40.).
IF (BEN_PARK EQ 2) THEN (BENEFIT = 40. PARKFEE = 50.).
IF (BEN_PARK EQ 3) THEN (BENEFIT = 40. PARKFEE = 60.).
IF (BEN_PARK EQ 4) THEN (BENEFIT = 40. PARKFEE = 70.).
IF (BEN_PARK EQ 5) THEN (BENEFIT = 40. PARKFEE = 80.).
IF (BEN_PARK EQ 6) THEN (BENEFIT = 50. PARKFEE = 50.).
IF (BEN_PARK EQ 7) THEN (BENEFIT = 50. PARKFEE = 60.).
IF (BEN_PARK EQ 8) THEN (BENEFIT = 50. PARKFEE = 70.).
IF (BEN_PARK EQ 9) THEN (BENEFIT = 50. PARKFEE = 80.).
IF (BEN_PARK EQ 10) THEN (BENEFIT = 60. PARKFEE = 60.).
IF (BEN_PARK EQ 11) THEN (BENEFIT = 60. PARKFEE = 70.).
IF (BEN_PARK EQ 12) THEN (BENEFIT = 60. PARKFEE = 80.).
IF (BEN_PARK EQ 13) THEN (BENEFIT = 70. PARKFEE = 70.).
IF (BEN_PARK EQ 14) THEN (BENEFIT = 70. PARKFEE = 80.).
IF (BEN_PARK EQ 15) THEN (BENEFIT = 80. PARKFEE = 80.).

IF (PAY_TIME EQ 1) THEN (CONG_PRC = 15. TT_SAVE = 10.).
IF (PAY_TIME EQ 2) THEN (CONG_PRC = 20. TT_SAVE = 10.).
IF (PAY_TIME EQ 3) THEN (CONG_PRC = 25. TT_SAVE = 10.).
IF (PAY_TIME EQ 4) THEN (CONG_PRC = 30. TT_SAVE = 10.).
IF (PAY_TIME EQ 5) THEN (CONG_PRC = 35. TT_SAVE = 10.).
IF (PAY_TIME EQ 6) THEN (CONG_PRC = 25. TT_SAVE = 20.).
IF (PAY_TIME EQ 7) THEN (CONG_PRC = 30. TT_SAVE = 20.).
IF (PAY_TIME EQ 8) THEN (CONG_PRC = 35. TT_SAVE = 20.).
IF (PAY_TIME EQ 9) THEN (CONG_PRC = 40. TT_SAVE = 20.).
IF (PAY_TIME EQ 10) THEN (CONG_PRC = 45. TT_SAVE = 20.).
IF (PAY_TIME EQ 11) THEN (CONG_PRC = 30. TT_SAVE = 30.).
IF (PAY_TIME EQ 12) THEN (CONG_PRC = 35. TT_SAVE = 30.).
IF (PAY_TIME EQ 13) THEN (CONG_PRC = 40. TT_SAVE = 30.).
IF (PAY_TIME EQ 14) THEN (CONG_PRC = 45. TT_SAVE = 30.).
IF (PAY_TIME EQ 15) THEN (CONG_PRC = 50. TT_SAVE = 30.).

ASSUMPTION: ONE MILE = 8 BLOCKS.
COM_DIST=HMWKDIST.
IF (HMWKUNIT EQ 2) THEN COM_DIST=HMWKDIST/8.

UNIVARIATE FREQUENCY DISTRIBUTIONS FOR AMOSVER1.DAT

Variable No. Name	Category Name	Category Frequency	Total Frequency	No. of Values Missing or Outside the Range
2 COMMUTER	ZERO	0	656	0
	ONE	312		
	TWO	281		
	THREE	44		
	GT_THREE	19		
3 RES_TYPE	DET_HOME	390	656	0
	ATT_HOME	93		
	APT_COND	168		
	MOBILEHM	2		
	HOTEL	0		
	GRPQRTS	1		
	OTHER	2		
4 TENURE	MISSING	1	656	0
	LT1YR	82		
	1-5YR	255		
	5-10YR	172		
	GT10YR	146		
5 OWNRENT	MISSING	2	65 6	0
	OWN	506		
	RENT	147		
	REFUSE	1		
6 HHLDSIZE	ONE	123	656	0
	TWO	210		
	THREE	144		
	FOUR	117		
	GTFOUR	62		
7 GT5YRS	ONE	131	656	0

	TWO	273		
	THREE	126		
	FOUR	94		
	GT_FOUR	32		
8 NVEHICLE	ZERO	20	656	0
	ONE	167		
	TWO	321		
	THREE	110		
	FOUR	30		
	GT_FOUR	8		
9 NBICYCLE	ZERO	253	656	0
	ONE	129		
	TWO	149		
	THREE	55		
	FOUR	43		
	GT_FOUR	27		
13 BUSUNIT	MISSING	79	656	0
	MILES	218		
	BLOCKS	359		
	REFUSE	0		
15 METRUNIT	MISSING	31	656	0
	MILES	553		
	BLOCKS	72		
	REFUSE	0		
18 SIDEWALK	YES	517	656	0
	NO	139		
	REFUSE	0		
19 BIKEPATH	YES	307	656	0
	NO	337		
	REFUSE	12		
20 INCOME	MISSING	7	656	0
	LT30K	84		
	30-50K	157		
	50-75K	166		

	75-100K	112		
	GT100K	85		
	REFUSE	45		
21 PRKCHRG	MISSING	65	656	0
	FREE	485		
	LT10$	14		
	10-20$	8		
	20-40$	19		
	40-75$	32		
	GT75$	33		
22 FREEPAID	MISSING	171	656	0
	FREE	438		
	EMP_PAID	47		
	REFUSE	0		
23 T_ACCESS	MISSING	566	656	0
	WALKONLY	53		
	SOV	25		
	DRIVOTHR	4		
	RIDEOTHR	3		
	BICYCLE	1		
	OTHER	4		
	REFUSE	0		
24 T_EGRESS	MISSING	566	656	0
	WALKONLY	77		
	SOV	1		
	DRIVOTHR	0		
	RIDEOTHR	1		
	BICYCLE	0		
	OTHER	11		
	REFUSE	0		
25 AGECATEG	5-10Y	0	656	0
	11-15Y	0		
	16-18Y	0		
	19-29Y	95		

	30-39Y	216		
	40-49Y	182		
	50-59Y	125		
	GT_60Y	36		
	REFUSE	2		
26 GENDER	MALE	382	656	0
	FEMALE	274		
	REFUSE	0		
27 LICENSE	LIC	640	656	0
	NO_LIC	16		
	REFUSE	0		
28 EMPLOY	EMP_FT	603	656	0
	EMP_PT	35		
	STUDENT	1		
	STU_PTWK	3		
	STU_FTWK	5		
	SEEKWORK	3		
	RETIRED	2		
	HOMEMAKE	1		
	DISABLED	0		
	VOLUNTEE	2		
	OTHER	1		
	REFUSE	0		
29 WRKPLACE	MISSING	11	656	0
	AT_HOME	11		
	OUT_HOME	634		
	REFUSE	0		
30 JOB2	MISSING	11	656	0
	YES	52		
	NO	593		
	REFUSE	0		
31 JOB2PLC	MISSING	603	656	0
	AT_HOME	15		
	OUT_HOME	38		

	REFUSE	0		
33 HMWKUNIT	MISSING	13	656	0
	MILES	628		
	BLOCKS	15		
	REFUSE	0		
35 WKHMUNIT	MISSING	13	656	0
	MILES	627		
	BLOCKS	16		
	REFUSE	0		
36 HMWKTIME	MISSING	15	656	0
	LT10MIN	75		
	10-30MIN	308		
	30-60MIN	220		
	GT60MIN	38		
37 NDAYSOV	0DAY	152	656	0
	1DAY	31		
	2DAY	25		
	3DAY	56		
	GT3DAY	392		
38 NDAYDRIV	0DAY	538	656	0
	1DAY	28		
	2DAY	11		
	3DAY	12		
	GT3DAY	67		
39 DRIVHHLD	MISSING	539	656	0
	YES	55		
	NO	57		
	SOME	5		
	DONTKNOW	0		
	REFUSE	0		
40 NDAYRIDE	0DAY	604	656	0
	1DAY	16		
	2DAY	9		
	3DAY	8		

	GT3DAY	19		
41 RIDEHHLD	MISSING	604	656	0
	YES	14		
	NO	36		
	SOME	2		
	DONTKNOW	0		
	REFUSE	0		
42 NDAYBUS	0DAY	623	656	0
	1DAY	8		
	2DAY	1		
	3DAY	7		
	GT3DAY	17		
43 NDAYMETR	0DAY	586	656	0
	1DAY	15		
	2DAY	9		
	3DAY	7		
	GT3DAY	39		
44 NDAYTRN	0DAY	646	656	0
	1DAY	0		
	2DAY	1		
	3DAY	2		
	GT3DAY	7		
45 NDAYMOP	0DAY	655	656	0
	1DAY	1		
	2DAY	0		
	3DAY	0		
	GT3DAY	0		
46 NDAYBIKE	0DAY	646	656	0
	1DAY	4		
	2DAY	2		
	3DAY	1		
	GT3DAY	3		
47 NDAYWALK	0DAY	638	656	0
	1DAY	5		

	2DAY	0		
	3DAY	0		
	GT3DAY	13		
48 NDAYHOME	0DAY	647	656	0
	1DAY	4		
	2DAY	1		
	3DAY	0		
	GT3DAY	4		
49 AVLSOV	YES	608	656	0
	NO	48		
	REFUSE	0		
50 AVLDRIV	MISSING	4	656	0
	YES	375		
	NO	277		
	REFUSE	0		
51 AVLRIDE	MISSING	5	656	0
	YES	316		
	NO	335		
	REFUSE	0		
52 AVLBUS	MISSING	7	656	0
	YES	206		
	NO	443		
	REFUSE	0		
53 AVLMETR	YES	195	656	0
	NO	461		
	REFUSE	0		
54 AVLTRN	MISSING	2	656	0
	YES	68		
	NO	586		
	REFUSE	0		
55 AVLMOP	YES	112	656	0
	NO	544		
	REFUSE	0		
56 AVLBIKE	YES	104	656	0

	NO	552		
	REFUSE	0		
57 AVLWALK	YES	602	656	0
	NO	54		
	REFUSE	0		
58 WK_AR_HR	LT5AM	49	656	0
	5-7AM	77		
	7-9AM	405		
	9-12NOON	96		
	12N-6PM	17		
	GT6PM	12		
60 EARLY_AR	VARIABLE	0	656	0
	MISSING	9		
	FIXED	340		
	LE_30MIN	86		
	30-60MIN	63		
	FLEXIBLE	158		
61 LATE_AR	VARIABLE	0	656	0
	MISSING	11		
	FIXED	336		
	LE_30MIN	96		
	30-60MIN	78		
	FLEXIBLE	135		
62 WK_LV_HR	LT5AM	41	656	0
	5-7AM	13		
	7-9AM	2		
	9AM-4PM	85		
	4PM-6PM	361		
	GT6PM	154		
64 EARLY_LV	VARIABLE	0	656	0
	MISSING	18		
	FIXED	313		
	LE_30MIN	87		
	30-60MIN	77		

	FLEXIBLE	161		
65 LATE_LV	VARIABLE	0	656	0
	MISSING	12		
	FIXED	274		
	LE_30MIN	58		
	30-60MIN	73		
	FLEXIBLE	239		
66 HW_CHILD	0DAY	574	656	0
	1+DAYS	82		
67 HW_NOTCH	0DAY	474	656	0
	1+DAYS	182		
68 HW_WKREL	0DAY	637	656	0
	1+DAYS	19		
71 HW_SRVPS	0DAY	640	656	0
	1+DAYS	16		
74 WH_CHILD	0DAY	562	656	0
	1+DAYS	94		
75 WH_NOTCH	0DAY	336	656	0
	1+DAYS	320		
76 WH_WKREL	0DAY	630	656	0
	1+DAYS	26		
79 WH_SRVPS	0DAY	640	656	0
	1+DAYS	16		
82 AW_TRIP	0DAY	396	656	0
	1+DAYS	260		
88 AW_CHILD	0DAY	655	656	0
	1+DAYS	1		
89 AW_EAT	0DAY	586	656	0
	1+DAYS	70		
90 CCAR_USE	NO_CCAR	611	656	0
	WRK_ONLY	24		
	GO_HM_WK	20		
	OTHER	1		
	REFUSE	0		

91 WALKTM1	10MIN	229	656	0
	15MIN	212		
	20MIN	215		
92 WALKTM2	10MIN	206	656	0
	15MIN	228		
	20MIN	222		
93 TAXQ37	1$	106	656	0
	2$	64		
	3$	120		
	4$	111		
	5$	112		
	6$	46		
	7$	48		
	8$	49		
94 TXQ38	1$	70	656	0
	2$	80		
	3$	118		
	4$	121		
	5$	110		
	6$	55		
	7$	49		
	8$	53		
95 TXQ39_60	1$	81	656	0
	2$	74		
	3$	129		
	4$	122		
	5$	116		
	6$	47		
	7$	45		
	8$	42		
96 BEN_PARK	0	43	656	0
	0	51		
	0	46		
	0	43		

	0	41		
	0	42		
	0	42		
	0	41		
	0	49		
	0	35		
	0	48		
	0	33		
	0	49		
	0	50		
	0	43		
97 PAY_TIME	0	36	656	0
	0	45		
	0	44		
	0	47		
	0	46		
	0	45		
	0	48		
	0	40		
	0	43		
	0	49		
	0	41		
	0	38		
	0	41		
	0	42		
	0	51		
99 PRKRES37	MISSING	2	656	0
	PAY	291		
	NO_PAY	363		
	REFUSE	0		
100 PRKRES38	MISSING	2	656	0
	PAY	290		
	NO_PAY	364		
	REFUSE	0		

101 TCMRES1	CH_DEPTM	4	656	0
	WALK	13		
	BIKE	7		
	CARPOOL	66		
	TRANSIT	72		
	AT_HOME	11		
	NOCHANGE	457		
	OTHER	26		
102 TCMRES2	CH_DEPTM	2	656	0
	WALK	4		
	BIKE	70		
	CARPOOL	20		
	TRANSIT	18		
	AT_HOME	2		
	NOCHANGE	535		
	OTHER	5		
103 TCMRES3	CH_DEPTM	2	656	0
	WALK	8		
	BIKE	76		
	CARPOOL	35		
	TRANSIT	31		
	AT_HOME	3		
	NOCHANGE	495		
	OTHER	6		
104 TCMRES4	CH_DEPTM	3	656	0
	WALK	9		
	BIKE	38		
	CARPOOL	57		
	TRANSIT	68		
	AT_HOME	4		
	NOCHANGE	466		
	OTHER	11		
105 TCMRES5	CH_DEPTM	130	656	0
	WALK	5		

	BIKE	26		
	CARPOOL	29		
	TRANSIT	50		
	AT_HOME	7		
	NOCHANGE	397		
	OTHER	12		
106 TCMRES6	CH_DEPTM	81	656	0
	WALK	7		
	BIKE	34		
	CARPOOL	42		
	TRANSIT	65		
	AT_HOME	5		
	NOCHANGE	405		
	OTHER	17		
107 BENEFIT	40$	224	656	0
	50$	174		
	60$	116		
	70$	99		
	80$	43		
108 PARKFEE	40$	43	656	0
	50$	93		
	60$	123		
	70$	181		
	80$	216		
109 CONG_PRC	15CENTS	36	656	0
	20CENTS	45		
	25CENTS	89		
	30CENTS	136		
	35CENTS	124		
	40CENTS	84		
	45CENTS	91		
	50CENTS	51		
110 TT_SAVE	10%	218	656	0
	20%	225		

	30%	213		
111 COM_DIST	LT5MILE	160	656	0
	5-15MI	266		
	15-25MI	125		
	25-50MI	97		
	GT50MILE	8		

PART 2: ACTIVITY AND TRIP RECORDS FOR TRAVEL DIARY DAY
FILENAME: TIMEUSE1.DAT
Number of Cases = 9674 (656 RESPONDENTS)

This data file contains the individual activity and trip records for each of 656 commuters who responded to the survey. The file was created by combining the following raw data files provided to RDC, Inc. by Strategic Consulting Research, Inc., the contracting firm that administered the survey and assembled the data bases:

ACTF1
ACTF2

The file format with variable definitions and codes is provided first, followed by general notes and descriptions of derived variables (not saved in the original data bases) if any.

VARIABLE DESCRIPTIONS

Variable No. Name	Variable Definition	Question in AMOS CATI Instument
1 HHID	Household/Commuter ID Code	
2 ACTRPNUM	A sequential counter of trips and activities	
3 ACTRPFLG	A binary flag indicating whether a trip record or an activity record.	
4 ALOCTDES	Activity Location if Activity Record OR Trip Destination if Trip Record	CATI-2: Q3/Q4/Q9
5 BEGINHR	Activity or Trip beginning time (hour) (provided in military time format)	CATI-2: Q1/Q32
6 BEGINMN	Activity or Trip beginning time (min)	CATI-2: Q1/Q32
7 PURPOSE	Activity Type if Activity Record OR Trip Purpose if Trip Record	CATI-2: Q5/Q25-31
8 ENDHR	Activity or Trip ending time (hour) (provided in military time format)	CATI-2: Q6/Q11/Q34

9 ENDMN	Activity or Trip ending time (min)	CATI-2: Q6/Q11/Q34
10 NEXTLOCN	Is next activity at the same location? (not applicable to trip records)	CATI-2: Q8/Q36

THE NEXT SET OF VARIABLES ARE RELEVANT ONLY FOR TRIP RECORDS, i.e., WHEN

ACTRPFLG=2.		
11 MODE	Mode used for trip	CATI-2: Q13
12 DRVRPSGR	If private vehicle, is respondent driver or passenger	CATI-2: Q14
13 VEHOCC	Vehicle occupancy, including respondent	CATI-2: Q15
14 HHMEMBER	If VEHOCC>1, how many occupants are household members?	CATI-2: Q16
15 PRKGCHRG	Parking Charge/Fee	CATI-2: Q17/Q19
16 PRKGUNIT	Unit of time for parking charge/fee	CATI-2: Q20
17 PRKGPAID	Who paid the parking charge/fee?	CATI-2: Q18
18 TRPFARE	Taxi or trip fare	CATI-2: Q21/Q22
19 FAREPAID	How was trip fare paid	CATI-2: Q23
20 EMPLDISC	Was fare discounted or partly employer subsidized?	CATI-2: Q24

VARIABLE CODES

VARIABLE NO. NAME	CODING SCHEME
3 ACTRPFLG	1=Activity
	2=Trip
4 ALOCTDES	1=Home
	2=Other private residence
	3=Work site
	4=Work related business site
	5=School (respondent's)
	6=School or day care to serve child
	7=Serve child for other purpose
	8=Serve passenger other than child
	9=Place of business (gas station, restaurant, etc.)

	10=Recreational/Entertainment
	11=Don’t Know
	12=Refused
	13=Other
	14=Change mode of travel
7 PURPOSE	1 WRK_WREL = WORK/WORK RELATED
	2 EAT_MEAL = MEAL PREP, EATING
	3 SOCLRECN = SOCIAL/RECREATION
	4 TV_VIEW = TV VIEWING IN HOME
	5 HM_ENTRT = OTHER ENTERTAINMENT
	6 HM_SHOP = IN-HOME SHOPPING
	7 HEXERCIS = IN-HOME EXERCISE
	8 HSTUDY= IN-HOME STUDY
	9 HPHONE= TELEPHONE (PERSONAL)
	10 HPRSNCRE = PERSONAL CARE
	11 HM_MAINT = HOME MAINTENANCE
	12 REST_NAP = REST OR SLEEP
	13 SLEEP = SLEPT FOR NIGHT
	14 HM_OTHR = IN-HOME OTHER ACTIVITY
	15 HCHLDCRE = IN-HOME CHILD CARE
	16 GROCSHOP = GROCERY SHOPPING
	17 MALLSHOP = DURABLE/MALL SHOPPING
	18 FUEL= GASOLINE/DIESEL
	19 MEDICAL = MEDICAL/DENTAL/HEALTH
	20 PRSNBSNS = PERSONAL BUSINESS
	21 MOVIES= MOVIES, THEATER
	22 PROSPORT = SPECTATOR PRO SPORTS
	23 LOCLSPRT = SPECTATOR LOCAL SPORTS
	24 PARTSPRT = PARTICIPANT SPORT/GAME
	25 AMUSEPRK = AMUSEMENT PARK
	26 CULTURAL = CULTURAL ACTIVITY
	27 CHLDSCHL = SERVE CHILD TO SCHOOL
	28 CHLDOTHR = SERVE CHILD FOR OTHER
	29 OTHRPSGR = SERVE OTHER PASSENGER

	30 CHNGMODE = CHANGE MODE
	88 HM_XMIS = IN-HOME UNKNOWN ACTIVITY (MISSING)
	99 OTHER = OUT-OF-HOME OTHER
10 NEXTLOCN	1=Same location
	2=Different location
11 MODE	1=Automobile
	2=Heavy Truck
	3=Taxi/Limousine
	4=Local Bus
	5=Intercity Bus (e.g., Greyhound)
	6=Charter/Commuter Bus
	7=Shuttle Bus
	8=School Bus
	9=Paratransit and dial-a-ride service
	10=Train: AMTRAK/MARC
	11=Train: Subway/Metro
	12=Light Rail/Tram/Streetcar
	13=Motorcycle
	14=Moped/Motorized Bike
	15=Bicycle
	16=Motorized Wheelchair
	17=Airplane
	18=Ferry
	19=Walking/Skating
	20=Don’t know
	21=Refused
	22=Other
12 DRVRPSGR	1=Driver
	2=Passenger
16 PRKGUNIT	1=Hour
	2=Day
	3=Week
	4=Month
	5=Semester/Quarter

	6=Year
	7=Other
17 PRKGPAID	1=Driver
	2=One or more passengers
	3=Driver and one or more passengers
	4=Employer
	5=Store/Restaurant/Other
	6=Don't Know
	7=Refused
19 FAREPAID	1=Cash only
	2=Pass
	3=Transfer only
	4=Cash and Transfer
	5=Ticket/Token
	6=Metro farecard
	7=Metro check
	8=Driver, no fare
	9=Don't know
	10=Refused
	11=Other means of payment
	12=Free, there was no fare
20 EMPLDISC	1=Discounted
	2=Partial employer payment
	3=No discount or partial payment
	4=Don't know
	5=Refused

NOTE

Negative values for any data field are defined as follows, unless otherwise specified above:
-1 = REFUSED
-2 = DON'T KNOW
-3 = SKIPPED (NOT APPLICABLE)
-4 = NOT APPLICABLE

DATA FILE FORMAT INPUT VARIABLES

Variable No. Name	Record No.	Column Beg.	Column End	Input Format
1 HHID	1	1	6	F6.0
2 ACTRPNUM	1	7	12	F6.0
3 ACTRPFLG	1	13	18	F6.0
4 ALOCTDES	1	19	24	F6.0
5 BEGINHR	1	25	30	F6.0
6 BEGINMN	1	31	36	F6.0
7 PURPOSE	1	37	42	F6.0
8 ENDHR	1	43	48	F6.0
9 ENDMN	1	49	54	F6.0
10 NEXTLOCN	1	55	60	F6.0
11 MODE	1	61	66	F6.0
12 DRVRPSGR	1	67	72	F6.0
13 VEHOCC	1	73	78	F6.0
14 HHMEMBER	2	1	7	F7.2
15 PRKGCHRG	2	8	14	F7.2
16 PRKGUNIT	2	15	21	F7.2
17 PRKGPAID	2	22	28	F7.2
18 TRPFARE	2	29	35	F7.2
19 FAREPAID	2	36	42	F7.2
20 EMPLDISC	2	43	49	F7.2

UNIVARIATE FREQUENCY DISTRIBUTIONS FOR TIMEUSE1.DAT

Variable No. Name	Category Frequency	Total
3 ACTRPFLG	9674	0
ACTIVITY	6636	
TRIP	3038	
4 ALOCTDES	9674	0
MISSING	7	
HOME	4686	
OTH_RES	177	
WORKSITE	2073	

WRK_REL	362	
SCHOOL	51	
CHLDSCHL	227	
SRVCHLD	56	
SRVPSGR	155	
PLCBSNS	1384	
RECREATN	133	
DONTKNOW	2	
REFUSED	2	
OTHER	97	
CHNGMODE	262	
UNKNOWN	0	
5 BEGINHR	9674	0
MISSING	789	
<7AM	1305	
7-9AM	1288	
9-12N	755	
12N-1PM	615	
1-5PM	1453	
5-7PM	1291	
>7PM	2178	
7 PURPOSE	9674	0
WRK_WREL	2464	
EAT_MEAL	1957	
SOCLRECN	320	
TV_VIEW	599	
HM_ENTRT	266	
HM_SHOP	13	
HEXERCIS	72	
HSTUDY	51	
HPHONE	50	
HPRSNCRE	1256	
HM_MAINT	87	
REST_NAP	59	

SLEEP	753	
HM_OTHR	132	
HCHLDCRE	159	
GROCSHOP	206	
MALLSHOP	363	
FUEL	56	
MEDICAL	42	
PRSNBSNS	212	
MOVIES	17	
PROSPORT	6	
LOCLSPRT	2	
PARTSPRT	57	
AMUSEPRK	0	
CULTURAL	10	
CHLDSCHL	0	
CHLDOTHR	2	
OTHRPSGR	4	
CHNGMODE	5	
HM_XMIS	228	
OTHER	226	
UNKNOWN	0	
10 NEXTLOCN	9674	0
NOTAPPL	3856	
SAME	2705	
DIFFERNT	3113	
UNKNOWN	0	
11 MODE	9674	0
MISSING	6387	
AUTO	2646	
HVYTRUCK	12	
TAXILIMO	18	
LOCALBUS	63	
ICITYBUS	0	
CTRBUS	1	

SHTLBUS	3	
SCHLBUS	4	
PARATRNS	3	
AMTRAK	8	
SUBWYMET	92	
LITERAIL	20	
MOTRBIKE	0	
MOPED	2	
BICYCLE	10	
WHLCHAIR	0	
AIRPLANE	0	
FERRY	0	
WALKSKAT	387	
DONTKNOW	0	
REFUSE	0	
OTHER	18	
UNKNOWN	0	
12 DRVRPSGR	9674	0
MISSING	7016	
DRIVER	2461	
PASSNGR	197	
DONTKNOW	0	
REFUSE0		
UNKNOWN	0	
13 VEHOCC	9674	0
MISSING	7016	
ONE	1916	
TWO	524	
THREE	135	
FOUR	60	
GTFOUR	23	
14 HHMEMBER	9674	0
MISSING	8917	
ONE	259	

TWO	376	
GTTWO	122	
15 PRKGCHRG	9674	0
FREE_NA	9550	
NOTFREE	124	
17 PRKGPAID	9674	0
MISSING	9529	
DRIVER	114	
PSGRS	3	
DRVRPSGR	7	
EMPLOYER	19	
PLCBSNS	1	
DONTKNOW	0	
REFUSE	0	
UNKNOWN	1	
18 TRPFARE	9674	0
FREE_NA	9655	
NOTFREE	19	
19 FAREPAID	9674	0
MISSING	9489	
CASH	75	
PASS	29	
XFER	5	
CASHXFER	2	
TICKET6		
FARECARD	65	
METRCHEK	0	
DRVRFREE	0	
DONTKNOW	0	
REFUSE	0	
OTHER	0	
FREE	3	
20 EMPLDISC	9674	0
MISSING	9493	

DISCOUNT	4	
EMPLPAY	12	
NODISC	164	
DONTKNOW	0	
REFUSE	1	

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Appendix D: Evaluation Module and Acceptance Routine

D.1 Approach

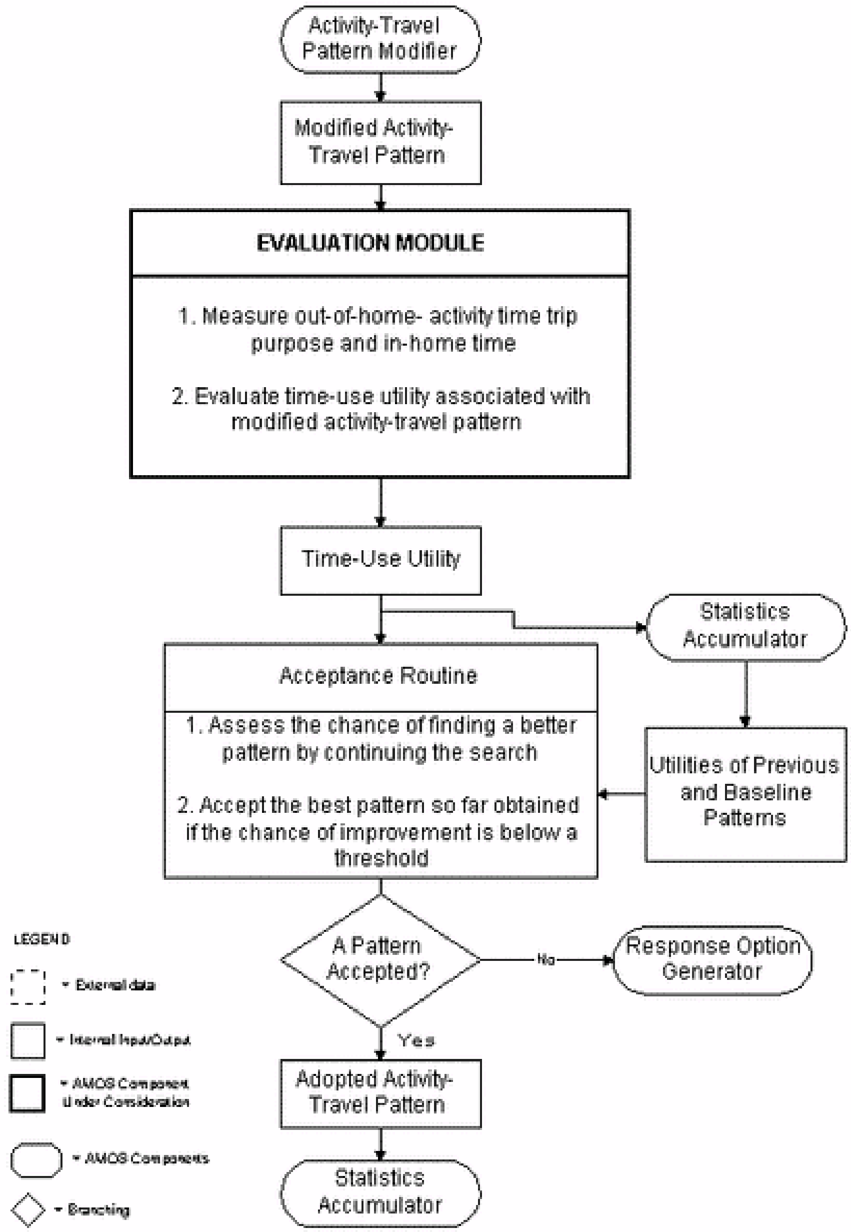
Figure D.1 depicts the structure of the Evaluation Module and Acceptance Routines. An accepted activity-travel pattern that passes all of the feasibility checks in the previous component of the AMOS model systems constitutes the input to this component. The evaluation routine first measures the amount of time spent on various activities outside the home, the total amount of time spent in-home, and the total amount of time spent traveling to various activities. The utility of each activity episode is computed as a function of the activity duration, activity type, density of opportunities for pursuing that activity, and the travel time expenditure for that activity episode. The utility associated with an entire activity-travel itinerary is then taken as the sum of the utilities derived from individual activity episodes.

Thus, AMOS uses a time-based utility measure to evaluate the welfare or level of satisfaction derived from an activity-travel pattern. The utilities of all feasible alternative patterns and the baseline travel pattern are then compared to assess the probability of finding a pattern with a higher utility by continuing the search. If this probability falls below a certain threshold that is defined by individual attributes and activity needs, then the search is terminated and the pattern with the highest time-use utility is accepted. The acceptance routine performs this assessment and selection process. If no pattern is accepted, then another TDM response option is generated and the process repeated. On the other hand, if a pattern is accepted, it is sent forward to the next component of the AMOS model system.

D.2. Time Utility Functions

The utility of a daily activity/travel pattern is viewed primarily as a function of the amounts of time expended for both out-of-home and in-home activities. The other two important dimensions are: monetary expenditures, and the "quality" of time for each activity, which is determined by the location, the co-participants, the amounts of non-monetary resources devoted to the activity, and other contributing factors. An elaborate discussion on the theoretical formulation of activity-based time utility functions may be found in RDC, Inc. (1995). As such, only a brief discussion is provided here.

Figure D-1: Evaluation Module and Acceptance (Search Termination) Routine



The utility of an activity episode, *q*, is formulated as

$$Uq = Bk(q)\ln(tq) = [bk(q)\{\ln(hrk(q)) + gk(q)\ln(Sq)\} + eq]\ln(tq),\ tq > 0$$

where

tq	=	activity duration of episode *q*
k(q)	=	activity type of episode *q*

bk(q), gk(q)	=	unknown coefficient
rk(q)	=	density of opportunities for activity k(q)
h	=	scaling constant
Sq	=	travel time expenditure for episode *q*, and
eq	=	i.i.d. random error term.

The coefficient, Bk(q) (>0), may be viewed as the modifier of the basic time utility, ln(tq). The modifier is assumed to vary by activity type and represents the locational attributes of activity episode *q* in this formulation.

In this formulation, the term, ln(hrk(q)) + gk(q)ln(Sq), reflects the consideration that the utility of an opportunity chosen for the activity on average increases with the number of opportunities out of which that opportunity has been chosen. It may be reasonably assumed that an opportunity chosen after traveling Sq is better than those opportunities closer than Sq; otherwise that distance will not be traveled

In applying the above, appropriate zonal density measures may be selected for rk(q) considering the type of activity. Determining Sq for linked trips is not straightforward. One approach is to use a measure of the deviation of the opportunity location from the line obtained by connecting the previous location and the next location (including the home base), e.g.,

max (tiq + tqj - tij, 0),

where i is the previous opportunity, j is the next opportunity, and tij is a measure of spatial separation between opportunity i and opportunity j.

Assuming that the total utility of the series of activities pursued during a day is the sum of the utilities of the respective activities, we let

U(Tit, Rit) = S Uq = S Bk(q)ln(tq),

where the summation is for all non-travel activities. This form of the utility function is used to evaluate alternative activity/travel patterns in AMOS. It is noteworthy that the same formulation can be used even if the total utility is considered a product of individual utilities.

This basic utility expression warrants two extensions:

- Incorporation of monetary expenditures
- Incorporation of differential effects of travel modes on the quality of travel time.

Monetary expenditures or the stock of instruments and devices available for activity engagement do affect the quality of time spent for the activity. For example, the same two-hour dinner may yield different levels of utility depending on the quality of the restaurant, which will be reflected in the monetary expenditure there. Unfortunately, such information is usually not available in travel behavior data sets. Because of this, it will be assumed that such differences can be represented by incorporating measured socio-economic attributes of the individual into the utility function, and by its random error term, eq. This calls for the following modification of Uq:

$$Uq = [bk(q)\{\ln(hrk(q)) + gk(q)\ln(Sq)\} + \mathbf{B}k(q)'\mathbf{X}i + eq] \ln(tq),\ tq > 0,$$

where **B**k(q) is the vector of coefficients and **X**i is the vector of the attributes of individual i.

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References

Goodwin, P.B., M.C. Dix and A.D. Layzell (1987) The case for heterodoxy in longitudinal analysis. *Transportation Research*, **21A**, 363-376.

Goodwin, P.B., R. Kitamura and H. Meurs (1990) Some principles of dynamic analysis of travel demand. In P.M. Jones (ed.), *New Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, Gower Publishing, Aldershot, England, pp. 56-72.

Goodwin, P. (1992) Panel analysis of travel behavior: Some empirical findings. Paper presented at the First U.S. Conference on Panels in Transportation Planning, Lake Arrowhead, CA.

Kitamura, R. (1988a) An evaluation of activity-based travel analysis. *Transportation*, **15**, 9-34.

Kitamura, R., C.V. Lula and E.I. Pas (1993) AMOS: An Activity-Based, Flexible and Truly Behavioral Tool for Evaluation of TDM Measures. *Proceedings of Seminar D, 21st PTRC Summer Annual Meeting*, PTRC Education and Research Services Ltd., London, pp. 283-294.

Kitamura, R. and T. Van der Hoorn (1987) Regularity and irreversibility of weekly travel behavior. *Transportation*, **14**, 227-251.

Kitamura, R. (1990) Panel analysis in transportation planning: An overview. *Transportation Research*, **24A**, 401-415.

RDC, Inc. (1995) Data Analysis and Policy Implications for Transportation Demand Management Strategies. Prepared for the U.S. Department of Transportation, Comsis Corporation Contract # 5660, RDC, Inc. Work Order #B-95-04.

RDC, Inc. (1993b) Further Comparative Analysis of Daily Activity and Travel Patterns and Development of a Time-Activity-Based Traveler Benefit Measure. Prepared for the Dutch Ministry of Transport and Public Works, the Hague, the Netherlands.

Recker, W.W., M.G. McNally, and G.S. Root (1986a, 1986b) A model of complex travel behavior: Part I v Theoretical development, and Part II - An operational model. *Transportation Research*, **20A**(4), 307-18, and 319-330.

Recker, W.W. (1995) The household activity pattern problem: General formulation and solution. *Transportation Research B*, **29B**(1), 61-77.

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Acknowledgments

RDC, Inc. (RDC) was engaged by the Metropolitan Washington Council of Governments (MWCOG) as part of the Travel Model Improvement Program (TMIP), jointly sponsored by the U.S. Department of Transportation (DOT) and the U.S. Environmental Protection Agency (EPA). In addition to MWCOG, the contractual support of COMSIS Corporation is gratefully acknowledged. The primary purpose of the project was to evaluate selected travel demand management (TDM) policies. To perform this applied research study, RDC, Inc. completed the development of its activity-mobility simulator (AMOS) that relies on a dynamic micro-simulation methodology to replicate household responses to alternative TDM policies.

RDC wishes to acknowledge the contribution of several individuals from the institutions cited above for their constant encouragement and assistance offered during the course of this research: Fred Ducca and Monica Francois at the Federal Highway Administration; Ron Jensen-Fisher at the Federal Transit Administration, Jon Kessler at the EPA; and Ron Kirby, Jim Hogan, Bob Griffiths, and Ron Milone at MWCOG. This research also benefitted from the contributions of Eric Pas at Duke University and Keith Lawton at Portland Metro, who assisted in the design and implementation of the household survey. The services of Mark McCourt at Strategic Consulting Research, Inc. in survey administration are gratefully acknowledged.

RDC acknowledges the commitment and dedication of its staff who were instrumental in conducting the research and making this report possible: Ram M. Pendyala, Prasuna Dvg. Reddy, Brandon Hawks and Qiuzi Cynthia Chen. Clarisse V. Lula is given special recognition by RDC for her commitment, leadership and technical support to this challenging and important research project. Finally, RDC gives special acknowledgment to Ryuichi Kitamura for the technical insight and leadership essential to the creation of AMOS, and its application to the Washington, D.C. metropolitan area reported herein.

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