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# An activity-based microsimulation analysis of transportation control measures

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**This paper describes the development and application of an activity-based microsimulation model system capable of simulating changes in individual travel patterns in response to a transportation control measure. A unique activity-based time use survey was conducted to obtain information on people's activity and travel patterns and their likely behavioral adjustment in response to various transportation control measures. This paper describes the survey and the use of the ensuing data set in estimating various components of the simulator, called AMOS. The first application in the Washington DC area demonstrated the capabilities of AMOS as a transportation policy analysis tool. Sample results from the Washington DC demonstration are presented.** 

*Keywords*: microsimulation model, travel patterns, transport control, Washington DC

## Introduction

Over the past several 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 (temporal shift). However, these strategies alone were not able to alleviate air quality, traffic congestion, noise, and safety problems associated with an ever-increasing travel demand. As a result, new strategies termed Transportation Control Measures (TCM) 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 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 on a per capita basis.

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 models do not explicitly model these relationships in a theoretically sound framework.

Consequently, activity-based approaches to travel demand forecasting were conceived and proposed in the travel behavior research arena (Kitamura, 1988). 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 interaction among various members of a household as households tend to allocate and coordinate their activities. As such, it has been argued that activity-based approaches provide a theoretically and conceptually stronger framework for modeling travel behavior in the current planning context.

Activity-based approaches focus on the timing, destination, duration, and constraints in human activity engagement. Implementation of these approaches requires activity and travel behavior data that is not collected in traditional household travel surveys. If the activity-based approach is going to be used in the context of evaluating or forecasting the impact of a proposed TCM, revealed activity-travel behavior data will have to be combined with stated adjustment data. Stated adjustment data provide information on how people may adjust their current travel patterns in response to hypothetical scenarios of TCM implementation.

This paper reports on the results of implementing an innovative activity-based microsimulation model to TCM impact evaluation in the Washington DC metropolitan area. A unique activity-based travel data set combining revealed preference and stated adjustment information was used in the model development and implementation phases of the effort. The model simulates changes in travel behavior for each individual and generates modified travel patterns that may be adopted in response to a TCM.

This paper consists of eight more sections. The next section provides a brief description of the activity-based microsimulation model and its components and operation. The third section describes the survey that was conducted in conjunction with this study while the fourth section summarizes key characteristics of the respondent sample. The fifth section provides an analysis of the stated responses offered by survey participants in response to hypothetical TCM scenarios. The sixth section describes model estimation results. In the seventh section, the implementation of the model in the Washington DC area is described in brief. The detailed TCM policy analysis results are offered in the eighth section while conclusions are drawn in the ninth section.

## Description of AMOS

The activity based microsimulation model that was developed and implemented in this effort is referred to as AMOS, an acronym for Activity Mobility Simulator. In its prototypical application, AMOS was intended to serve as a short term transportation planning and policy analysis tool. AMOS is an activity-based microsimulator 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 engagement and travel behavior pattern that a person is likely to adopt in response to a TCM. This is accomplished through the implementation of several modules. The modules comprising AMOS are briefly described in this section.

The first module is called the Baseline Activity-Travel Analyzer. The baseline activity-travel analyzer reads individual trip records from a typical travel diary data set and compares them with network data for logical consistency and missing information. It then generates a coherent baseline activity-travel pattern for each individual. In addition, for commuters, it examines for the presence of stops on the way to or from work and for the use of a personal vehicle while at work. These commute characteristics will be used in ensuing components of AMOS to constrain the choice of mode to work.

The second component of AMOS is the TDM Response Option Generator. This module creates the 'basic' or 'primary' response of an individual to a TDM strategy or TCM. The generator consists of a neural network model that is trained using survey responses obtained from hypothetical TCM scenarios. The baseline activity-travel pattern from the previous module, demographic and socio-economic attributes, and the characteristics of the TCM under investigation serve as inputs to this module. The output of this module is defined by the basic behavioral response that a person is likely to exhibit in response to a TCM. The TCMs may be characterized by changes in cost, travel time, modal attributes, and/or constraints that they bring about.

The Activity-Travel Pattern Modifier constitutes the third module of AMOS. This module lies at the heart of AMOS and consists of an activity-trip resequencing and rescheduling algorithm. It furnishes one or more modified but feasible alternative activity-travel patterns based on the primary level response provided by the TDM Response Option Generator. For example, if the response option generator indicated a mode shift to transit as the possible primary level response that an individual may exhibit, the modifier will deduce the secondary and tertiary changes that will be brought about in the travel pattern due to the mode change. It then constructs a coherent modified activity-travel pattern that will be evaluated for possible adoption by the individual. The inputs of this module include the baseline activity-travel pattern, network data, land use data, socio-economic and demographic data, and the response option from the TDM Response Option Generator. The output of this module is a modified activity-travel pattern. The feasibility of the modified activity-travel pattern is checked for consistency and logic against a set of rule-based constraints that people must adhere to. There are physiological constraints (e.g., a person must sleep and eat), spatial constraints (e.g., destination of one trip serves as the origin for the next trip), temporal constraints (e.g., a day consists of 24 h), modal constraints (e.g., one can not drive if no vehicle is available), and institutional constraints (e.g., business establishments are open during certain hours).

The modified but feasible alternative activity-travel pattern generated by the modifier must be evaluated for potential adoption. The fourth component of AMOS, namely, Evaluation Module and Acceptance Routine, serves this purpose. This component evaluates the utility associated with an activity-travel pattern based on the time allocated to various activities and travel in the pattern (Kitamura *et al.*, 1995a). Operationally, its built-in acceptance routine assesses 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. The search termination rules are defined so as to permit the acceptance of sub-optimal choices of travel patterns. This is based on the notion of 'satisficing' which postulates that an individual will experiment with a limited set of alternatives before choosing one that is satisfactory. The model recognizes that people do not have perfect information, can not exhaustively enumerate and experiment with all possible alternatives, and are often unable to select the optimal choice.

The final module in AMOS serves as an output device. This module, called the Statistics Accumulator, reads all feasible and accepted activity-travel patterns provided by the Evaluation Module and Acceptance Routine to generate descriptive measures of travel on a daily basis. These measures include vehicle miles traveled, trip frequencies by purpose and mode, number of stops, number of trip chains by type, activity duration by purpose, travel times by purpose, vehicle occupancy, cold and hot starts, etc. In addition, all of these measures are provided by time-of-day. In conjunction with the baseline activity-travel patterns, the accumulator is able to provide measures of change in travel demand as a result of a TCM implementation.

As such, AMOS consists of a series of inter-related components that collectively serve as a comprehensive transportation planning and policy analysis tool. Detailed operational descriptions, assumptions, and underlying algorithms of all AMOS components can be found in Kitamura *et al.* (1995b). A review of other activity-based travel modeling tools can be found in Pendyala *et al.* (1995).

## AMOS survey

The development and application of AMOS involved an elaborate survey effort (hereafter, AMOS survey) involving the collection of both revealed preference and stated adjustment data. The survey furnished the data needed to train the neural network in the TDM Response Option Generator module of AMOS. Upon completion of neural network training, household travel diary data from the Washington DC metropolitan area provided the baseline activity-travel patterns to which AMOS could be applied. This section describes the AMOS survey methodology and administration.

The objective of the AMOS survey was to obtain a data set that could be used to model individual responses to various TCMs. To this end, the survey included an activity-based time use section to obtain revealed preference information on daily activity and travel behavior, and a stated adjustment (or stated adaptation) portion to obtain information on how individuals would respond in the event of a TCM implementation. As the initial development of AMOS and the TCMs considered were primarily targeted at commuters, the target population for the survey consisted of adults who commuted (to/from work or school) at least three days a week. Only one commuter was interviewed in each household, thus precluding the ability to capture interactions among household members.

The survey was administered in three phases using computer aided telephone interview (CATI) techniques. In the first phase, a CATI was conducted to screen survey participants, obtain information on commute characteristics, work schedules, and demographics, and to assign a travel day for which the respondent would report his or her activity/travel pattern in ensuing phases of the survey. In the second phase, a memory jogger was mailed to the participants so that they could record their activities and travel for the assigned day. In the third phase, the activity and travel information was retrieved over the phone using CATI.

The stated adaptation portion of the survey was also administered in the third phase. TCM scenarios were customized to each individual's commute situation so that they were meaningful and realistic to the survey participants. Participants were presented with six TCMs (one scenario per TCM). The TCMs included in the survey are:

- *TCM #1: Parking Pricing*
  An incremental parking surcharge imposed at the work place with ranges $1 to $3 per day in suburban areas and $3 to $8 in downtown areas.
- *TCM #2: Improved Bicycle/Pedestrian Facilities*
  A description of improved bicycle and pedestrian friendly facilities including well-marked and well-lit bicycle paths and sidewalks and a secure place to park a bike wherever a person went.
- *TCM #3: Parking Pricing and Improved Bicycle/Pedestrian Facilities*
  A combination of TCM #1 and TCM #2.
- *TCM #4: Parking Pricing and Employer Supplied Commuter Voucher*
  A monthly parking surcharge imposed at the work place along with an employer supplied commuter voucher that could be used to cover transportation costs. Both had ranges of $40 to $80 per month.
- *TCM #5: Congestion Pricing and Travel Time Reduction*
  Peak period congestion pricing imposed along entire commute route with a range of $0.15 to $0.50 per mile together with a travel time reduction of 10% to 30%. Peak period defined as 06.00–09.00 hr and 16.00–19.00 hr.
- *TCM #6: Parking Pricing/Employer Voucher and Congestion Pricing/Travel Time Reduction*
  A combination of TCM #4 and TCM #5.

After presenting a scenario, the respondent was asked what he or she would do as a consequence of the TCM implementation. The respondent was not prompted with a list of possible changes unless necessary. The respondents' stated adjustments were coded into one of eight possible response options:

- Do nothing different
- Change departure time to work or school
- Walk to work or school
- Bicycle to work or school
- Car/Van pool to work or school
- Take transit to work or school
- Work at home
- Other

Upon the respondent providing a stated adjustment, a series of follow-up questions were presented to the individual to determine the impacts of the stated adjustment on their activity-travel pattern. For example, suppose an individual indicates that he or she will switch to transit in response to congestion pricing. Then, if the individual currently stops to drop off a child at school on the way to work, a follow-up question is posed asking how that stop would be handled after the switch to transit. In this manner, the survey derived information about likely secondary and tertiary changes in the activity-travel itinerary and ensured that the respondents thought about their entire itinerary when providing a stated response to a TCM scenario.

Considering the length and complexity of the survey, the response rates obtained were as expected. A total of 2664 calls were answered by a person. A total of 48% or 1283 persons completed Phase 1 of the survey; 1003 of the 1283 persons qualified and agreed to participate in Phase 2. Out of the 1003 persons, 65% or 656 commuters responded to all phases of the survey and provided complete information. The analysis in this paper is done using the sample of 656 commuters who provided complete data.

## Sample characteristics

This section provides a brief overview of the sample characteristics. The respondent sample consisted of 656 commuters belonging to 656 households. The average household size is 2.7, while the average number of commuters per household is 1.7. On average, there are two vehicles and 1.4 bicycles per household. About 90% of the households have at least one vehicle per commuter indicating a high degree of vehicle availability for commuting purposes. About one-fifth of the households have at least one child less than 5 years of age.

Table 1 provides further details regarding the characteristics of the commuter sample which was used to develop AMOS. Almost all of the respondents are licensed and employed. Nearly 58% of the respondents

**Table 1** Respondent characteristics ($n = 656$ respondents)

| Characteristic | Average value |
|---|---|
| % 30–49 years of 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)** | **15.2** |
| % <5 miles | 22% |
| % 5–25 miles | 61% |
| **Home–work travel time (min)** | **31.7** |
| % <10 min | 12% |
| % 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% |

are male. About 70% of the respondents indicate driving alone (SOV) as their usual mode of transport to work (used three 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 min.

Quite a few of the respondents indicated that they trip chained at least one day the previous week (either during the journey to or from work). About 13% of the respondents stopped on the way to or from work to serve a child on one or more days. Nearly one-half of the respondents indicated that they stopped on the way home from work for an activity other than serving a child. In this context, it is important to note that the implementation of a TCM may bring about changes in trip chaining patterns, which in turn, may affect how an individual responds to that TCM.

## Analysis of stated adjustments to TDM strategies

As mentioned previously, the respondents were presented with six hypothetical customized TCM scenarios and asked how they would respond in the event of their implementation. Their responses were coded into one of eight possible categories. In this paper, only a few representative sample results are provided for the sake of brevity. Complete results and cross-tabulations can be found in RDC, Inc. (1995).

Table 2 provides the distribution of stated responses for TCM #4: Parking Pricing with Employer Commuter Voucher, TCM#5: Congestion Pricing with Travel Time Reduction, and TCM #6: Combination of TCM #4 and TCM #5. In addition, statistical tests examining the null hypothesis of equality across response distributions are also presented.

An examination of the response distributions indicates that, for these TCMs, about 60 to 70% of the respondents would not change their current travel choices even after the introduction of the TCM. Congestion pricing yields the largest percentage change (nearly 40 percent would either change departure time or mode to work). In general, the indications provided are as expected. Parking pricing has little impact on departure time, but substantial impact on mode switching. The response distribution for TCM #4 is significantly different from that of TCM #5 at the 0.05 level of significance. On the other hand, neither the response distribution of TCM #4 nor that of TCM #5 is significantly different from that of the combination TCM (TCM #6) at the 0.05 level. The respondents who indicated that they would not change in response to congestion pricing also indicated that they would not change in response to the combination TCM. It appears that this 60% of the sample can not or will not respond to a TCM, regardless of the TCM implemented.

Interesting results were obtained when the response distributions were cross-tabulated against various socio-economic, demographic, and travel characteristics. An example of a cross-tabulation indicating the effects of trip chaining on the response distribution is presented in this paper. Table 3 shows the distribution of responses to congestion pricing for those who made no stops on the way from home to work versus those who made one or more stops on at least one day (during the previous week).

Of the 656 respondents, 226 indicated that they stopped on at least one day the previous week during the home-to-work trip. 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 shifts, 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. On the other hand, with regard to mode shifts, 20% of those who did not trip chain were willing to change mode. The corresponding percentage for those who trip chained was only 11%. Trip chaining is found to be significantly related to the response distribution at a $p$-value of 0.0628.

The descriptive tabulations provided in this section provide insights into the types of relationships that can

**Table 2** Distribution of stated responses to TCM scenarios ($n=656$ respondents)

| Response option | Parking pricing w/Voucher TCM #4 | Congestion pricing w/Travel time red TCM #5 | Combination TCM TCM #6 |
|---|---|---|---|
| No change | 71% | 61% | 62% |
| Change departure time to work | 1% | 20% | 12% |
| Switch to transit | 10% | 8% | 10% |
| Switch to car/van pool | 9% | 4% | 6% |
| Switch to bicycle | 6% | 4% | 5% |
| Switch to walk | 1% | 1% | 1% |
| Work at home | 1% | 1% | 1% |
| Other | 2% | 2% | 3% |

$\chi^2$ test-statistic for TCM #4 vs. TCM #5 = 20.5, df = 7, $p=0.0046$.
$\chi^2$ test-statistic for TCM #4 vs. TCM #6 = 10.8, df = 7, $p=0.1474$.
$\chi^2$ test-statistic for TCM #5 vs. TCM #6 = 2.94, df = 7, $p=0.8908$.

**Table 3** Congestion pricing response distribution by trip chaining

| TCM 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% |
| ***Change mode*** | ***20%*** | ***11%*** |
| 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% |

$\chi^2$ test-statistic = 13.406; df = 7; $p=0.0628$.

be explored using the AMOS survey data set. Further exploratory analysis of the data set revealed the set of variables significantly affecting response distributions to various TCMs. These variables were used to train the neural network in the TDM Response Option Generator. The neural network training and its calibration results are described in the next section.

## Neural network training

The TDM response option generator consists of a neural network that provides the primary level basic response of an individual to a TCM. This section provides a brief overview of the neural network specification and training results.

A neural network may be considered a general-purpose function estimator or pattern recognizer. It 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 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 neural network methodology is adopted in AMOS as it draws from the theory of connectionism postulated in the field of cognitive sciences. According to that theory, humans process information by breaking it down into a multitude of inter-connected elements. Through the use of an assembly of inter-connected neurons, a neural network is able to depict the connectionist behavior of humans (Benjafield, 1992).

Training the neural network involves the estimation of weights associated with each of the neuron links. Once it is trained, a neural network can provide an appropriate output in response to various patterns of inputs. In AMOS, baseline travel characteristics, land use and socio-economic data, transportation supply data, demographic characteristics, and attributes of the TCM under investigation serve as inputs. The output comprises a set of behavioral responses defined by the eight response option categories mentioned in the previous section.

The neural network was trained using data from the AMOS survey. However, as the trained neural network was going to be applied to the 1994 household travel diary data of the Metropolitan Washington Council of Governments (MWCOG), only those variables in the AMOS survey database that were also available in the MWCOG database could be used for training purposes. Based on this criterion and the desire to maximize the use of the information in the database, a set of 36 input nodes (variables) together with eight output nodes (one node for each response option) were identified.

Broadly, the 36 input nodes encompassed an array of demographic, socio-economic, land use, transportation network, and TCM characteristics in addition to the baseline travel patterns. The method of backpropogation was used to adjust the weights associated with the links in the network so as to maximize the predictive accuracy of the network. The data set was divided randomly into two subsets; one subset was used for estimation (training set) and the other for validation (validation set). The predictive accuracy is measured in terms of the percentage of cases in the validation set whose output nodes are correctly classified when compared against their stated response. Based on considerations of complexity and predictive sensitivity and accuracy, a network with two hidden layers was chosen for implementation within AMOS.

When the training is complete, a certain output node (of the possible eight) corresponding to one behavioral response option is activated for each respondent. This deterministic activation level is then converted to a probability measure using standard econometric maximum likelihood estimation procedures. A conversion function is statistically estimated such that the neural network best replicates the observed responses in the training data set. In this way, the stochastic nature of human travel choice processes is explicitly captured in AMOS.

## Application of AMOS in Washington DC area

This section discusses the implementation of AMOS in the Washington DC area for the Metropolitan Washington Council of Governments (MWCOG) and provides an example of how a baseline travel itinerary may be modified in response to a TCM.

AMOS was 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 mode. AMOS therefore has the level of geographical resolution that equals that of the MWCOG's TAZ system. The implementation effort thus utilizes as much spatial and modal information as available from the MWCOG planning databases.

Baseline travel patterns were obtained from the 1994 MWCOG household travel diary survey. MWCOG provided complete data (with trip origins and destinations geocoded at the TAZ level) for a small subsample of 98 commuters. AMOS has been applied to this subsample of commuters to analyze the impacts of various TCMs on a sample-wide basis (the subsample is too small to permit a rigorous regional analysis).

A few selected characteristics of the MWCOG survey subsample are highlighted below:

- The average age of the sample 38 years, with about 90% between the age of 16 and 65 years.
- About 50% of the sample resides in households with two vehicles. Only two commuters reported a vehicle ownership of zero.

- About 80% of the households are one- or two-commuter households. On the other hand, the household size is more uniformly distributed, with about 50% of the sample indicating a household size greater than two. These households were characterized by the presence of young children.
- The average commute time (including any stops) for the sample is about 30 min with the distribution slightly skewed in favor of travel times below the average value.
- About 60% of the sample commutes by SOV, 15% by car or van pool, and only 2% by transit (bus or rail). Bicycle and walk modes, when combined, were second only to SOV with a combined share of 17%. As such, this sample under-represents the presence of transit users in the population.
- From the baseline travel patterns, it was found that about 40% of the 98 commuters report at least one stop either on the way to or from work indicating a substantial presence of trip chaining.

The neural network that was trained using the AMOS survey data was applied to the MWCOG survey subsample of 98 commuters to first predict their basic (primary) response to a TCM. However, this response alone 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, and vehicle miles traveled. In order to obtain such statistics, the basic response option must be used to deduce secondary and tertiary changes that may be brought about in an individual's activity-travel pattern.

As described in the second section of this paper, the activity-travel pattern modifier uses a rule-based algorithm to determine alternative, but feasible activity-travel patterns that a commuter may adopt in the new travel environment. In applying AMOS to the MWCOG survey subsample, 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 (generated by the neural network).

Several assumptions were made to facilitate the implementation of the modifier. Some of the assumptions were institutional in nature; for example, business hours for offices were assumed to be 09.00 hr–17.00 hr. Also, work durations were assumed to be fixed according to the baseline travel pattern. Similarly, assumptions were made regarding store hours for shopping, destination locations, activity schedules, and non-work activity durations.

Table 4 presents an example of a baseline travel pattern and a modified, but feasible pattern generated by AMOS in response to congestion pricing (TCM #5). The table presents only one among the several alternative patterns generated by the modifier. The evaluation module and acceptance routine determines the specific pattern that may ultimately be adopted.

This commuter travels to work by automobile as a driver during the peak period. The TDM response

**Table 4** Baseline and modified travel pattern for sample case (TCM #5: congestion pricing with travel time reduction)

*Household ID: 10196665; Person ID: 2; Age: 38; Sex: Male*

| Trip no. | Origin TAZ | Destn TAZ | Origin locn | Dest locn | Depart time | Arrive time | Mode | Driver passenger |
|---|---|---|---|---|---|---|---|---|
| *Baseline pattern* | | | | | | | | |
| 1 | 217 | 7 | Home | Work | 08.18 | 08.38 | 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 | ChldCare | 22.00 | 22.12 | Auto | Passenger |
| 6 | 110 | 217 | ChldCare | Home | 22.13 | 22.25 | Auto | Driver |
| ***Summary characteristics*** | | | | | | | | |
| Auto psgr trips: | 3 | Work trips: | 1 | Peak trips: | 2 | | | |
| Auto drvr trips: | 3 | Home trips: | 3 | Total trips: | 6 | | | |
| Commute mode: | Auto driver | | | | | | | |

| Trip no. | Origin TAZ | Destn TAZ | Origin locn | Destn locn | Depart time | Arrive time | Mode | Driver/ passenger |
|---|---|---|---|---|---|---|---|---|
| *Modified pattern* | | | | | | | | |
| **Response option: change departure time to work** | | | | | | | | |
| 1 | 217 | 7 | Home | Work | 09.00 | 09.20 | 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* | | | | | | | | |
| Auto psgr trips: | 3 | Work trips: | 1 | Peak trips: | 0 | | | |
| Auto drvr trips: | 3 | Home trips: | 3 | Total trips: | 6 | | | |
| Commute mode: | Auto driver | | | | | | | |

option generator (neural network) provided a primary level response option as 'change departure time to work' as one probable choice in response to peak period (07.00 hr–09.00 hr and 16.00–18.00 hr) congestion pricing. As such, the response option generated by the neural network is consistent with the TCM under investigation. In the baseline pattern, the individual makes two trips in the peak period that would be subject to congestion pricing. The modifier shifted both of these trips out of the peak period to avoid the congestion pricing. The trip to work in the morning now commences at 09.00 hr instead of 08.18 hr; and the trip from work commences at 18.12 hr instead of 17.30 hr (note that the work duration is kept fixed). As a result of the TCM implementation, both peak period trips are eliminated. However, neither the total trip frequency (by purpose) nor the travel mode changes.

This section has illustrated how the activity-travel pattern modifier, in conjunction with the TDM response option generator, provides alternative activity-travel patterns that may be adopted in response to a TCM. The modified patterns can be compared against the baseline patterns to obtain measures of changes in travel characteristics. The procedure described here was applied to the entire sample of commuters to perform a sample-wide policy analysis of TCM impacts. This is described in the next section.

## Policy analysis

As noted in the previous section, trip diaries are available from the 1994 MWCOG survey for conducting a policy analysis from only a very small sample of 98 commuters who are not representative of the population. Considering potential magnitudes of sampling errors associated with such a small sample, the results presented in this section should not be considered to represent an assessment of the merits of the TCM analyzed. Rather, the results presented in this section should be taken as numerical examples which illustrate how the activity-based policy tool applies to TCM analysis and how it evaluates TCM impacts while considering daily travel patterns in their entirety. The small sample size also precludes performing an analysis of TCM impacts by commuter market segment.

The example in the previous section showed how a commuter's daily itinerary is reconstructed based on the TDM response option predicted by the neural network. Several evaluation measures are used in this study to assess the impacts of a TCM. Changes in daily travel patterns are aggregated and sample-wide mean values are obtained for the following measures:

- Daily trip frequencies by purpose and mode
- Travel time by mode
- Modal shares
- Peak period trip frequencies by purpose and mode
- Peak period travel time
- Peak period modal split

The first step in the policy analysis is to define parameter values that characterize the TCM under investigation. In this paper, policy analysis results are presented for only one TCM, namely, TCM #5: Congestion Pricing with Travel Time Reduction. For the sake of brevity, policy analysis results for the other TCMs are not presented here. For conducting a congestion pricing policy analysis, two parameter values had to be established. First, the congestion price was set at \$0.50 per mile and second, the travel time reduction was set at 30%.

A total of 20 simulation runs were performed to analyze the impacts of congestion pricing. An average value over all simulation runs was used to measure changes in travel characteristics. Table 5 presents results of the policy analysis by comparing baseline travel characteristics with those obtained from the activity based microsimulation analysis.

**Table 5** AMOS simulation results for congestion pricing

| Travel indicator | Total | | a.m. Peak | | p.m. Peak | | Off-peak | |
|---|---|---|---|---|---|---|---|---|
| | Baseline | Simulation | Baseline | Simulation | Baseline | Simulation | Baseline | Simulation |
| **Trip purpose** | | | | | | | | |
| Work | 42.2% | 43.0% | 64.0% | 64.4% | 31.1% | 35.6% | 36.6% | 36.5% |
| Non-work | 57.8% | 57.0% | 36.0% | 35.6% | 68.9% | 64.4% | 63.4% | 63.5% |
| **Travel mode** | | | | | | | | |
| Auto-Driver | 54.0% | 50.2% | 65.1% | 56.3% | 54.7% | 51.9% | 45.5% | 39.7% |
| Auto-Psgr | 18.4% | 17.0% | 10.5% | 10.3% | 18.9% | 18.3% | 23.6% | 22.2% |
| Other | 27.6% | 32.8% | 24.4% | 33.4% | 26.4% | 29.8% | 30.9% | 38.1% |
| **Trip duration (min)** | | | | | | | | |
| Total | 18.5 | 19.0 | 21.7 | 23.0 | 22.0 | 22.6 | 13.4 | 13.5 |
| Auto-Driver | 21.6 | 21.4 | 24.5 | 23.5 | 24.9 | 24.5 | 15.2 | 16.1 |
| Auto-Psgr | 17.0 | 17.3 | 16.4 | 16.4 | 21.4 | 21.8 | 14.2 | 14.5 |
| Other | 13.6 | 16.2 | 16.4 | 24.2 | 16.2 | 19.9 | 10.1 | 10.2 |
| **Percent hot starts** | 37.7% | 36.8% | 34.9% | 34.5% | 35.9% | 36.5% | 37.8% | 34.9% |
| **Percent of trips** | 100% | 100% | 27.3% | 26.9% | 33.7% | 32.2% | 39.0% | 41.0% |
| **Trips per person** | 3.21 | 3.30 | | | | | | |

The overall distribution between work and non-work trips does not show any substantial changes with the TCM in place. This applies to all time periods, whether peak or off-peak. During the peak periods (when congestion pricing is in effect) a slight increase in the percentage of work trips is noted. This is expected as discretionary non-work trips may be rescheduled and moved out of the peak period to avoid congestion pricing while work trips may not exhibit the same degree of flexibility.

Analysis of modal shares shows substantial effects of the TCM. The share of auto-driver and auto-passenger trips (which are subject to congestion pricing) decrease during all time periods with the greatest decrease seen during the morning peak period. During the afternoon/evening peak period, the decrease is not as pronounced, possibly due to the constraints associated with activity engagement (trip chaining while serving children, personal business, shopping, etc.). The decreases seen in the auto-driver mode are larger than those seen in the auto-passenger mode, where passengers share the cost of the congestion pricing.

In general, average trip durations show virtually no change between the baseline case and the simulation runs. Similarly, the percentage of hot starts also showed virtually no change except in the off-peak period where it decreased from 37.8% to 34.9%. This may be attributable to the decrease in auto-driver mode share for the work trip. If a person chooses to use transit and the automobile is left at home, the individual may undertake shopping and other activities in a separate home-based trip chain which will entail a cold start.

Interestingly, the total trip frequency shows a slight increase from 3.21 hr to 3.30 hr. This may be explained by the breaking up of trip chains as people abandon their automobile for the trip to work. When using the automobile for their commute, individuals could link their other activities (shopping, etc.) on the way to or from work. If they were to use transit (say, after the introduction of congestion pricing as in this case), then such activities are more easily pursued after returning home where an automobile is available. The generation of a separate trip chain to undertake these activities will drive up the overall trip frequency. The decrease in the percentage of trips in the peak periods and the concomitant increase in the off-peak period (39.0% vs. 41.0%) serves as further evidence of this phenomenon.

The exercise here shows that activity-based microsimulation models such as AMOS serve as practical tools capable of analyzing transportation policies while simulating daily travel patterns in their entirety. However, as noted earlier, the results in this section are merely illustrative of the capabilities of AMOS. The size of the subsample used in the demonstration warrants neither a generalization of the results obtained here nor a general assessment of the relative effectiveness of the TCM scenario examined here.

## Conclusions

This study reports on the development and implementation of a full-fledged activity-based model system for transportation policy analysis. Despite the theoretical arguments that warrant their practical application, activity-based approaches remained within the domain of academia for nearly two decades. The development of AMOS and its implementation in the Washington DC area represent significant steps forward in moving these approaches into transportation planning practice. 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.

AMOS, an activity-based microsimulation model system, has been applied to the evaluation of a set of transportation control measures using a small sample of trip diaries from the 1994 household travel diary survey of the Metropolitan Washington Council of Governments. The effort demonstrated that the 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 are stated adjustment survey results from the area, which are used to customize a component of AMOS to the area residents' responsiveness to TCMs.

The effort also showed that travel forecasts can be developed while treating the daily travel patterns of individuals in their entirety, without breaking them up into a series of independent trips and compromising the interdependencies and continuities that exist across a series of trips. This allows the assessment of TCM impacts in a more coherent framework while accounting for secondary and tertiary changes in a traveler's daily itinerary that are brought about as a result of a primary change in response to a TCM. For example, if a person switches from the auto mode to transit for the commute trip (primary change), then stops previously undertaken on the way to or from work may have to be rescheduled into separate home-based trip chains (secondary and tertiary changes).

Research activities are currently ongoing on several fronts to further enhance the capabilities of AMOS and transform it from a short term policy analysis tool into a complete long range forecasting system. New features that are being incorporated into AMOS include the ability to model household vehicle transactions, utilization, and allocation, and perform synthetic generation of households and their activity-travel patterns. Future research activities will attempt at incorporating models of inter-personal interaction and multi-day behavior.

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