Sensitivity Analysis on Activity-Based Travel Demand Models: MORPC's Example

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Introduction

Activity-based travel demand forecasting models have gained a well known reputation on their ability of accommodating in the model factors and variables related to new transportation policies and travel demand management strategies. Compared to the traditional 4-step approach, activity-based models are built upon sound behavioral theory to model the travel decision making process at the individual-level. Activity-based models use the form of discrete choice models derived from utility-maximizing behavior theory (*Train, 2003*). A number of socio-demographic characteristics of individuals and transportation system characteristics can be included in utility functions, and thus activity-based models are believed to be able to evaluate various alternative scenarios as long as variables related to the alternatives can be accommodated in the model.

The efficacy of activity-based models on evaluating various policies and strategies would largely depend on the coefficients associated to the policy-related variables in the model formula. Most policy scenarios are hypothetical rather than actual and few data from the real world are available for the purpose of validation. In this sense, most policy evaluations are similar to sensitivity analysis on those "policy-related" variables. It therefore becomes necessary to investigate if activity-based models are sensitive to the variables of interest in a reasonable way.

Sensitivity analysis involves relating variations in an independent variable to the resulting changes in the dependent variable (*Barton-Aschman, 1997*). The recently published TRB Special Report 288 indicated that "sensitivity testing is key to checking the reasonableness of travel forecasts." Before claiming any potential advantages of activity-based models, sensitivity analysis should be conducted to determine the range of alternatives over which the model is valid (*Cambridge Systematics, 2008*). Most activity-based models apply micro-simulation technique at the fully-disaggregate level of persons and households, which requires intensive use of computing resources. The run time of an activity-based model is usually measured in days rather than minutes or hours. Therefore, to conduct a comprehensive sensitivity analysis for an activity-based model becomes a challenge because of the limited computing resources.

The Mid-Ohio Regional Planning Commission (MORPC) is one of several MPOs that have operational activity-based travel demand models in the nation. Like a lot of other MPOs, MORPC experienced similar pressures from all sources for the request to model travel demand changes caused by the hike of gas prices in the summer of 2008. A corresponding sensitivity analysis was conducted on MORPC's activity-based model. In this paper, the procedure used for the sensitivity analysis is presented as well as the results. The purpose of the paper is to provide a practical example on how a sensitivity analysis was conducted on an activity-based model and the potential benefits the analysis could bring.

Scenarios

In MORPC's activity-based model, gas price is embedded in a variable called "auto operating cost". Griesenbeck and Garry (*2009*) provided a breakdown of the components in auto operating cost. To simplify the analysis presented here, four scenarios of different auto operating costs were used to simulate changes in gas price. The 2005 auto operating cost ($0.12 per mile) in MORPC's model was used as a Base scenario for comparison. Three other auto operating costs ($0.06, $0.24 and $0.36 per mile respectively) were used to represent a large range of variation in gas prices. Table 1 lists the four scenarios.

Table 1: Four Scenarios regarding Auto Operating Cost in Sensitivity Analysis

Scenario No.	Name	Description
1	Half	Auto operating cost = $0.06 per mile
2	Base	Auto operating cost = $0.12 per mile
3	Double	Auto operating cost = $0.24 per mile
4	Triple	Auto operating cost = $0.36 per mile

MORPC's model consists of a set of discrete choice model components, a description of which can be found elsewhere (*Anderson et al., 2003*). In order to conduct an analysis on a model's sensitivity to any input variable, it is critical to have a thorough understanding of the model flow and components to which the variable of interest is an input. A detailed MORPC model flow chart including all the sub-model components was developed during this sensitivity analysis (in Figure 1). In the flow chart, sub-models with "direct" inputs related to travel costs are labeled by a blue dollar sign. As can be seen, only mode-choice models have travel cost as "direct" input.

One underlying theory of discrete choice model is random utility maximization. All discrete choice models in MORPC's model are logit models. Under the logit assumptions, the expected maximum "utility" of a set of given choices can be expressed by a log-sum term. Therefore, the log-sum term can be used as a linkage between "downstream" choice models and "upper stream" choice models. Before implementing a "upper stream" choice model, the log-sums of the "downstream" choice model could be calculated and thus used as an input (or, "fedback") to any "upper stream" choice models to model the potential impacts from the choice that would be made in the "downstream" choice model. Illustrated in Figure 1, the log-sums of model choice models are "fedback" to destination choice models and/or time-of-day choice models.

In conducting this sensitivity analysis, it is expected that variations in travel cost inputs would not only impact mode choices but also destination and/or time-of-day choices. Correspondingly, various measures were developed to capture the resulting changes in the outputs of affected sub-models caused by the variation in auto operating costs. Some of the results are presented in the next section.

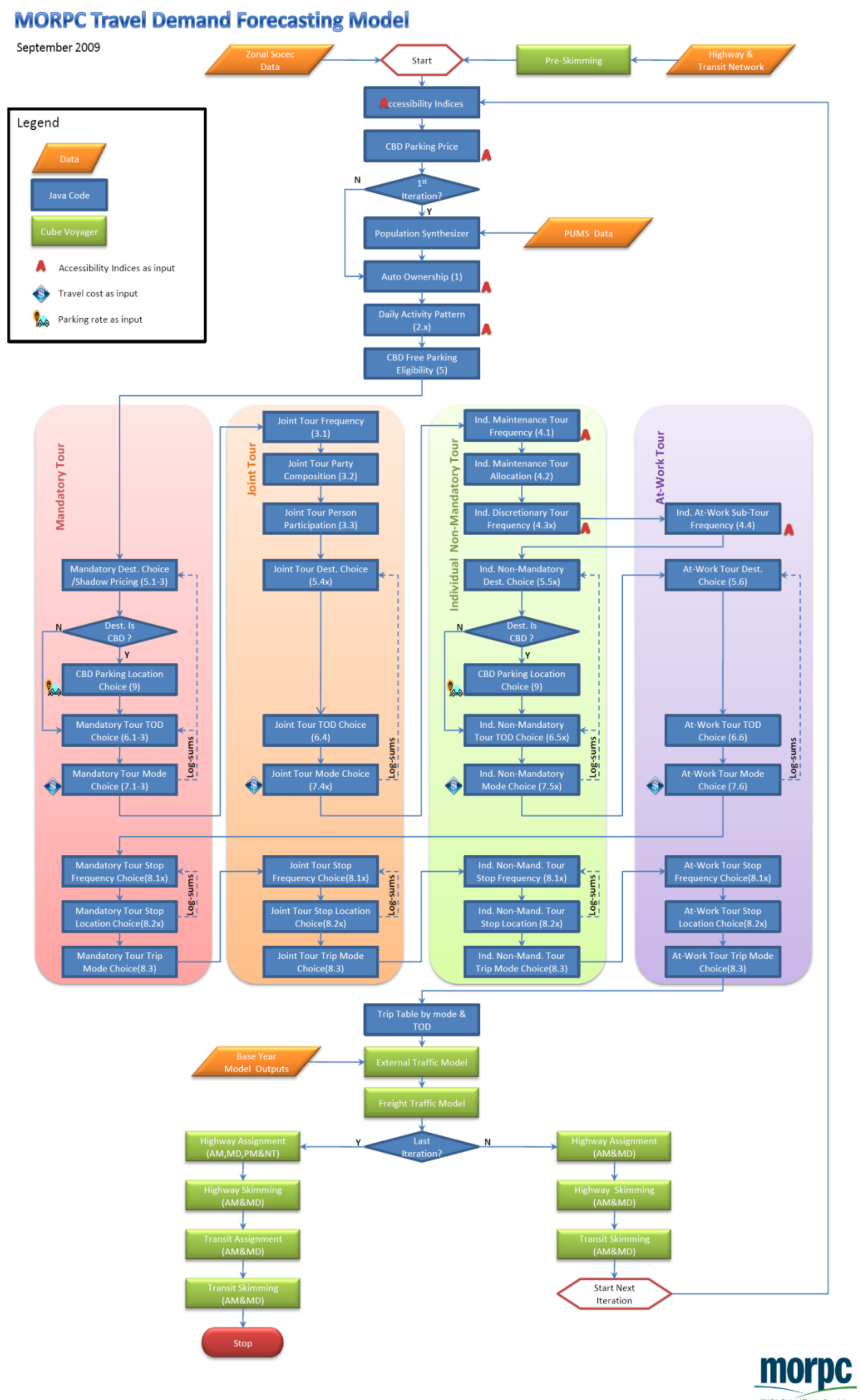

Figure 1. MORPC Travel Demand Model Flow Chart (for the use of sensitivity analysis)

Measures and Findings

Number of Half-Tours

In MORPC's model, tour rather than trip is used as the unit of travel, where a tour is defined as a closed chain of trips starting and ending at the same base location (anchor). To avoid the possible impact of stop frequency choice changes on the number of trips, the total number of half tours (from anchor to primary destination and from primary destination to anchor) was used as a measure of travel demand produced by the model. Here, primary destination is the location where the tour is mainly headed for rather than the intermediate stops. The total number of personal half tours, respectively for each of the four scenarios, is given in Table 2. Their relative differences to Base Scenario (2) were calculated. As can be seen, the number of personal half tours decreases when the auto operating cost rises. This makes sense intuitively, however, reasons for this change need to be interpreted carefully because there is no direct or log-sum "feedback" input of "auto operating cost" into tour frequency choice models. One of possible reasons might be that the increase of "auto operating cost" causes some people to shift commuting mode from auto to others, and correspondingly reduces those people's available time windows and capability to make other types of tours. The next measure will categorize the number of tours by tour type to further investigate the possible reason.

Table 2: Total Number of Person Half Tours for Four Scenarios

Scenario	1. Half	2. Base	3. Double	4. Triple
Number of person half tours	4,689,188	4,681,048	4,674,406	4,667,424
Relative difference to "Base" Scenario	0.2%	0.0%	-0.1%	-0.3%

Number of Half-Tours by Tour Type

There are four types of tours in MORPC's model: Mandatory (i.e., work/university/school) tours, Household Joint tour, Individual Non-Mandatory tours, and At-Work tours. The sub-models for the four types of tours were different and highlighted in the colored blocks in Figure 1. Figure 2 shows the relative differences of the four scenarios to the Base scenario in the number of tours by tour type.

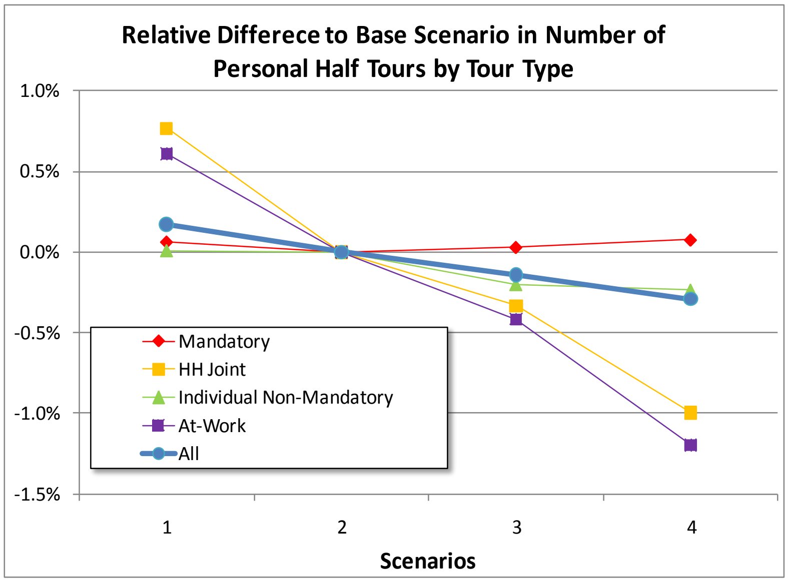

Figure 2: Relative Difference to Base Scenario in Number of Personal Half Tours by Tour Type

The number of mandatory tours showed little changes (less than 0.1%) with the variation in auto operating costs. The same is true for the number of individual non-mandatory tours (less than 0.2%). In the choice models determining the frequency of these two types of tours, no variables related to "auto operating cost" are involved. Therefore, considering their relative level of magnitude, the differences in the number of these two types of tour were most likely caused by the randomness from the Monte Carlo simulation process that most activity-based models (including MORPC's model) adopt.

The number of household joint tours showed a clear decreasing trend when the auto operating cost rises. In the household joint tour frequency choice model, there is a variable called "time window overlaps" between members of the household. The longer "time window overlaps" of its members are available, the more household joint tours the household could make. When Household members shifted from auto (fast) to other modes (slow) due to the increase of auto operating cost, shorter "time window overlaps" would be available in the household so that fewer household joint tours could be made by the household.

The number of at-work tours showed a similar trend as the number of household joint tours did. In the at-work tour frequency choice model, a dummy variable for drive-alone (SOV) mode for the work tour is included and its coefficient associated with the choice of making at-work tours is positive. That means, when a person makes the work tour by drive-alone mode, s/he would be more likely to make at-work tours. Therefore, it explains why the number of at-work tours decreases when the auto operating cost rises.

The combined changes in the number of household joint tours and at-work tours contribute to the changes in the number of all types of tours shown in Table 2.

Number of Half-Tours by Mode

Auto operating cost is a direct input to mode choice models. The number of personal half tours by mode can then serve as a measure to check the shifts among different modes due to the variation in auto operating cost. Four modes were examined: Single Occupancy Vehicle (SOV); High Occupancy Vehicle (HOV); Transit (bus); and Non-Motorized (walk and bike). Figure 3 presents the relative differences of the four scenarios to the Base scenario in the number of personal tours by mode.

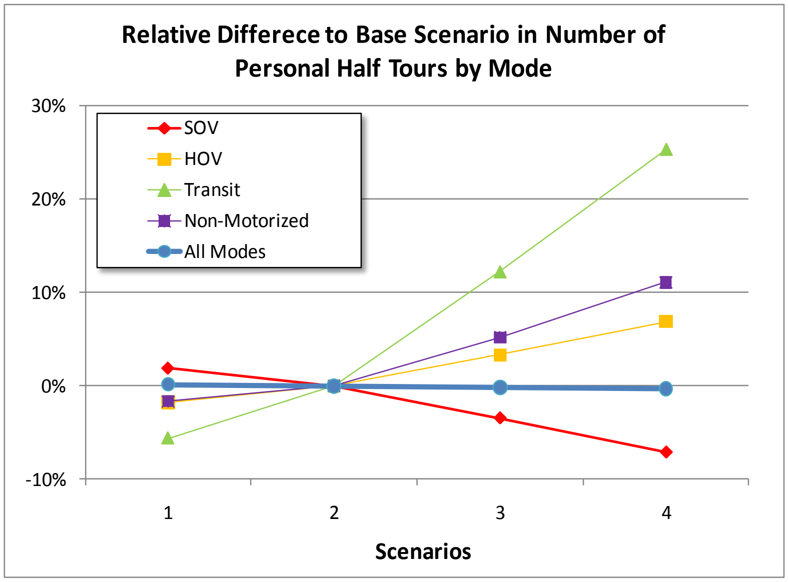

Figure 3: Relative Difference to Base Scenario in Number of Half Tours by Mode

When auto operating cost rises, the number of half tours made by SOV decreases while the number of half tours made by all other modes (HOV, transit and non-motorized) increases. These results appear intuitive and show the sensitivity of mode choice models to the auto operating cost.

Number of Half-Tours by Time-of-Day

Considering the log-sum term “feedback” from mode choice models to time-of-day choice models, the number of tours was examined by the four time-of-day periods, i.e., AM (6:30-9:30am), MD (9:30am – 3:30pm), PM (3:30pm – 6:30pm) and NT (6:30pm – 6:30am). Their relative differences of the four scenarios to the Base scenario are presented in Figure 4.

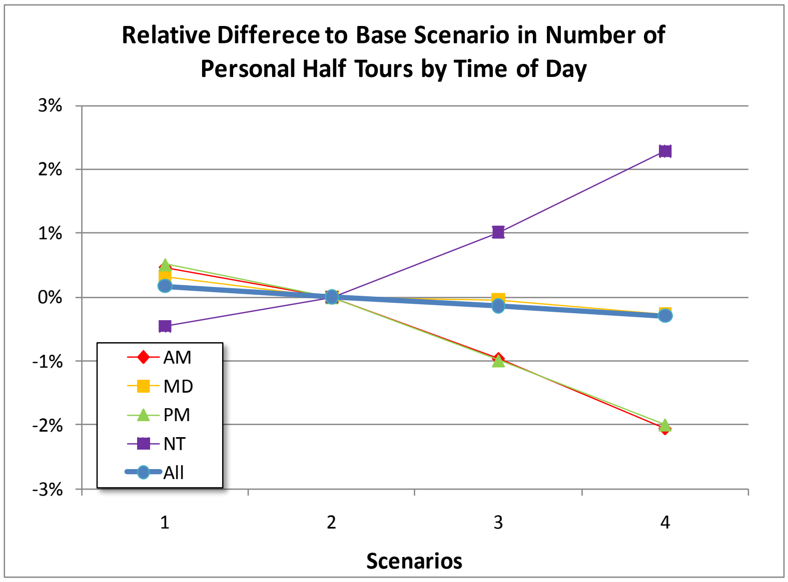

Figure 4: Relative Difference to Base Scenario in Number of Half Tours by Time of Day

When auto operating cost rises, the number of AM half tours decreases at the same rate as the number of PM half tours does; the number of MD half tours decreases but at a relatively low rate; however, the number of NT half tours increases counter-intuitively.

In MORPC's model, the log-sum term of mode choice models is only "fedback" into the time-of-day choice models for work tours, university tours and escorting tours. Work and university tours are dominant tours in mandatory tours, while escorting tours belong to individual non-mandatory tours and only occupy a small proportion. Therefore, the log-sum tem "feedback" of mode choice models would mainly affect the time-of-day distribution of mandatory tours. Figure 5 shows the relative differences of the four scenarios to the Base scenario in the number of mandatory tours by time-of-day. The trends in Figure 5 resembled a magnified version of the trends in Figure 4 because of different comparison base.

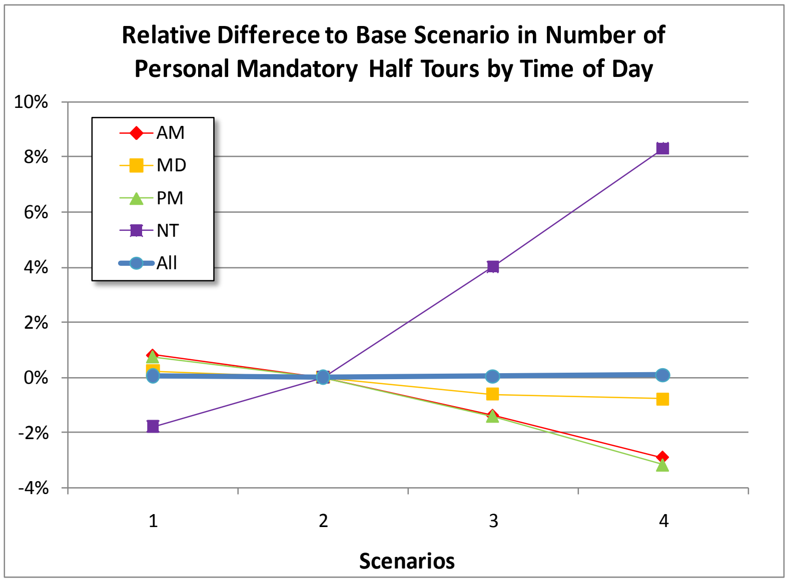

Figure 5: Relative Difference to Base Scenario in Number of Mandatory Half Tours by Time of Day

By investigating the time-of-day choice models for work/university tours, it was found that the coefficients associated with the mode-choice log-sum term varied with different combinations of the departure and arrival time-of-day periods of the tours. The mode-choice log-term coefficients for both early morning departure-early morning arrival and night departure-night arrival were set to zero because of lack of data for estimation. The coefficients for all other combinations of departure and arrival time-of-day periods were positive. The increase of auto operating cost would result in a decrease of the mode-choice log-sum term because log-sum terms are monotonic with respect to the systematic utilities in logit choice models. Therefore, when auto operating cost rises, any choice of departure and arrival time-of-day period combinations associated with a positive coefficient of mode-choice log-sum term would have fewer utility while the utilities for both early morning departure-early morning arrival and night departure-night arrival remain the same. Because only the relativity of choices' utilities matters in discrete choice models, increasing auto operating cost resulted in an illogical shift of mandatory tours to early morning and night hours (which are categorized as NT). This problem is being fixed by re-estimating the time-of-day choice models along with an ongoing mode-choice model update.

"Non-Stop" Distance of Half-Tours by SOV

Figure 1 shows that mode-choice log-sum term is fedback into primary destination choice models. In order to avoid the potential masking effects from changes in stop choices, the "direct" network distance from anchor to primary destination (named "Non-Stop" distance of half tour) was used to capture the impact of auto operating cost on the destination choices. Relative differences of the four scenarios to the Base scenario in tours made by SOV (i.e., drive-alone) are presented in Figure 6.

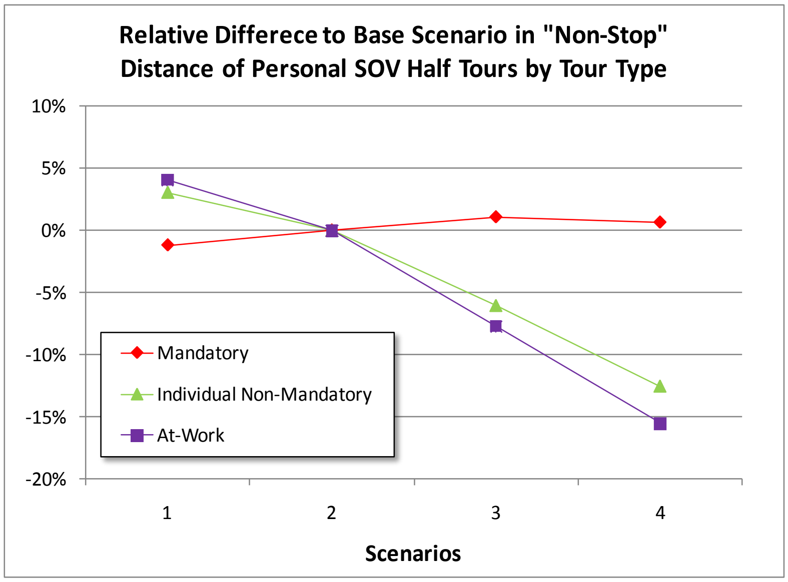

Figure 6: Relative Difference to Base Scenario in "Non-Stop" Distance of SOV Half Tours by Tour Type

As can be seen, "driving-alone" people would like to choose closer locations for individual non-mandatory and at-work tours when auto operating cost goes up. This appears intuitive.

However, no significant changes other than the "randomness" were found in the "non-stop" distance of mandatory tours made by SOV. The reason might be the shadow pricing technique employed in MORPC's model for constraining destination choice for mandatory tours based on the "employment" attractions of each TAZ. Hence, there is not much "freedom" to change work locations in the model.

VMT

As was highly reported on in the summer of 2008, VMT is a common measure for the impacts of gas price on travel demand. Table 3 shows the changes in VMT for the four scenarios. VMT in Tables 3 consists of all estimated travel in the model region including commercial truck travel and external travel. In MORPC's model, both commercial truck model and external traffic model are insensitive to the auto operating cost. The VMT changes in Table 3 are caused by the changes in personal travel within the model region, therefore, the resulting elasticity derived from Table 3 would be less than the range reported elsewhere (*Griesenbeck and Garry, 2009*).

Table 3: Total Number of Person Half Tours for Four Scenarios

Scenario	1. Half	2. Base	3. Double	4. Triple
VMT (1000's)	44,322	43,479	42,023	40,626
Relative difference to "Base" Scenario	1.9%	0.0%	-3.3%	-6.6%

Conclusions

The results from a simple sensitivity analysis on MORPC's activity-based travel model were presented. A detailed model flowchart was created to better understand specific input variables of interest in the sensitivity analysis. In the example presented, the auto operating cost (as an indicator of gas price) was the variable of interest. Various measures were developed to capture the possible impacts of the auto operating cost on the model outputs. Sensitivity analysis on more input variables is in progress.

Lessons were learned during the analysis. First, the sensitivity analysis resulted in a better understanding of MORPC's activity-based model, which has hundreds of input variables and intricate relationships among numerous sub-choice models. Implicit relationships were revealed during the process. Second, the sensitivity analysis proved to be a great debug tool to reveal bugs in the model. Any counter-intuitive results would flag a warning for possibly wrong coefficients, or wrong configuration of the model structure. Third, meaningful measures were valuable for sensitivity analysis. Innovative measures can help to shed light on the activity-based model.

According to MORPC's example, sensitivity analysis should be included as an essential part of model calibration and validation, especially for activity-based models with sophisticated structure. Before claiming any potential advantages of activity-based models over traditional approaches, sensitivity analysis is needed for the proof.

Because of the lack of data and comparable studies, most results of sensitivity analysis can only be compared against intuition. Although some procedures for sensitivity analysis can be found elsewhere (*Barton-Aschman, 1997*), it is highly recommended to create a comprehensive guidebook for conducting sensitivity analysis on travel demand models and providing reasonable ranges of elasticity of various variables.

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