AN ASSESSMENT TOOL FOR THE APPROPRIATENESS OF ACTIVITY-BASED TRAVEL DEMAND MODELS

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AN ASSESSMENT TOOL FOR THE APPROPRIATENESS OF ACTIVITY-BASED TRAVEL DEMAND MODELS

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LIST OF SYMBOLS AND ABBREVIATIONS

MPO	Metropolitan Planning Organization
CAAA	Clean Air Act Amendments
ISTEA	Intermodal Surface Transportation Efficiency Act
ACS	American Community Survey
PUMS	Public Use Microdata Samples
TAZ	Travel Analysis Zone
HBW	Home-Based Work
HBO	Home-Based Other
NHB	Non-Home Based
ARC	Atlanta Regional Commission
NCHRP	National Cooperative Highway Research Program
MNL	Multinomial Logit Model
IIA	Independence of Irrelevant Alternatives
NL	Nested Logit Model
WFRC	Wasatch Front Regional Council
PSRC	Puget Sound Regional Council

SUMMARY

As transportation policies are changing to encourage alternative modes of transportation to reduce congestion problems and air quality impacts, more planning organizations are considering or implementing activity-based travel demand models to forecast future travel patterns. The proclivity towards operating activity-based models is the capability to model disaggregate travel data and to better understand the model results that are generated with respect to the latest transportation policy implemenations.

An analytical review of the differences between trip-based models and activity-based models conducted through an examination of literature, interviews, and data pertaining to variables that are better represented in activity-based models.

A survey was then sent to the top fifty most populous regions in the United States to gauge the interest and usage of activity-based models. Further assessment was performed for those regions that provided information to the initial outreach effort. A series of parameters with known linkages to the advantages of activity-based models was devised in order to rate and provide a recommendation to each region as to whether they should pursue an activity-based model or not.

The results of the analysis show that the parameters used in this effort are often too broad to make a sound judgment about how a region should proceed with their modeling techniques. There are often other factors unrelated to transportation policies that can influence a region to move toward activity-based models or to discourage a region from using activity-based models. Though the assessment tool provides a means to begin a conversation about advancing modeling practices, it does not provide a definitive authorization for a region to change modeling procedures.

CHAPTER 1

INTRODUCTION

Travel demand models are used by Metropolitan Planning Organizations (MPOs) and other related agencies and consultants to help forecast future population growth and travel patterns to aid in the development of regional transportation plans. There are two model approaches that are highly regarded in the field of travel demand modeling: the trip-based model and the activity-based model. The trip-based model is the classical model that has been in existence in the United States since the 1950s when travel forecasts were important to deciding on where roads should be built to provide the best accessibility for the public.

The activity-based models are more advanced and take into account more precise information about individuals in a model region and can predict travel patterns based on a host of variables related to the personal preferences and behavior of the individual. These models are also able to provide insightful information about the change in travel patterns due to the implementation of transportation policies that have grown in popularity since the passing of the Clean Air Act Amendments (CAAA) of 1990 and the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991.

The purpose of this thesis is to first assess the current use of activity-based models in the United States and then to use a rubric that was developed based on the advantages that activity-based models offer to provide a recommendation as to whether a region should convert to an activity-based model. This is of importance because major cities that are experiencing congestion and environmental problems are in need of better prediction tools to forecast what future transportation patterns will bring to the region.

Chapter 2 summarizes the literature on travel demand modeling and provides a review of the differences between trip-based and activity-based models. A brief overview of the activity-based models that are currently in use is also included. Chapter 3 presents the methodology used to create the rubric that provides the recommendations to each model region; Chapter 4 presents the results of this research and Chapter 5 provides a discussion about the discrepancies that occurred between the recommendations provided and the actual state of activity-based modeling procedures in the country. Chapter 6 provides conclusions and recommendations.

CHAPTER 2

LITERATURE REVIEW

To provide a basic understanding of travel demand modeling and the two major schools of thought, the literature summarized in this chapter includes a discussion of the history and importance of travel demand modeling, the major concerns with the classical modeling approach, and the emergence of activity-based models. In addition, this chapter describes the general concerns of converting to an advanced model in terms of costs, user experience, and overall improvement the activity-based models can produce over the traditional models. This chapter will conclude with a synopsis of the activity-based models that are currently in use or are in the final stages of development across the United States.

2.1 Introduction to Travel Demand Models

Travel demand models are used by Metropolitan Planning Organizations (MPOs) and other related agencies and consultants to help forecast future population growth and travel patterns to aid in the development of regional transportation plans. To predict travel patterns, household and population information must first be gathered from various sources such as the decennial U.S. Census, the American Community Survey (ACS), ACS Public Use Microdata Samples (PUMS), the National Household Travel Survey and/or local area population data [1]. These data are subsequently combined with specific highway and transit network usage data for the metropolitan region of interest. Travel data can be collected from sources including household travel diaries, vehicle intercept surveys, transit onboard surveys, and parking surveys. Another key input of the travel demand model is population growth forecasts. After the growth predictions have been estimated by the MPO, all of the aforementioned information can be coalesced in the model and users can run forecasts for predetermined years. Many different planning scenarios can be input in the model to compare the effects of changes to the transportation system, provided that the model is developed and calibrated to answer such policy questions. These scenarios can include but are not limited to assessing the impacts of adding freeway lanes or incorporating managed toll lanes to mitigate congestion, implementing improvements or additions to the transit system, or building major land use developments such as transit oriented developments. As stated in the Transportation Research Board Special Report 288, "…forecasts derived from these models enable policy makers to make informed decisions on investments and policies relating to the transportation system" [2].

2.1.1 Trip-Based Models

Trip-based models are what have been previously referred to in this thesis as the traditional model approach. They are also commonly called four-step models because of the four major steps that comprise their structure. As shown in Figure 1, the traditional model includes the following steps: Trip Generation – determining how many trips are made; Trip Distribution – linking trips by origin and destination; Mode Choice – determining which modes of travel are used; and Route Assignment – determining the specific paths over each modal network [3]. Each of these steps will be described in more detail in later sections.

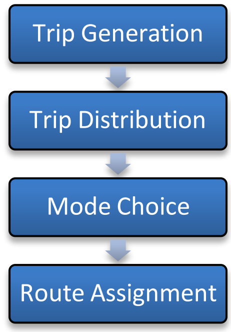

Figure 1 - Four-Step Model Process [4]

One example of a more advanced schematic of the four-step process is shown in Figure 2. The four major components are shown along with model input information and the corresponding flow of this data through all of the model elements.

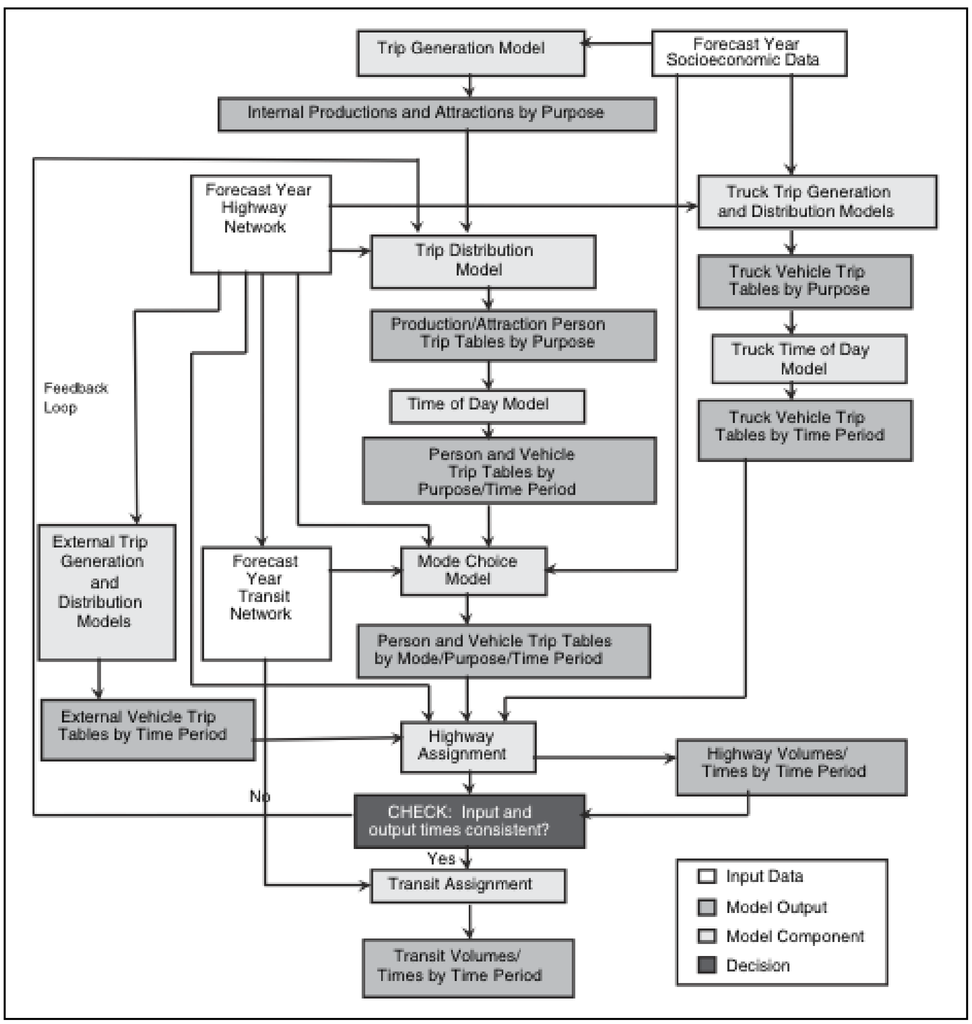

Figure 2 – Advanced Four-step Model Process [1]

The trip-based model uses the trip as the unit of travel, in contrast to other models that use tours or activities. It is also important to note that trip-based models focus their efforts on producing physical travel patterns, whereas the more advanced activity-based models place a greater focus on traveler behavior [3]. To obtain estimates of actual trips taken by the population, household travel surveys that track each individual's daily movements are often administered to a sample of residents. The survey also includes household characteristic information such as income, household size, and the number of vehicles available to the household in order to replicate similar travel patterns across the entire population. Other important elements in the model include highway and transit network data, land use characteristics, and other zonal attributes [5]. The next four sections will provide more detail of the four components of the trip-based model and explain how each of the elements mentioned above contribute to forecasting trips over an entire metropolitan region.

2.1.1.1 Trip Generation

The first step of the trip-based model is trip generation. The main purpose of trip generation is to estimate the total number of trips taken within a set of travel analysis zones (TAZs). These trips are predicted on either the household or individual level within each TAZ and are defined by trip purpose. Observed travel information gathered by travel surveys and other sources are used to generate the predictions from the regression and cross-classification models. Productions and attractions are forecasted separately and are not equal within the analysis zone because they come from different data sources and are estimated by different prediction methods. Adjustments that constrain the attractions to equal the productions must be made to balance these discrepancies. The final results of this step are the so-called "trip ends" for each TAZ [6].

The model area is broken into hundreds or thousands of TAZs, depending on the size of the region and the capability of the model to operate with precise detail. For example, the Atlanta travel demand model utilizes 2024 internal and 91 external TAZs; whereas the Portland, Oregon model consists of 1260 total zones. Modelers use TAZs to break up the entire region into manageable subareas that are reasonably homogenous in terms of land use and population characteristics. These TAZs often align with census tracts to make gathering and analyzing data more convenient. The TAZs are also designated to reduce the variability of households within each zone because research has shown that households with similar characteristics tend to have similar travel patterns, which is why surveys can be used to represent an entire subarea. The household characteristics that most affect travel behavior are presented below and discussed throughout this paper.

As stated above, trip generation is utilized to predict the total number of trips into and out of each TAZ. The trips generated include both departure and arrival trips. These trip ends are commonly referred to as productions (trip origins) and attractions (trip destinations) [6]. Productions and attractions are estimated separately because of the differences in confidence for predicting each type of trip. Productions typically originate or end at the home; with traveler information gathered from regional household surveys, site Census data on residential location makes it possible to factor up survey trip production rates. Data on trip attractions by location are often more difficult to collect, depending on trip purpose. For example, Census data on the number of workers in a

TAZ is more readily obtained than data on the number of people visiting the shops in a destination zone [7]. The variables that have proven to work well in predicting household trip productions are income, car ownership, family size, and household structure. Variables that have often been used for predicting trip attractions include employment levels and densities, land area or land use intensities, value of land, residential density, and locational accessibility [8].

It should also be noted that trips are estimated by trip purpose. Many early trip-based modeling efforts in the United States used three main trip purpose types – Home-Based Work (HBW), Home-Based Other (HBO), and Non-Home Based (NHB) – that are used by metropolitan regions, but some MPOs expand these three main purposes into more specific trip types. Other trip types include but are not limited to Home-Based School, Home-Based University, Home-Based Shopping, Home-Based Recreation, Non-Home Based Work, Non-Home Based Other, External Trips, and Commercial Trips. Note that for origin-to-destination trip volume estimation (such as the number of trips loaded onto the regional transportation network for highway routing purposes in step 4 above), a trip starting at the home and ending at school is expressed the same as a trip starting at school and ending at the home. This trip purpose would be Home-Based School. This is important because not only does it simplify the amount of trip types that the model must distinguish between, but also this principle of modeling individual trips is the key difference between the classical model and the activity-based model. The following sections on the strengths and weaknesses of travel demand models will detail more thoroughly how different approaches to designating trips by purpose or activity can affect the reliability of the model.

After the modeler has determined which types of trips will be predicted, the travel demand model is then equipped with the necessary codes and programs to predict the appropriate trips. For example, the Atlanta travel demand model uses six trip types and three types of trip-takers. However, there are some trips that would not be suitable for certain trip-makers to take. For example, a non-worker does not take any Home-Based Work trips. Table 1 below shows the combinations of trip purposes and trip-makers that the Atlanta Regional Commission (ARC) model calculates [9].

Table 1 - ARC Possible Combinations for Trip Generation

Trip Purpose	Adult Worker	Adult Non-Worker	Child
HB Work	X		
HB Shop	X	X	X
HB University	X	X	
HB School	X	X	X
HB Other	X	X	X
Non-Home-Based	X	X	X

There are two main methods – regression and cross-classification – used to forecast the number of trips made to and from each TAZ. The scope of this thesis does not include the statistical reasoning behind these two methods; it only serves to provide the reader with a background on how the travel demand model uses household statistics to predict the number and types of trips taken. The regression method can be used to predict trips by creating a linear or non-linear equation that incorporates independent variables, such as the household characteristics that were previously mentioned, into a model to evaluate their effect on trip generation. Several variables can be tested in the regression model, but only those that are deemed significant based on t-statistics should be used in the final equation. The variables that have been routinely used in trip generation estimation are household income, car ownership, family size, and household structure [8]. Separate equations are used for each trip purpose, given the statistically significant differences commonly observed in trip rates by purpose. The regression method is simple and inexpensive to generate. However, it does carry with it assumptions and generalities about trip-making. These assumptions will be addressed in the weaknesses of trip-based models section of this Literature Review.

The other widely used method for predicting trips is the cross-classification method, also sometimes called category analysis in transportation literature. In cross-classification, the basic assumptions are that households falling into the same set of multi-characteristic classes are likely to have similar trip rates and that differences in trip rates are much larger between classes than within them. The use of categorical variables is possible and can provide a better understanding of travel behavior among different socioeconomic groups. Table 2 is an example from the Puget Sound Regional Council that shows how three household characteristics can be used to estimate the number of work trips taken by a household. This trip data can then be used across each TAZ by incorporating the numbers given in Table 2 into the model based on the number of households that share the same number of occupants, number of workers, and are in the same income group. Attractions are predicted in the same manner but the categories used are typically based on the type of land use, employment density, and other variables associated with non-residential sites.

Table 2 - Home-Based Work Trip Production Per Household [10]

Household Size	Number of Workers in Household	Income				
		Less than $15,000	$15,000-$24,999	$25,000-$44,999	$45,000-$74,999	$75,000 and Above
1 person	0	0.02	0.01	0.07	0.26	0.19
	1	0.75	1.02	1.17	1.37	1.30
2 persons	0	0.00	0.07	0.01	0.15	0.33
	1	0.08	0.41	0.62	1.06	1.24
	2	1.24	1.57	1.78	2.22	2.40
3 persons	0	0.00	0.00	0.15	0.11	0.21
	1	0.20	0.40	0.77	0.99	1.09
	2	1.33	1.52	1.89	2.12	2.21
	3+	2.52	2.72	3.09	3.31	3.41
4+ persons	0	0.00	0.17	0.09	0.22	0.17
	1	0.47	1.10	1.02	1.15	1.10
	2	1.07	1.71	1.62	1.75	1.71
	3+	2.62	3.26	3.17	3.30	3.26

From the 2007 PSRC Model Documentation

Another approach with the cross-classification method is to estimate trip rates for each trip purpose based on certain household characteristics. Meyer and Miller provide an example of how this method works. The number of households and the number of trips made are determined given the household characteristics that the modeler has decided upon. These data are provided by the various sources that are used to gather travel information, such as household travel diaries and transit surveys. In the example that Meyer and Miller provide, family size and the number of automobiles available are used to categorize the data [6]. Given the number of households and the number of trips taken, the per-household trip rate can be calculated. The forecasted number of households in each zone is then multiplied by this trip rate to provide the number of trips taken in the corresponding zone.

2.1.1.2 Trip Distribution

The second step of the trip-based model is trip distribution. The purpose of this step is to connect the trip ends determined in trip generation, resulting in a matrix comprised of origin-to-destination trip volumes to and from each TAZ. The most common approach to predict the origin and destination zones is a spatial interaction (SIA) model such as the gravity model. This model is derived from Newton's Law of Gravity and uses the following equation [10]:

$$T_{ij} = \frac{P_i * (A_j * F_{ij} * K_{ij})}{SUM(A_j * F_{ij} * K_{ij})}$$

Where:

T_{ij} = number of trips produced in Zone i and attracted to Zone j

P_i = number of trips produced in Zone i

A_j = number of trips attracted to Zone j

F_{ij} = friction factor, function of impedance of travel from i to j

K_{ij} = zone-to-zone adjustment factor

Many early SIA models were based on Newton's Law of Gravity, which states that all matter attracts all other matter with a force proportional to the product of their masses and inversely proportional to the square of the distance between them [11]. The gravity model uses this principle to describe the relationship between travel zones. For example, if a TAZ has a high concentration of retail activity or employment, there is a higher likelihood that people will travel to this zone. However, the less attractive this zone is in terms of distance-based costs in comparison to other zones, the less likely people will go there, other things being equal.

The first three variables listed above are self-explanatory. The friction factor and the adjustment factor are used to recreate realistic travel behavior from zone to zone. The friction factor takes into account the distance-based cost of traveling between zones, making travel between zones with high costs less desirable. Costs in this instance can be travel time, distance, monetary out-of pocket costs, or general costs associated with maintaining a vehicle [6]. The friction factor is adjusted until the predicted and observed trip distributions match within a predetermined threshold, usually by fitting or calibrating to a target such as the observed average trip distance or trip cost.

Though the gravity model is often used in the trip distribution step, this method is criticized because it employs a limited number of explanatory variables. Because the basic model often does not fit observed data very well, this model has often led to the use of adjustment factors such as the K_{ij}s shown in the above equation. Where such adjustment factors are calculated as the ratio between the observed trips and predicted trips between each zone pair, they represent only the current situation and offer little insight into how such a relationship will change in future years. As a result, they cannot be relied upon to accurately predict trip volumes in future years [12].

An alternative approach to the gravity model and similar aggregate SIA modeling approaches is a destination choice model based on individual traveler characteristics and other travel concerns besides the aggregate measures of destination attractiveness and travel costs, either distance-based or monetary [2]. By using techniques that incorporate traveler socioeconomic statistics, the modeler is able to forecast future travel patterns with more certainty. Such disaggregate trip distribution models are calibrated directly to the survey responses of individual travelers, usually as part of regional household surveys. The gravity model only takes into account the attractiveness of a zone based on the distance-based cost of travel and type of development present.

Whether a simple gravity model that is calibrated to already aggregated Census or other planning level data is used, or a disaggregate model that is calibrated to the responses of a set of individually surveyed traveler responses that is then factored up to regional trip activity levels for planning and forecasting purposes is used, both represent simple, direct origin-to-destination trip distribution models. Concerning the use of gravity models in trip distribution, NCHRP Report 716 [1] states:

> *While best practice for trip distribution models would be considered to be a logit destination choice model, the gravity model is far more commonly used, primarily because the gravity model is far easier to estimate…and because of the ease of application and calibration using travel modeling software.*

2.1.1.3 Mode Choice

The third step in the classical model is mode choice. This element is concerned with predicting the number of trips from each origin to each destination that will use each transportation mode [4]. The three main types of modes used by MPOs include automobile, public transit, and non-motorized. The mode choice is determined by calculating which mode offers the traveler the highest utility. Utility is best described as the satisfaction that the mode provides to the trip maker. The utility equation for each mode is found by summing variables that affect the desirability of the mode and the error term that represents unknowns that the modeler cannot account for empirically. Each variable is based on both the attributes of the mode alternative and attributes of the traveler [13]. There are three groups that factors influencing mode choice typically fall into: characteristics of the trip maker, characteristics of the journey, and characteristics of the transport facility [8].

The common method used to predict the allocation of trips for each mode is the multinomial logit (MNL) model. Once the utility equations have been calculated, the probability of choosing any mode is simply the exponential function of that particular utility divided by the sum of the exponential function of all of the utilities. The equations below express the probability of choosing drive alone (DA), shared ride (SR), or transit (TR) [14]:

$$\Pr(DA) = \frac{\exp(V_{DA})}{\exp(V_{DA}) + \exp(V_{SR}) + \exp(V_{TR})}$$

$$\Pr(SR) = \frac{\exp(V_{SR})}{\exp(V_{DA}) + \exp(V_{SR}) + \exp(V_{TR})}$$

$$\Pr(TR) = \frac{\exp(V_{TR})}{\exp(V_{DA}) + \exp(V_{SR}) + \exp(V_{TR})}$$

A major characteristic of the mode choice model is that it needs to be a discrete choice model (for every trip that is taken, a mode must be determined from a finite set of options). To perform the MNL model, the Independence of Irrelevant Alternatives (IIA) property must be satisfied. The above equations assume that each transportation option has unique characteristics that set it apart from the other options. Unfortunately, sometimes the mode choice options have similar characteristics that affect the validity of the MNL model. A common example of this is the theory of the red bus and blue bus. Both buses have the same utility equation; the only difference is the color of the bus. By having separate utility functions for related modes, the probability of choosing a "bus" over the other modes is artificially increased.

One way to mitigate the problem associated with the IIA property is to use a Nested Logit (NL) model instead of the MNL model. The NL method allows for like transportation modes to be considered in the same model because these modes are all grouped together into subsets in a nested formation. With this configuration, each nest is represented as one alternative that can be weighed against the other available modes [8]. Figure 3 below shows the nested logit model the ARC uses to perform mode choice.

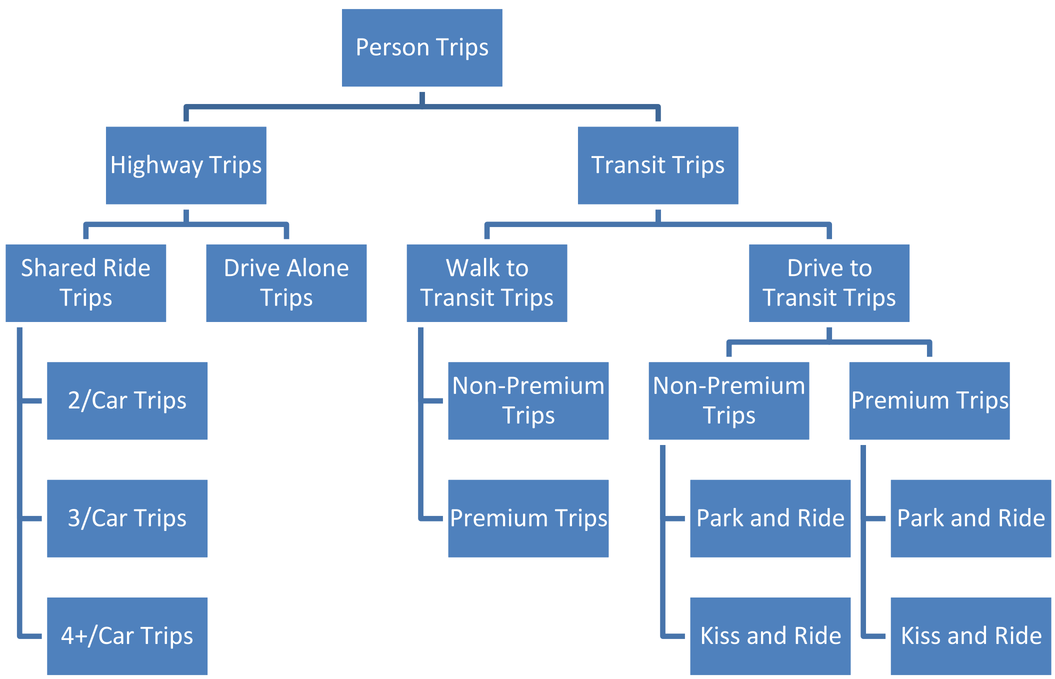

Figure 3 – Atlanta Regional Commission Nested Logit Model Structure [9]

There are three levels of nesting in ARC's mode choice model, but there are many different forms that the nesting structure can take. The Wasatch Front Regional Council (WFRC) in Salt Lake City breaks down mode choice by motorized and non-motorized trips first. Figure 4 shows the nested logit structure for WFRC. Many models also differentiate between possible accesses to the mode, such as how an individual arrives to a transit station (walking, biking, being dropped off, or parking and riding).

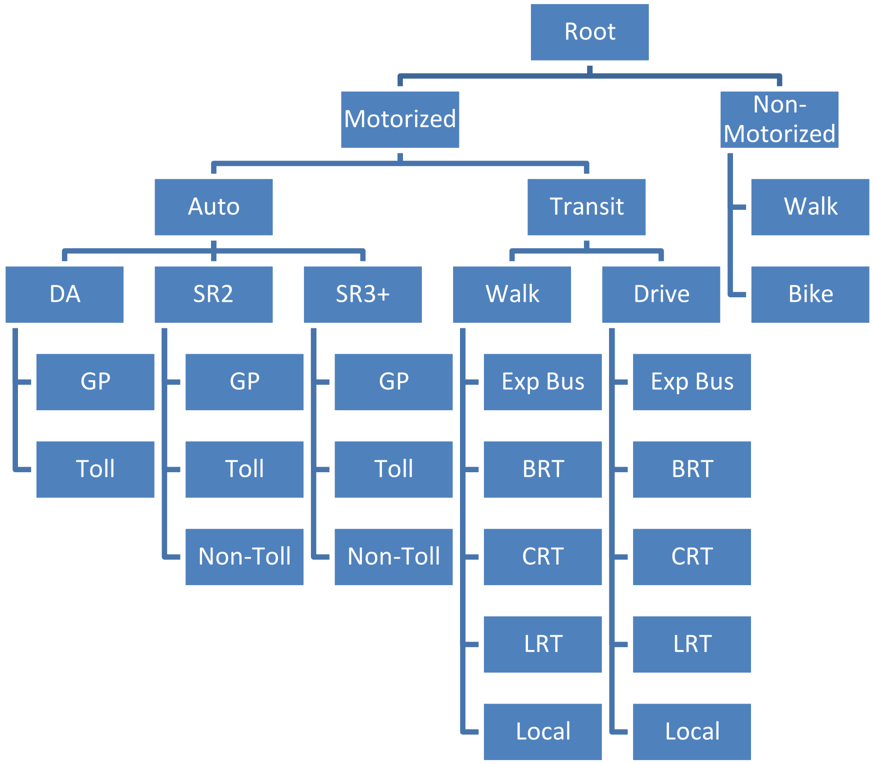

Figure 4 - Wasatch Front Regional Council Nested Logit Model Structure [15]

The major component of Mode Choice is a set of utility equations that can be used to predict the likelihood that any given mode is chosen for the trip in question. Table 3 provides an example from the Puget Sound Regional Council of the model parameters for home-based work trips. Each mode's utility equation consists of variables related to the attributes of the mode and attributes of the trip maker. Once these equations have been applied to every proposed trip, the mode with the highest utility is chosen for each trip and the origin-destination matrix from trip distribution is updated to a matrix of each trip by mode. The transit and highway networks can then be loaded with their respective trips and the final step of the model, route assignment, is ready to operate.

Table 3 – Example of Home-Based Work Mode Choice Model Parameters [10]

Variable	Drive Alone	Shared Ride 2	Shared Ride 3+	Transit-Auto Access	Transit-Walk Access	Bicycle	Walk
Level of Service							
In-Vehicle Travel Time (Minutes)	-0.0253	-0.0253	-0.0253	-0.0253	-0.0253		
Out-of-Vehicle Travel Time (Minutes) - Walk Time and Wait Time <7 Minutes				-0.0633	-0.0633		
Out-of-Vehicle Travel Time (Minutes) - Wait Time >7 Minutes				-0.0506	-0.0506		
Number of Transit Boardings				-0.3060	-0.3060		
Walk Time (Minutes)							-0.0788
Bicycle Time (Minutes)						-0.1020	
Ratio of Drive Time to Total Time				-6.0000			
Travel Cost (Cents) for Low-Income Households (Income 1)	-0.0038	-0.0038	-0.0038	-0.0038	-0.0038		
Travel Cost (Cents) for Low-Medium Income Households (Income 2)	-0.0021	-0.0021	-0.0021	-0.0021	-0.0021		
Travel Cost (Cents) for Medium-High Income Households (Income 3)	-0.0014	-0.0014	-0.0014	-0.0014	-0.0014		
Travel Cost (Cents) for High-Income Households (Income 4)	-0.0011	-0.0011	-0.0011	-0.0011	-0.0011		
Socioeconomic							
Market Segmentation Parameter				See Table 8.3			
CBD Variable		0.199	-0.268	2.167	0.593	0.173	1.688
Alternative-Specific Constant		-2.355	-3.968	-0.169	0.351	-1.151	0.491

2.1.1.4 Route Assignment

The final step of the trip-based model is route assignment. There are many different ways to estimate the paths used for travel, but this section will not delve into each method. An overview of the critical components and the final outcome is instead provided.

Within the travel demand model, all highway and transit networks are coded to reflect actual roads and transit routes. These networks are used extensively in this last step of the model. The basic premise of route assignment is to take all of the trips that have been predicted in previous steps and determine the probable roads or transit lines that will be used to fulfill the origin-to-destination trip. In general, it is assumed that the shortest path (in terms of time) will be the chosen route. However, in reality there are external factors that have an impact on the optimal path. For example, a route that would be the shortest path (in terms of time) during non-peak hours could be a much longer path during the peak hour due to the increase in the number of vehicles on that road. Other examples include the rationality or perception of travel savings to the driver. These externalities should be accounted for in the route assignment step.

There are two major components of assigning trips to the network: a tree-building process for searching out the 'best' route for each interzonal movement in a network and a procedure for allocating the interzonal modal trip volume among the paths [4]. Tree-building is the process of determining the shortest route between two points. There are two widely accepted algorithms that are used to perform this step, but this section is not intended to dissect these processes. It is more important to understand the concept that before routes can be assigned, alternatives must be evaluated and the best route is chosen from said alternatives. To make route assignment reflect reality, trips are loaded onto the network over time. As trips are loaded onto the network, the model continuously finds the best path given the new constraints. This is an iterative process that is repeated until the assignment model converges.

After the route assignment is complete, the travel demand model provides an estimation of all of the trips taken across the region on an average day. The number of trips for each link on the network is available for each predetermined time period throughout the day. The model can then be run for future design years to predict areas that will likely see increases in demand. The transportation networks and land use patterns must be estimated for the future years to enable the model to predict accurately where demand will change. The results from this analysis can assist regional planners in deciding how growth in specific TAZs will affect the overall model area and can aid in predicting, for example, future fossil fuel consumption and related air quality concerns.

2.1.2 Activity-Based Models

Activity-based models use tours as the unit of analysis instead of trips. These models first emerged in the 1980s as a challenge to the travel forecasting techniques that had been used for many decades [4]. The trip-based models have many shortcomings that will be discussed further in the next section of this literature review. This section will focus on the major differences between the classical model and the activity-based model.

The following characteristics set the activity-based model apart from the classic model [16]:

1. Travel demand is derived from activity participation
2. Activity participation involves activity generation, spatial choice, and scheduling
3. Activity and travel behavior is delimited (or even defined) by constraints
4. Linkages exist between activities, locations, times, and individuals

Each of these characteristics is discussed in more detail in the following subsections.

To begin to understand the activity-based model, it is important to first understand the difference between trips and tours. Where the classical model focuses on each trip separately and by purpose, the activity model combines many of these trips together into tours. Throughout a travel day, the individual can participate in multiple tours. Figure 5 shows and example of how trips and tours are distinguished and how multiple tours can be taken in a day. An arrow from origin to destination designates each trip segment. Each tour, in the figure referred to as journey, is comprised of trips and is shown clustered together and grouped by color. For example, the work tour is made up of a trip from home to work, a trip from work to day-care, and a trip from day-care back home.

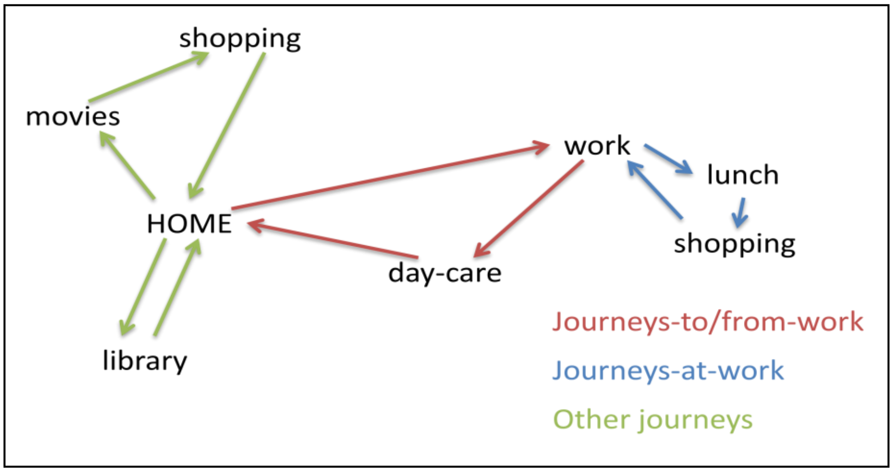

Figure 5 - Example of Tours [17]

The activity-based model has a formation similar to the trip-based model, but without the defined steps. The classic model aggregates population information over each TAZ and uses these averages to determine what types of trips are taken, the zones they are taken to and from, the mode by which they are taken, and finally the route taken. The activity-based models also use household information to determine trips taken across the region; however, the information needed for these models is much more detailed and requires temporal and spatial data. Instead of going through each step to predict what trips are taken, the activity-based model assigns values to different types of tours that can then be used to calculate the likelihood of certain trips being taken by particular individuals in the household. As stated in one of the characteristics above, the model also uses certain constraints to model realistic behavior.

Table 4 below, from the National Cooperative Highway Research Program Report 406, shows the structure of a good practice activity-based model. The table shows each stage of the network, the individual outcomes for the respective stage, and the final representation of the data, as it is stored in the model.

Table 4 - Structure of a Good Practice Activity-Based Model [18]

Model stage	Data and outcomes	Data representation
Inputs	Highway network	Lists of totals by TAZ
	Transit network	
	Households and employment by TAZ	
Population Synthesis	List of representative households with associated income, size, and other attributes	List of each household, person, tour, or trip
Long-term	Usual workplace location	
	Auto ownership	
Generation	Number of activities by purpose	
	Formation of activities into tours	
	Joint travel	
Tour Level	Destination	
	Time of day	
	Mode	
Trip Level	Stop location	
	Time of day	
	Mode	
Assignment	Auto volumes on each link	Matrices by TAZ
	Transit volumes on each link	Loaded networks
	Auto and transit travel times	

The model stages in the table are listed in a type of hierarchy in which the predictions in the lower stages are conditional on the higher-level stages [19]. In regard to the hierarchy, Lee and McNally state [20]:

> *Work and social activities usually fill daily schedules before any other events. General in-home activities and recreation/entertainment activities tend to be done spontaneously when free time is available. Activities with shorter duration are often opportunistically inserted in a schedule already anchored by activities with longer duration. For out-of-home activities, travel time required to reach an activity influences the planning horizon of*

the activity. The longer it takes to reach an activity the earlier the activity is planned.

The hierarchy of trips is often expressed as categories of trips. The three main categories are mandatory activities (fixed frequency, location, and timing); flexible or maintenance activities (performed on a regular basis but having characteristics that can vary); and optional activities (discretionary and all characteristics may vary) [21].

The activity-based model uses a population synthesizer to create synthetic households across the model region based on observed household composition. Demographic and socioeconomic data are gathered from various sources such as the Public Use Microdata Samples (PUMS) to simulate individuals and households based on a representative sample from the model area [19]. Often, household size and income are the variables used to coordinate the information between these two datasets. In the trip-based model, households were averaged across an entire TAZ. The TAZs are theoretically homogeneous subareas, but it can quickly become impractical to simulate each household. The activity models are designed to operate with large amounts of detailed data and thus provide a more accurate representation of the population characteristics. Once these households have been generated in the population synthesizer, trips made by individuals in the households are then predicted.

The following sections will provide more information about the four characteristics of activity-based models that were previously mentioned.

2.1.2.1 Travel is Derived from Activity Participation

The activity-based model operates on the premise that travel is derived by the desire or need to participate in activities. For example, a person who is employed will make trips to work. Their motivation is to travel to work, not to make a home-based work trip [18]. Figure 6 below shows a comparison of how the trip-based model classifies trips for a travel day and how the activity-based model uses activity participation to define what type of travel is being done throughout the travel day, given the same travel pattern.

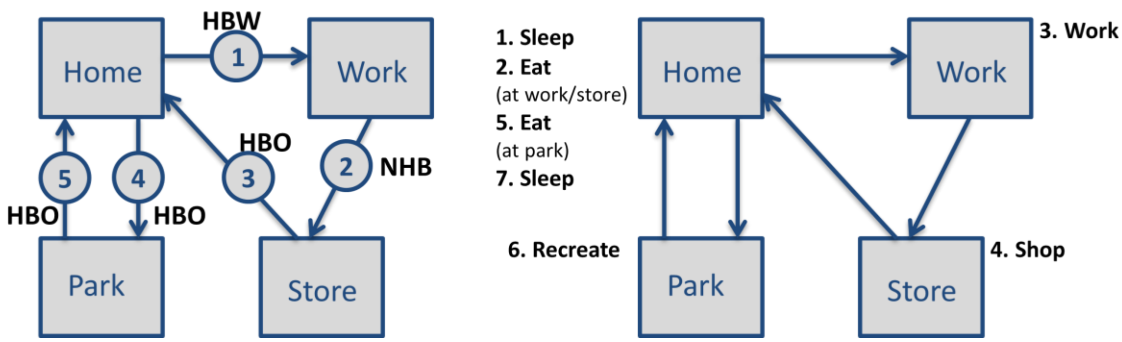

Figure 6 - Comparison of Trips and Activities Within the Same Travel Day [18]

The use of activity participation allows for the model to predict trips with more detail, especially the trips that are made to destinations other than work or home. In the example above, the trip-based model does not distinguish between a trip to the store and a trip to the park. The activity-based model expresses that these two types of trips are different and the model can assign appropriate estimation parameters to these trips that will simulate traveler decisions to make each trip. This is important because these trips that would be designated as home-based other trips in the classic model can now be specified and estimated more accurately by assigning them in the hierarchy and attaching the appropriate temporal and spatial constraints that are unique to their characteristics, provided that adequate data are available to develop such relationships.

The activity pattern also provides a way for the activity-based model to predict trips with more confidence. Because travel is analyzed using tours, it is important to determine the main reason for the travel to take place, which is where the activity pattern comes into play. Bowman and Ben-Akiva describe the activity pattern as follows [22]:

> *The activity pattern consists of important decisions that provide overall structure for the day's activities and travel. In the prototype the activity pattern includes (a) the primary – most important – activity of the day, with one alternative being to remain at home for all the day's activities; (b) the type of tour for the primary activity, including the number, purpose and sequence of activity stops; and (c) the number and purpose of secondary – additional – tours.*

The activity pattern is a logit model that determines the probability of a tour schedule based on the utility of each portion of the tour. Priority is given to work and school trips, then maintenance trips such as household or personal business trips, and finally leisure trips. Activities with longer duration are given higher priority when purposes among the same priority level are available to be chosen from [22]. Figure 7 shows the hierarchy and potential options of tours in the activity pattern. Once the activity pattern has been chosen, each level is estimated by the maximum utility of the activity.

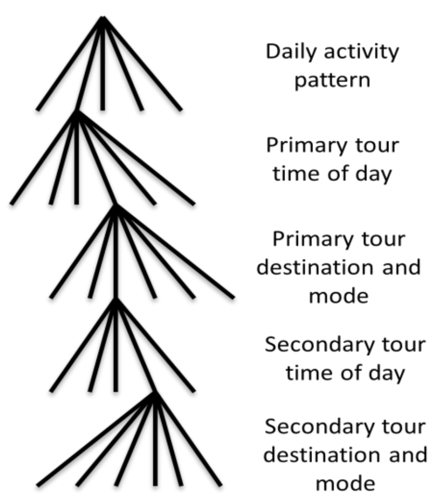

Figure 7 - Activity Schedule Hierarchy [23]

Activity participation can also be designated by household participation because the relationship between household members is often a significant factor to include when trying to portray realistic travel patterns. Vovsha et al describe four household participation categories [24]:

1. Individual – tours for individual activities are scheduled for each person
2. Coordinated – activities are scheduled for each person, but include a mechanism to coordinate with the schedule of other household members
3. Allocated – activities reflect entire household needs, but are scheduled for one individual
4. Joint – activities represent entire household needs and are scheduled for multiple members of the household

These participation categories can then be merged with the three purpose categories described previously to create a matrix of possible travel combinations. This matrix is presented below in Table 5. As the table shows, by creating constraints, the model can be

Table 5 - Modeled Activity-Travel Purpose and Participation Categories [24]

Purpose	Household Participation			
	Individual	Coordinated	Allocated	Joint
Mandatory		X		
Maintenance			X	X
Leisure	X			X

simplified by reducing the number of travel options it must calculate. Instead of twelve possible combinations, the model can run five scenarios while still providing realistic travel possibilities.

2.1.2.2 Participation Involves Activity Generation, Spatial Choice, and Scheduling

It is widely accepted that travel is derived from the need to participate in activities. The previous section has touched on the aspect of traveling for purposes, but did not include the importance that time and location have on decisions to travel. The hierarchy uses purposes to dictate the types of activities that each household member participates in. The time and location are most likely fixed for long-term decisions, but maintenance and discretionary activities are susceptible to variation in time and location.

The activity-based model provides a platform designed to take into account that people often combine many trips into one tour. This combining of trips is referred to as trip-chaining. There is not a standard definition for trip-chaining, but the most simple explanation is "the linking of trips to visit more than one destination after leaving home" [25]. The timing and location of mandatory trips significantly impacts the generation of multiple trips. The trip-chaining concept focuses on the relationship and interdependence of timing, duration, location, frequency and sequencing of activities, nature and number of stops, and trip length [26]. For example, if a person must be at work between the hours of 8 am and 5 pm, he/she will need to make their maintenance trips either before work or after work. The hours of operation of the place to which the maintenance trip is made is also important and must be taken into account. Finally, the location or accessibility of the maintenance trip relative to the route between home and work must be considered to justify making the extra trip. Because so many people make trips between home and work or combine several trips into one tour, it is imperative to model this behavior in order to get an accurate representation of regional travel patterns. The activity-based model uses time and spatial constraints as well as a hierarchy to model trip-chaining behavior better than the trip-based approach.

2.1.2.3 Behavior is Controlled by Constraints

Another important characteristic of the activity-based model is the use of constraints in order to predict travel patterns. To create travel alternatives that can be replicated, the model must create rules that dictate when and where travel may occur. These rules put a limit on the travel possibilities so that the model may eventually converge and not try to process an infinite number of options. Constraints may also be used to define how members of the household travel collectively. This concept was described briefly in Table 5, which shows the possible combinations of household participation given the travel purposes. The relationships between household members are especially important when there are children in the household that cannot travel without an adult.

The three major constraints that are often used in the activity-based model are:

1. Coupling – include circumstances where an individual must rely on someone else or another resource to participate in an activity, e.g., when a child needs a parent to drive them to their activity
2. Authority – administrative restrictions are placed on the ability of the activity to be done, i.e., the hours of operation of establishments
3. Capability – relate to the possibility of activities occurring based on technology or natural limitations [27] and are exemplified in the concept known as the time-space prism

2.1.2.4 Activities, Locations, Times, and Individuals are Linked

Torsten Hagerstrand coined the idea of the time-space prism. He explained this theory as the notion that "people live in a time-space continuum and can only function in different locations at different points in time by experiencing the time and cost of movement between the locations" [28]. In the classic trip-based model, separate trips are predicted and they are not estimated based on the relationship to other trips that could factor into how travel occurs within an entire day. Because the trip-based model uses aggregated data, the law of large numbers comes into play and trips balance out over the model area. However, activity-based models predict trips for every person in the model area by first using the population synthesizer and then using household characteristic information to predict specific travel patterns. The model can output daily schedules for a synthetic person much like the one shown in Figure 8. This figure represents the location and time that a person spends doing a designated activity, though the model creates actual locations with spatial reference. Figure 8 also demonstrates the amount of time it takes to travel to and from each activity.

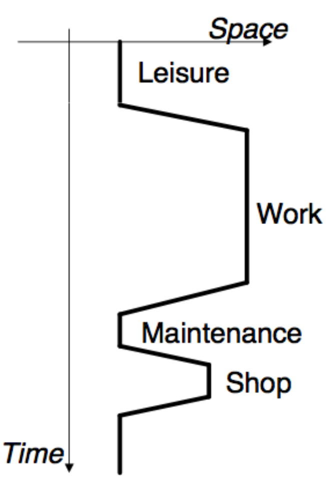

Figure 8 - Example of Time-Space Relationship [19]

2.1.2.5 Behavior Modeling

One of the major differences between the trip-based model and the activity-based model is that the trip-based model explains travel patterns and the activity-based model focuses on traveler behavior [3]. The activity-based model can do this because of the complexity of the model, provided that the disaggregate data are available to develop a robust model. Instead of aggregating all of the travel data among zones across the region, the activity-based model predicts travel by a household's socioeconomic characteristics. By assigning an activity to one's travel plan, the model can differentiate between trips that would have otherwise been lumped together into a broad trip purpose in the four-step model.

According to the Dynamic Traffic Assignment Primer, these advanced models "seek to represent travel choices made by individuals" [29]. The activity-based model can incorporate personal preferences and environmental conditions that might affect the individual's decision to travel. The use of time and spatial constraints along with the individual's position within the household allows the activity-based model to create realistic daily travel patterns for the present day and for future scenarios. This is important because by modeling on a household level, when the model inserts future transportation options such as managed lanes, the output of the model will show changes in travel patterns for the whole region and this can be broken down even further to see what groups are most affected by the enhancements.

2.2 Weaknesses of the Trip-Based Model

This section will focus on the weaknesses of the trip-based model. The classical travel demand model was developed in the 1950s as a tool to evaluate the best options for major capital investments in the transportation infrastructure [17], [30], [31]. This was an era when cars were becoming affordable to the average American and the repercussions of excessive use of the automobile were not a significant concern. Unfortunately, this lack of foresight brought negative ramifications in the form of congestion problems, diminishing air quality, and the consumption of pollution inducing fossil fuels. These major issues have led transportation professionals to a new realm of planning for the future that entails promoting policies focused on reducing motorized trips, increasing the share of non-motorized trips, and encouraging shorter trips and more travel by transit, paratransit, and ride-sharing [32]. Modelers have devoted a large focus on studying the effects that various policies have on future travel patterns because of the passing of the Clean Air Act Amendments (CAAA) of 1990 and the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 [5], [31]. These legislations mandate that metropolitan areas comply with air quality standards and emphasize the importance of mitigating congestion, otherwise MPOs jeopardize federal transportation money. Because these policies were not in place when the four-step model was developed, many of the weaknesses associated with this modeling approach are related to the basic structure of the four-step model that was developed to be responsive to decisions to add lanes to highways. The following sections provide some of the most important weaknesses of the trip-based model that make this approach an inferior method to the activity-based models.

2.2.1 Structure of the Trip-Based (Four-Step) Model

The four-step model gets its name from the fact that there are four major steps in this type of model. The individual steps are often developed and applied separately, which leads to different results being produced from trip generation, trip distribution, mode choice, and route assignment [31]. When trying to model certain transportation policies, this is a problem because one step's input data may not be sensitive to the policy and thus the entire model result would be affected. An example of this problem is when parking policy is implemented in a downtown area, which would influence a portion of the population to choose a different location to visit to avoid the parking costs. The change in trip attraction would not be accounted for because the trip attraction step relies on the trip generation step, which is not typically sensitive to parking costs [33]. This insensitivity to policy propagates through the whole model and leads to inaccurate travel forecasts. To calibrate the model to match current year data, k-factors are often introduced along with adjustments to each step to match known traffic and ridership counts. While these adjustments make the present year data acceptable, these factors are not reliable to use in future forecasts [24].

2.2.2 Focus on Individual Trips

Trip-based models use one-way, single-person trips as the unit of analysis. This method of modeling does not take into account that many individual trips are linked together into one tour because of the spatial and temporal dependencies that activities have among each other [34]. Modeling travel as tours can help obtain more realistic modern travel patterns because the complexity of travel has increased since these models originated in the 1950s [35]. People are now able to stop for coffee on the way to work (as reflected in the popularity of fast-food restaurants). These new travel patterns cannot be modeled appropriately with the classical methods.

The trip-based model does not typically take into account the time of day choice or the duration of the activities in which people are participating. This model uses broad ranges of time such as the A.M. peak, mid-day, and P.M. peak periods. This aggregation of time does not generally allow for an accurate description of when traffic congestion is worst, which is critical to know when implementing congestion management strategies. Finally, because the four-step model only accounts for trips taken outside the home, an entire portion of the population who work from home or perform other activities inside the home may be disregarded.

2.2.3 Insensitivity to Policy

As mentioned above, the trip-based models do not necessarily do a good job of accurately portraying the shift in travel demand when certain policies, such as parking pricing, are implemented. These models also have difficulty with modeling congestion pricing techniques because they use large blocks of time to define the peak period. The practice of using congestion pricing relies on the demand at certain times of the day to control the prices that people are willing to pay on these facilities. Because the trip-based models cannot truly factor in the effects of transportation policies, they do not provide an accurate portrayal of how the shifts in travel patterns of certain demographics would produce induced demand on transportation facilities.

2.2.4 Lack of Behavior Analysis

The trip-based models do not generally take into account the relationships between household individuals when the trip generation step is performed. Because of the insensitivity to transportation policy, the trip-based model lacks the precision to pinpoint how certain groups respond to the policies that are implemented. A more detailed explanation of how behavior is used in travel demand modeling is presented in the following section, Advantages of Activity-Based Models.

2.2.5 Aggregation Biases

The trip-based model operates under the premise that trips are averaged across travel analysis zones. Although the production of trips is modeled based on specific demographic characteristics, the destination choice is modeled by regression or gravity models that use area characteristics to deduce where trips will be taken [31]. The travel analysis zones are treated as homogeneous zones and trips are assumed to arrive and egress from the centroid of these zones. This assumption does not allow for precise locations to be studied independently to gather details about why trips may or may not be generating there, either for the current model year or for future model years when land use scenarios could be utilized to predict demand.

Trip-based models also exhibit temporal aggregation bias. There are typically only a few time periods (A.M. peak, P.M. peak, and off-peak) that are modeled in the classical approach. It is assumed that traffic conditions are constant within each of these time periods, which can cause a misrepresentation of the volumes on the transportation network during these given times and is not sensitive to changes in congestion [24].

2.3 Advantages of the Activity-Based Model

Many of the advantages of the activity-based model are directly related to the weaknesses of the trip-based model. The three major advantages are the ability to model traveler behavior, the assumption that travel is taken in response to the desire to perform an activity within a given activity schedule and the sensitivity to transportation policy implementation.

The activity-based model treats daily activity-travel patterns as a whole and can create unique travel patterns based on the simulated demographic characteristics of that individual [33]. Demographic characteristics include income level, availability of automobiles, the household makeup and the relationships between members of the household. For example, the activity-based model can distinguish that a single working mother of two would have responsibilities associated with traveling to work and running errands and providing transportation for her two children; whereas a single adult male living alone would have less responsibility for others and would possibly take more discretionary or recreational trips. The activity-based model also takes into account the existence of long-term destinations such as workplace location. This inclusion of long-term choices adds a constraint on the traveler and matches the worker to the workplace to create a realistic travel pattern for that individual [36]. The use of tours instead of trips to model travel patterns is also related to the ability to incorporate traveler behavior because these tours are predicted based on the aforementioned demographic characteristics.

The sensitivity to transportation policy implementation is a major advantage to the activity-based model. The interest in activity-based models has risen significantly in recent years because of the positive outcomes that the working models have produced related to policy sensitivity. There are mandates that require a certain amount of detail that future forecasts must be able to show in regard to environmental concerns related to the development of transportation improvement projects. The restrictions on air quality conformity that the CAAA provide have played a major role in MPOs thinking that activity-based models are theoretically better suited to model transportation policies to knowing that they need to provide more detailed answers to policymakers about how transportation alternatives can affect the region. The activity-based models can also assist in Environmental Justice analysis to evaluate whether transportation projects provide inequitable distributions of environmental burdens because these models can help to better pinpoint how transportation policies are likely to change the travel behavior of demographic groups.

2.4 Activity-Based Models Currently in Use

There are several cities that currently use an activity-based model for their primary travel demand model – Columbus, Ohio; Denver, Colorado; New York, New York; Sacramento, California; San Diego, California, and San Francisco, California. These regions have been widely documented as being forerunners in the activity-based modeling realm. The idea of converting to activity-based models has permeated the modeling world and quite a few other MPOs are in the process of developing more sophisticated models. The regions that have activity-based models under development and have models that are developed but not yet fully functional are shown below in Figure 1 along with the model regions mentioned above.

Figure 9 - Activity-Based Model Usage in the United States [37]

This section briefly describes the reasons that each of the MPOs that are currently operating an activity-based model as the primary travel demand model decided to develop an activity-based model and how they have used the model to their advantage.

The first fully functional activity-based model to be developed that is still in operation was the New York Best Practices Model. This model was implemented in 2002 as a means to replicate travel patterns of individuals in the model region [2]. Due to the complexity of the region and the number of TAZs, it was not feasible to implement a trip-based model for New York because the number of matrices that would have been produced from each step were beyond the computational capabilities [38]. The first module of the New York model, which is comparable to the trip generation step of the trip-based model, generates tours for the region. This module consists of three successive models that include a household population synthesizer that replicates all of the individuals in the region based on socioeconomic characteristics; an automobile-ownership model that is sensitive to household characteristics and residential zone; and a tour-frequency model that operates at the person-level to predict tours based on household interaction and travel purposes [39]. The Best Practices Model has been used for air quality conformity analysis, major investment studies, the analysis for the transportation improvement program and regional transportation plan, and was used for the Manhattan pricing study [2].

The San Francisco activity-based model was originally developed and put into production in the early 2000s. The impetus for developing this advanced model was the need to answer questions from decision-makers about the implications of individual transportation investment and policy choices [38]. The model has been used to analyze the effects of congestion pricing and other transportation management policies. The major benefit that the MPO has experienced with the advanced model is the ability to pinpoint individual groups who may be affected by certain policies, e.g., the impact on income groups when a toll is forecasted for an existing roadway. In a trip-based model, due to the structure of model, results pertaining to the effects of certain transportation investments are obscured by aggregation biases. In the activity-based model, the impacts of a policy or investment can be isolated according to characteristics such as gender, income, automobile availability, and household structure. This explicit information also enables the modeler to better understand the traveler behavior choices that may affect destination choices, modal preferences, and the time of day in which to travel [2].

The Columbus, Ohio model is another of the first generation activity-based models. The main transportation concern for the Columbus region is travel growth and expanding the transportation network to provide capacity [3]. The decision to convert to the advanced model was made because a consultant enticed the MPO with the ability to provide an activity-based model within the same time-frame and budget that they could offer a trip-based model [38]. This model incorporates intra-household relationships and uses time increments of one-hour instead of the peak and non-peak periods that trip-based models employ [40]. These components allow for the model to be used to determine the implications of transportation policies that involve shared rides and time-specific constraints such as parking policies, telecommuting, reversible lanes, HOV lanes, and peak spreading [3]. The activity-based model is used to study transit alternatives, air quality conformity, and transportation alternatives for the long-range plan.

The Sacramento, California activity-based model was developed in order to scrutinize the factors that affect travel changes and the production of greenhouse gases [3]. The model has been used to analyze various transportation policies that target improving the air quality in Sacramento and verify whether these policies have a positive impact not only on the air quality but on traveler mobility as well. The effects of land use such as mixes of land use, density, and the availability to take short distance trips or transit can also be created in the activity-based model in Sacramento [38]. As with other regions, Sacramento has benefited from the disaggregate nature of the activity-based model to provide detailed information about the effect of policies on individuals, rather than a conglomerate of unrelated socioeconomic groups across the model region.

The San Diego, California and Denver, Colorado activity-based models have just recently been put into production. The San Diego region was influenced by the other major model regions in California to develop an advanced model. The benefits that San Francisco and Sacramento had seen with their models in regard to pinpointing individuals who may be directly affected by the implementation of certain transportation investments was a major factor for San Diego to move toward an activity-based model. There was also encouragement from the California Transportation Commission to keep up with the state-of-the-practice [38]. The Denver activity-based model was developed in order to take advantage of the benefits that other MPOs had seen with the implementation of advanced models. Of particular concern to Denver were the benefits with respect to answering complex policy questions, analyzing the effects of different land-use scenarios, tolling, modeling non-motorized transportation, modeling the effects of greenhouse gases, and modeling the effects of an aging population on the transportation network [38].

CHAPTER 3

METHODOLOGY

The purpose of this thesis was to first assess the use of activity-based models in the United States and second to evaluate the opportunity for an MPO to adopt an advanced model. To provide a manageable scale for this endeavor, the top fifty most populous cities in the United States were targeted for evaluation. An individual in the modeling department from each region's MPO was initially contacted with an email introducing myself and asking for participation in this research. A survey, which is attached as Appendix A, was provided to the individual to either fill out immediately or to peruse and contact me via phone to discuss their modeling techniques with more detail. The questions in the survey were targeted to gain information about each region's population characteristics, current and future conditions of the transportation network, environmental concerns for the region, current model specifics, and the attitude of the MPO in regard to activity-based models. After compiling the results from the survey, each affirmative answer to the criteria was given a point to tally in the overall total. Each region that met the majority of the criteria was deemed to benefit from converting to an activity-based model. The following sections describe the motivation and importance of each of the criteria that were used to decide the recommendation for each MPO.

3.1 Population Characteristics

As stated previously, the activity-based model focuses on understanding travel behavior; whereas, the trip-based model focuses on travel patterns across the entire region. Through countless modeling procedures over the years, it has been found that certain household characteristics (income, car availability, household size, and household structure) are indicative of the types of trips that individuals will take [8]. The activity-based model introduces the concept of predicting household trips based on the relationship between the individuals in the household. The trip-based model has difficulty in predicting non-home based trips because of the structure of the model, but because the activity-based model attempts to incorporate trip chaining, these types of trips are predicted with more reliability. Therefore, the percentage of households with children, the percentage of households with non-workers, and the percentage of households with zero automobiles available were found for each model region because these characteristics could have a great effect on the validity of the trip-based model and trips could be predicted better by using the activity-based model.

3.1.1 Households with Children

The activity-based model takes into account the relationship between household members when determining what kinds of activities individuals will partake in during the travel day. A significant relationship to account for is the presence of children who are incapable of making independent trips. Households with children often experience more constraining activities than those without children [20]. The age of the children in the household is also a significant factor. According to Strathman et al., lifestyle stages have the following effect on trip-chaining [38]:

> *Households with preschool children had a higher proportion of simple home-destination-home shopping trips and correspondingly fewer complicated work commute chains. Households with school age children experienced increasingly complex passenger and household needs-serving chains.*

The American Fact Finder tool on the U.S. Census Bureau website was used to find the number of households with at least one child. The Profile of General Population and Housing Characteristics was used to find the total number of households and the number of households with children for each county in the model region [39]. The percentage of households with children was then found for the entire region by summing the totals for each of the counties that make up the MPO model area. After determining the percentage for all of the cities that responded to this survey, it was found that there was not an overwhelming majority of households with children in any of the regions; therefore, the third quartile of all of the participating cities was used as a breaking point to decide whether to give an affirmative position for this criterion. The third quartile was used for this and other metrics as a way to distinguish the regions that exhibited greater than average statistics.

3.1.2 Number of Working Adults in Household

The trip-based model is able to predict home-based work trips with the most certainty because these trips are generally long-term and mandatory trips. Given the appropriate household and employment information, these trips can be predicted with the most precision. However, not every household consists of only working adults and not all trips are to and from work. Ben-Akiva and Bowman state [23]:

> *Of the 9100 travel hours reported in the travel survey, the work commute requires only 24 per cent, whereas travel for activities chained with the commute, non-work primary tours and secondary tours require 15 per cent, 43 per cent, and 17 per cent, respectively. This reveals the weakness of the usual work-trip-based accessibility measure. Such a measure*

properly represents accessibility only for the group of individuals who make a single work tour without stopping for other activities during the tour.

The Employment Characteristics of Families data was used to determine the number of workers and non-workers in the household for each county comprising the participating model regions. The corresponding tables took the form similar to Table 6 below.

Table 6 - Example Table from Employment Characteristics of Families

Subject	Estimate	No. Workers
Families	Total Households	
EMPLOYMENT STATUS		
Married-couple families	Total Married-Couple Families	
Both husband and wife in labor force	%	2
Husband in labor force, wife not in labor force	%	1
Wife in labor force, husband not in labor force	%	1
Both husband and wife not in labor force	%	0
Other families	Total Other Families	
Female householder, no husband present	%	
In labor force	%	1
Not in labor force	%	0
Male householder, no wife present	%	
In labor force	%	1
Not in labor force	%	0

The households with one less worker than the number of adults were of particular importance in this research because households with two working adults would have more predictable work travel patterns that the trip-based model would be able to model and households with no workers would have atypical travel patterns that would be difficult to predict even with the activity-based model. The percentage of households with one less worker than adults in the married-couple families was found by adding the alternatives for one worker. For other families, the alternatives for zero workers were added. These percentages were then averaged together to determine the percentage of all households comprised of one less worker than adults. Again, the third quartile was used as a breaking point to determine if the region would be given a tally for this criterion.

3.1.3 Automobile Availability

New transportation policies dedicated to promoting smarter travel options aim to reduce the number of single-occupancy vehicle trips and encourage other forms of transportation such as walking, biking, taking transit, or carpooling. The availability of automobiles is critical because this information dictates the mode a person is able to choose for their trip. The activity-based model provides a better travel estimate because it models traveler behavior as well as uses household characteristic information, such as how many cars are available, to predict trips. The activity-based model also takes into account the relationship between members of a household and is therefore more apt at determining when individuals share rides.

The availability of automobiles for households was acquired from ACS data on the American FactFinder website [40]. There are four options listed in the ACS data in regard to automobiles: zero cars, one car, two cars, and three or more cars. The percent of households with zero cars was used in the criteria because areas where many people are not able to use an automobile to travel would benefit from an activity-based model because their travel options are limited to alternative modes that new transportation policies target. The third quartile, which was found to be greater than 3.92%, was used as the threshold between giving a recommendation for this category or not.

3.1.4 Population Growth Rate

The population growth rate of a metropolitan region plays a major role in what decisions will be made for the future of the transportation system. Activity-based models are more sensitive to changing demography and can replicate travel growth factors in long-term planning better than traditional models [44]. If a region is experiencing considerable growth, they will be more likely to implement policies to mitigate the inevitable congestion that will arise, especially in the current economic hardship where new construction is rare. The activity-based model can forecast future travel patterns based on transportation policies with more accuracy than the trip-based model because the activity-based model operates using traveler behavior data [45]. If a region is experiencing an incredibly high rate of growth, it was assumed that the activity-based model would not provide an exceptionally better forecast because of the amount of uncertainty that would result in this growth. Therefore, the cities that had a population growth rate greater than three standard deviations and that were less than 1 were not given a point towards a recommendation for converting to an activity-based model. The growth rate was calculated from population statistics from the 2000 and 2010 Census.

3.2 Highway Network

The current state of the transportation network was considered because knowing the unique issues for each model region would affect whether an activity-based model would be beneficial to the area. Future transportation planning efforts are dependent on the current level of service. If an area has a major issue with congestion and building more highway lanes is not a viable option, other measures must be considered to mitigate the problem. There are several cities that have adopted the practice of using managed lanes and other policies to alleviate the burden of congestion. The activity-based model has gained recognition in the modeling community because of the ability to address changes in travel caused by implementing new policies aimed at promoting sustainable growth. The NCHRP Report 406 states, "The true advantage is that they are sensitive to a broader range of policies and can answer more complicated questions" [18]. The next three subsections describe the motivation behind using the three criteria related to the highway network to judge the usefulness of an activity-based model.

3.2.1 Congestion Index

Congestion was used as a measurement tool because the cities that are facing this problem are likely to be considering techniques to mitigate congestion other than those associated with adding capacity. The activity-based model is able to address the changes in traveler behavior when policies such as carpooling and managed lanes are put into practice because the model takes into account the possibility and likelihood of household members sharing rides. The Texas Transportation Institute's (TTI) roadway congestion index for the year 2010 was used to verify the severity of congestion for each of the participating model regions [46]. The regions with a congestion index greater than 1 were given a positive score for this measure.

3.2.2 Peak Hour Traffic

The normal morning and evening commute times are referred to as peak travel times. In addition to the congestion index, the TTI Congestion Report also calculates the number of hours that roadways are congested for urban areas across the country. This statistic is important to study because the activity-based model is able to account for peak spreading. The NCHRP Report 406 describes why trip-based models lack accuracy in this circumstance [18]:

> *Trip-based models cannot account for the constraints of adjacent activities or travel, and therefore risk overstating travelers' willingness to*

shift times of day in response to congestion or pricing. Activity-based models that include a time-of-day choice and are sensitive to level-of-service can model these scenarios with more confidence.

The cities with a daily peak hour greater than four hours (including morning and evening peak hours) were given a point towards the recommendation of an activity-based model.

3.2.3 Freight Congestion

Congestion on the highways is not only attributed to passenger vehicles. A critical factor to consider when modeling travel demand is the amount of congestion caused by truck deliveries because this movement can alter the distribution of traffic and affect travel patterns. These deliveries include in-town drop-offs as well as interstate freight transport. In Atlanta, truck traffic is prohibited from traveling on the interstates that run through the middle of the city unless they are making local deliveries. Otherwise, trucks much use the bypass – Interstate 285 – to travel around the city. The abundance of trucks often makes the I-285 corridor severely congested and can influence travelers to alter their travel decisions.

The 250 most freight-related congested highway locations in the country were found in order to assess which model regions included in this research were affected the most [43]. The locations in this data were ranked based on the average severity of congestion during weekdays in 2010. The metric used to determine congestion is average speed (including peak and non-peak). Free-flow speed was assumed to be 55 mph.

The locations in this data are mostly interstate interchanges, resulting in many of the model regions in this thesis having multiple congested locations. In order to provide an accurate representation of congestion, the ranking system shown in Table 7 was developed to determine the total amount of congestion that the model area experiences.

Table 7 - Ranking System for Freight Congestion Locations

Average Speed	Score
>= 55 mph	1
50-55 mph	2
45-50 mph	3
40-45 mph	4
<40 mph	5

This system was important to implement because the number of congested locations does not necessarily correlate with the severity of congestion in the region. For example, if a city had five congested locations on the list of the top 250 sites, but the average speed for all of the five locations was at least 55 mph, just looking at the number of locations would not portray a factual description of the severity of congestion for that region. Therefore, each location was designated a score based on the ranking system in Table 7 and the scores for each of the locations in the region of interest were summed to give an overall congestion total. For the cities that received a total score of 10 or greater, the activity-based model was recommended for this criterion.

3.3 Environmental Conditions

A major concern for large metropolitan areas is air quality. Congestion is a major contributor to air pollution in urban areas, which is why new techniques are being developed and implemented to focus on reducing congestion in lieu of adding capacity. New transportation planning agendas have been set forth in part by the Clean Air Act Amendments (CAAA) of 1990 [5]. One of the most attractive qualities of the activity-based model is the ability to dissect the model and determine what specific policies affect travel demand. Knowing these specifics and pairing this information with the more accurate travel forecasts that activity-based models provide, modelers and policymakers can assess the most effective ways to reduce automobile emissions and comply with the clean air standards. If a participating city was designated a non-attainment area for any pollutant, it was given a point for this parameter because these regions must demonstrate compliance with environmental conformity regulations.

3.4 Model Specifics

The trip-based model contains inherent weaknesses such as the lack of incorporating temporal and spatial constraints, aggregation of trips across entire travel analysis zones, and grouping trips by trip purpose and not activity participation. In the trip-based model, travel within TAZs is either not accounted for or modeled separately; the focus is on travel between TAZs. This procedure inhibits the ability to model short trips that are likely to be taken via non-motorized modes. One of the goals of new transportation policies is to reduce the dependence on automobile trips and encourage the use of non-motorized modes. Therefore, modeling non-motorized trips is important not only because it provides an account for short trips between zones, but also factoring in these trips can be useful for modeling new policies that directly affect the change in mode share. For the cities that currently use a trip-based model and were found to model non-motorized trips, this measure was given a point towards recommendation of an activity-based model.

Initially, the survey techniques of each MPO were considered because of the importance of collecting information about trip times and purposes in order to incorporate this data into an activity-based model. However, it was found that all cities that provided feedback now use travel diaries that track travel by time of day, location, and purpose. In regard to the information that is needed to develop an activity-based model from the household surveys, Vovsha et al suggest that the structure of the household surveys is equally suitable for estimation of conventional and activity-based models [24].

3.5 MPO Interest

The general attitude of the MPO is important to consider because in order to enact a change in modeling procedures, there must be a champion that is a proponent of the new method. In the research, it was found that there are many reasons that MPOs are discouraged from making the transition to the activity-based model. Most of these hesitations are due to the extra costs that the advanced models carry due to the detailed data that is needed to create and run the more precise models. Other concerns are that there is not enough proof that the models can predict future travel patterns with more accuracy than the traditional models. If the MPO expressed that they were interested in and/or developing an activity-based model, the criteria was counted in the overall tally for recommendation of converting to an advanced model.

3.6 Work Mode Share

As stated above, the policies that govern the direction of transportation projects in the country focus on reducing single-occupancy vehicle trips and promoting the use of alternative modes. The mode share of trips to work was found via the Means of Transportation to Work database of the American Community Survey of 2010 [40]. For regions that have a high percentage of trips taken by transit, nonmotorized modes, or in carpools, the activity-based model would provide more precise estimates of travel to work. In order to reduce the number of automobile trips, many companies have adopted telecommuting options that enable employees to work from home. The trip-based model only estimates trips taken outside of the home; whereas, the activity-based model realizes that sometimes activities can be performed at the home and are more sensitive to policies that promote telecommuting. The work trip is especially important because these trips are long-term decisions that are taken regularly during the week and at the same general time each day. It is therefore critical to provide an accurate estimate of work trips to create a practical representation of congestion during peak travel periods.

The U.S. Census gathers modal information for the following modes: drive alone, shared ride, public transit, walk, work from home, and bicycle/taxi/motorcycle. The percentage of each of these modes was found for the model regions in this thesis. The third quartile values were used as the breaking point for a recommendation for the shared ride, walk, and work from home modes. Instead of using the third quartile for transit trips, the cities with more than 10% of work trips taken by transit were given a point towards recommendation. There is a disparity in the transit ridership for the cities in this survey so the cities that showed a much higher percentage of transit trips than the average were selected because the activity-based models are more beneficial for areas with low percentages of single-occupancy vehicle trips, which correlates with high transit use.

3.7 Current Transportation Demand Management Practices

Transportation demand management is the practice of implementing strategies that reduce the need and desire to travel by single-passenger automobiles or provide ways to redistribute travel patterns through space and time. Congestion in urban areas is a major problem for a host of reasons. First of all, congestion is a key contributor to pollution due to emissions from burning gasoline. Poor air quality causes respiratory problems and other health issues to residents. Finally, the increased travel time that is a result of congestion causes individuals to spend more of their valuable time sitting in traffic. Transportation demand management policies aim to change the way people travel by providing travel options that benefit individuals in regard to improving their quality of life by reducing congestion and improving air quality. The activity-based model is a better modeling tool when demand management practices are employed because these advanced models take into account the underlying reasons trips are made, when they are made, and where they are made [5]. This also includes the ability to incorporate the underlying factors, such as transportation policies, that individuals use to determine what mode to use to participate in their activity. The practices discussed below can have an impact on how people choose the mode to use for their travel purposes.

3.7.1 Parking Management

Parking management techniques are used to discourage the use of automobile trips, especially in dense areas such as the central business district. Common practices include creating freeze zones where parking is prohibited, charging for parking, providing preferential spaces for carpools, or eliminating the minimum number of spaces required for retail developments. Many of the innovative parking strategies in the country that have shown positive results in reducing congestion were found in the U.S. Parking Policies document [44]. The long-term transportation plan for each MPO was reviewed to determine what other parking strategies are currently being used or will be adopted in the future. If a parking management method was explicitly documented in the transportation plan, the region was given a recommendation to convert to an activity-based model for that criterion.

3.7.2 Bicycle and Pedestrian Facilities

Activity-based models are beneficial in areas where there are a large proportion of trips made by modes other than single-passenger vehicles. The latest transportation policies that focus on reducing congestion also include a strong emphasis on encouraging nonmotorized travel. The transportation plans for each MPO were analyzed to verify if the region places an emphasis on improving the pedestrian and bicycle facilities. All of the cities included in this research have a multitude of pedestrian and bicycle projects included in their strategic plans. Therefore, all of the regions were given a point towards recommendation for this metric.

3.7.3 Commute Options

The final type of demand management practice that was studied was the idea of commute options. Commute options consist of shared ride techniques such as carpools and vanpools. Other measures include promoting telecommuting and alternative work hours to employers in the region. As stated previously, the activity-based models can provide better estimation of regional travel for areas where policies are in place to discourage single-occupancy vehicle trips. The activity-based models can also incorporate the concept of telecommuting because these models take into account that an activity can be performed without leaving the household. It was found that all of the participating regions have various services dedicated to providing commute options to the public. Each city was awarded a point towards recommendation of an activity-based model for this criterion.

3.8 Future Plans

The future transportation plans of the region are necessary to include in this analysis because travel demand modeling is the practice of forecasting future transportation needs. The activity-based models are more apt at predicting travel patterns that are associated with the implementation of policies aimed at reducing drive-alone trips and promoting alternative modes of transportation. Some of the policies that are currently being utilized were discussed in the previous section, but this section focuses on future implementation.

3.8.1 Congestion Pricing

Congestion pricing is a mitigation approach that uses the principle of supply and demand to balance the roadway network during peak hours. Those individuals willing to pay to travel during the congested timeframe have the opportunity to do so and those who do not wish to pay have other alternatives. All individuals have a value of time that dictates their willingness to pay in the presence of these types of pricing practices. Activity-based models predict travel patterns and activity participation based on the characteristics of the individual; therefore, advanced models are able to provide a sensible estimate of how congestion pricing affects individual traveler behavior. Based on the survey responses provided, the regions that acknowledged plans to implement congestion pricing were given a point for this condition.

3.8.2 Transit System Expansion

The transportation policies that are crucial to the development of an efficient system that reduces congestion and improves air quality relate to plans that incorporate new measures apart from building more highways. The performance of the transit system plays a role in the desirability of riders to take advantage of this transportation mode. The regional transportation plan for each region was studied to determine if there are plans to expand the transit system to allow more connectivity across the region. If there are plans to expand the transit system or to improve service, the region was given a recommendation for an activity-based model for this measure because it is assumed that the plans are based on forecasts that predict an increased demand for the transit system.

CHAPTER 4

RESULTS

This chapter utilizes the criteria described in the methodology chapter of this thesis. Table 8 displays all of the urban areas that were targeted for this endeavor.

Table 8 - Top Fifty Most Populous Regions and Response Results

	Major City	State	Population	No Response	Status Quo Response	Detailed Response	Phone Call
1	New York	NY	18,897,109			X	
2	Los Angeles	CA	12,828,837		X		
3	Chicago	IL	9,461,105		X		
4	Dallas	TX	6,371,773			X	
5	Philadelphia	PA	5,965,343		X		
6	Houston	TX	5,946,800		X		
7	Washington DC		5,582,170			X	
8	Miami	FL	5,564,635	X			
9	Atlanta	GA	5,268,860			X	
10	Boston	MA	4,552,402			X	
11	San Francisco	CA	4,335,391	X			
12	Detroit	MI	4,296,250		X		
13	Phoenix	AR	4,192,887			X	
14	Seattle	WA	3,439,809	X			
15	Minneapolis	MN	3,317,308		X		
16	San Diego	CA	3,095,313				X
17	St. Louis	MO	2,812,896		X		
18	Tampa	FL	2,783,243	X			
19	Baltimore	MD	2,710,489	X			
20	Denver	CO	2,543,482				X
21	Pittsburgh	PA	2,356,285	X			
22	Portland	OR	2,226,009				X
23	Sacramento	CA	2,149,127	X			
24	San Antonio	TX	2,142,508		X		
25	Orlando	FL	2,134,411	X			
26	Cincinnati	OH	2,130,151	X			
27	Cleveland	OH	2,077,240			X	
28	Kansas City	MO	2,035,334		X		
29	Las Vegas	NV	1,951,269			X	
30	Columbus	OH	1,836,536		X		
31	Charlotte	NC	1,758,038	X			
32	Indianapolis	IN	1,756,241	X			
33	Austin	TX	1,716,289	X			
34	Virginia Beach	VA	1,671,683	X			
35	Providence	RI	1,600,852	X			
36	Nashville	TN	1,589,934	X			
37	Milwaukee	WI	1,555,908	X			
38	Jacksonville	FL	1,345,596			X	
39	Memphis	TN	1,316,100	X			
40	Louisville	KY	1,307,647			X	
41	Richmond	VA	1,258,251	X			
42	Oklahoma City	OK	1,252,987	X			
43	Hartford	CT	1,212,381		X		
44	New Orleans	LA	1,167,764	X			
45	Buffalo	NY	1,135,509			X	
46	Raleigh	NC	1,130,490	X			
47	Birmingham	AL	1,128,047	X			
48	Salt Lake City	UT	1,124,197			X	
49	Rochester	NY	1,054,323	X			
50	Tucson	AZ	980,263	X			
Total				24	11	12	3
Response Rate				**48.00%**	**22.00%**	**24.00%**	**6.00%**

The initial goal was to receive responses from the top 50 most populous regions in the country, but not every city responded to the questionnaire. For the 26 regions that did respond, there were varying levels of response, which are also shown in Table 8. The first response category is the “Status Quo Response”. The replies grouped in this classification are those where the respondent took the time to answer the questions in the survey, but did not elaborate or provide supplemental information that would be beneficial for this research. The second category, shown in the table above as “Detailed Response,” consists of replies where the respondent took the time to gather information and resources to assist in describing how the MPO uses its travel demand model. These responses also included insight into any concerns that the modelers have about converting to an activity-based model. This feedback is helpful because it allows the respondent to point out unique characteristics of the model region. The last category is comprised of MPOs where the individuals were reached via a phone call so that the information being relayed was made perfectly clear to the researcher. These responses were the most helpful because they allowed for the opportunity to ask follow-up questions immediately, in the event that responses needed to be clarified.

The response rates for each category are shown at the bottom of Table 8. Twenty-four out of the 50 regions (48%) did not provide feedback on the survey and 52% did provided respond. Twenty-two percent of the responses were status quo, 24% were detailed, and 6% were over the phone. The cities that responded were evaluated to try to determine a trend that made these areas more likely to respond than the non-respondents. Table 8 lists the model regions by population, which does not appear to indicate any obvious trend between the size of the model region and the willingness to assist in this research effort. The familiarity and interest in activity-based models was also used to attempt to determine a trend in responsive cities. Table 9 shows all of the targeted cities

Table 9 - Response Rates Determined by Interest in Activity-Based Models

	Major City	State	Population	No Response	Have ABM	Interest in ABM	No Interest
1	New York	NY	18,897,109		X		
2	Los Angeles	CA	12,828,837			X	
3	Chicago	IL	9,461,105			X	
4	Dallas	TX	6,371,773			X	
5	Philadelphia	PA	5,965,343			X	
6	Houston	TX	5,946,800			X	
7	Washington DC		5,582,170				X
8	Miami	FL	5,564,635	X			
9	Atlanta	GA	5,268,860			X	
10	Boston	MA	4,552,402			X	
11	San Francisco	CA	4,335,391	X			
12	Detroit	MI	4,296,250			X	
13	Phoenix	AR	4,192,887			X	
14	Seattle	WA	3,439,809	X			
15	Minneapolis	MN	3,317,308			X	
16	San Diego	CA	3,095,313			X	
17	St. Louis	MO	2,812,896				X
18	Tampa	FL	2,783,243	X			
19	Baltimore	MD	2,710,489	X			
20	Denver	CO	2,543,482		X		
21	Pittsburgh	PA	2,356,285	X			
22	Portland	OR	2,226,009			X	
23	Sacramento	CA	2,149,127	X			
24	San Antonio	TX	2,142,508				X
25	Orlando	FL	2,134,411	X			
26	Cincinnati	OH	2,130,151	X			
27	Cleveland	OH	2,077,240			X	
28	Kansas City	MO	2,035,334				X
29	Las Vegas	NV	1,951,269				X
30	Columbus	OH	1,836,536		X		
31	Charlotte	NC	1,758,038	X			
32	Indianapolis	IN	1,756,241	X			
33	Austin	TX	1,716,289	X			
34	Virginia Beach	VA	1,671,683	X			
35	Providence	RI	1,600,852	X			
36	Nashville	TN	1,589,934	X			
37	Milwaukee	WI	1,555,908	X			
38	Jacksonville	FL	1,345,596			X	
39	Memphis	TN	1,316,100	X			
40	Louisville	KY	1,307,647				X
41	Richmond	VA	1,258,251	X			
42	Oklahoma City	OK	1,252,987	X			
43	Hartford	CT	1,212,381				X
44	New Orleans	LA	1,167,764	X			
45	Buffalo	NY	1,135,509				X
46	Raleigh	NC	1,130,490	X			
47	Birmingham	AL	1,128,047	X			
48	Salt Lake City	UT	1,124,197				X
49	Rochester	NY	1,054,323	X			
50	Tucson	AZ	980,263	X			
Total				24	3	14	9
Response Rate				**48.00%**	**11.54%**	**53.85%**	**34.62%**

along with their respective interest in activity-based models. Of the 26 MPOs that participated in the survey, 65% are either currently using an activity-based model or are interested in converting to one in the foreseeable future. Although the interest in advanced models for the cities that did not respond is not known, for the cities that did respond, it seems as though the regions that are pursuing the implementation of activity-based models are more eager to share knowledge and experience about the subject than those respondents that do not have an interest in activity-based models. This could have affected the number of recommendations given in favor of converting to an activity-based model because the regions interested in advanced models are likely to have concerns about the validity of the classical models due to a need to provide sophisticated results related to transportation policies.

4.1 Results of Evaluation Criteria for Participating Cities

The previous chapter described the significance of each criterion and how the results were tallied. The following sections present the findings for each of the parameters.

4.1.1 Population Characteristics

Table 10 shows the percentages that were found from census data for each of the parameters that are associated with population characteristics for all of the participating regions. As previously discussed, the third quartile was used as a breaking point for the percentage of households with children, the percentage of households with one less working adult than the number of adults in the household, and the percentage of households with zero cars available. The cities, in which the percentages were greater than 31.5%, 41%, and 3.92%, for the respective criteria, were given a point towards the total tally. For growth rate, all of the cities that experienced a growth rate between 1.0

and 3.0 between the 2000 and 2010 Census were given a recommendation for this metric. The cities that were given a point for any of these criteria are shown highlighted in blue. The average and third quartile results are also shown at the bottom of the table.

Table 10 - Findings for Population Characteristic Measures

City	Population Characteristics						
	Children	Workers	Automobile Availability				Growth
	(% HH)	(% HH)	% 0 cars	% 1 car	% 2 cars	% 3+ cars	Rate
Atlanta	33.52	34.2	3.81	25.47	44.07	26.66	2.0
Boston	21.48	34.3	23.12	40.46	26.11	10.31	0.5
Buffalo	25.75	41.0	4.72	24.45	45.37	25.46	-0.3
Chicago	31.46	37.4	6.03	24.60	42.00	27.37	0.4
Cleveland	26.89	39.3	3.84	23.13	45.21	27.81	-0.3
Columbus	29.92	35.0	2.86	22.59	47.49	27.06	1.4
Dallas	35.33	37.3	2.20	22.41	46.39	29.00	2.3
Denver	30.11	35.9	2.77	22.17	44.52	30.55	1.4
Detroit	29.17	42.3	3.09	23.40	44.02	29.49	-0.3
Hartford	29.17	34.5	3.77	20.30	44.45	31.48	0.5
Houston	36.06	39.6	2.92	23.13	45.27	28.68	2.6
Jacksonville	29.56	41.2	2.63	23.48	46.69	27.21	2.0
Kansas City	31.10	35.1	2.21	20.35	46.20	31.24	1.1
Las Vegas	30.71	39.2	3.79	25.82	44.37	26.02	4.2
Los Angeles	34.26	40.8	3.42	20.36	39.15	37.06	0.9
Louisville	28.43	39.4	3.07	21.81	43.88	31.23	1.0
Minneapolis	30.40	32.6	3.07	20.38	46.76	29.79	0.8
New York	28.88	40.8	31.73	27.45	24.76	16.07	0.2
Philadelphia	29.42	37.7	6.56	23.45	43.05	26.94	0.4
Phoenix	31.53	43.6	3.01	23.58	46.15	27.25	2.9
Portland	29.76	39.5	3.95	21.85	44.82	29.39	1.5
Salt Lake City	38.23	39.5	1.93	16.24	41.57	40.26	1.8
San Antonio	33.32	41.2	3.04	22.61	43.70	30.65	2.6
San Diego	31.30	43.4	2.86	19.84	42.85	34.45	1.0
St. Louis	30.13	37.8	1.92	18.62	45.40	34.07	0.5
Washington DC	31.33	45.4	6.20	23.75	40.03	30.02	1.6
Average	**30.66**	**38.76**	**5.33**	**23.14**	**42.86**	**28.67**	**1.26**
Third Quartile	**31.51**	**40.92**	**3.92**	**23.71**	**45.39**	**31.09**	**1.94**

Note: Highlighted values result in a point towards recommendation.

4.1.2 Highway Network

Table 11 shows the values for the congestion index, peak hour, and freight congestion that were found for each city. The total number of congested locations provided from the freight analysis is shown alongside the total severity of the congestion caused by truck freight. This is provided to show that many cities have several sites on their highway network that are prone to freight-related congestion. Both statistics are integral to understanding how severe the congestion problem is, as was explained in the previous chapter. The cities that were awarded a point towards recommendation are shown highlighted in blue.

Table 11 - Findings for Highway Network Measures

City	Highway Network			
	Congestion Index	Peak Hour	Freight Congestion	
			Total Severity	No. Locations
Atlanta	1.27	5	18	7
Boston	1.09	5	12	5
Buffalo	0.73	4	8	3
Chicago	1.15	5.25	17	5
Cleveland	0.84	4	2	1
Columbus	1.04	4	4	2
Dallas	1.17	5	10	3
Denver	1.13	5.25	8	3
Detroit	1.14	5	6	2
Hartford	0.94	3.5	3	1
Houston	1.15	5.75	33	10
Jacksonville	1.1	4	3	1
Kansas City	0.77	4	5	2
Las Vegas	1.31	4	2	1
Los Angeles	1.54	8	17	6
Louisville	1.03	4	5	2
Minneapolis	1.1	5	19	5
New York	1.1	6.75	5	1
Philadelphia	1.07	5	8	2
Phoenix	1.24	5	4	2
Portland	1.14	4.5	8	3
Salt Lake City	0.97	4	4	3
San Antonio	1.1	4	3	2
San Diego	1.32	5	2	1
St. Louis	0.87	4	8	3
Washington DC	1.3	7	10	3

Note: Highlighted values result in a point towards recommendation.

4.1.3 Work Mode Share

The mode share of work trips is shown in Table 12. All of the travel modes that were shown in the ACS table are shown here, but only the shared ride, public transit, walk, and work from home modes are used in this analysis. The third quartile, which is shown at the bottom of the table, was used to determine the threshold between giving a point towards recommendation or not. The cities that received a recommendation for an activity-based model are shown highlighted in blue.

Table 12 - Findings for Work Mode Share Measures

City	Work Trip Mode Share					
	% Drive Alone	% Shared Ride	% Public Transit	% Walk	% Other Modes	% Work from Home
Atlanta	76.36	9.89	4.33	1.37	1.89	6.16
Boston	42.67	8.17	31.47	11.80	2.41	3.46
Buffalo	82.50	7.53	3.64	2.66	1.42	2.25
Chicago	69.85	8.92	12.35	2.87	1.72	4.28
Cleveland	82.89	7.13	3.61	1.82	1.06	3.49
Columbus	82.67	8.23	1.87	1.88	1.16	4.18
Dallas	80.80	10.86	1.51	1.23	1.46	4.14
Denver	74.65	9.67	4.73	2.32	2.38	6.25
Detroit	84.08	8.47	1.74	1.67	1.01	3.03
Hartford	82.35	8.10	3.38	1.89	1.43	2.85
Houston	78.57	12.32	2.50	1.46	1.86	3.31
Jacksonville	81.67	10.19	1.13	1.32	1.95	3.74
Kansas City	83.11	8.87	1.36	1.28	1.33	4.06
Las Vegas	78.97	10.50	3.74	1.54	1.95	3.31
Los Angeles	74.53	11.72	4.94	2.16	1.97	4.67
Louisville	82.50	9.83	2.37	1.62	0.96	2.72
Minneapolis	77.92	8.25	5.39	2.25	1.69	4.50
New York	40.14	5.94	40.46	7.36	2.11	4.00
Philadelphia	73.37	7.91	10.28	3.37	1.43	3.65
Phoenix	76.81	11.83	1.97	1.40	2.05	5.94
Portland	71.86	8.75	6.47	3.13	3.29	6.50
Salt Lake City	77.26	12.00	2.99	1.92	1.70	4.13
San Antonio	80.17	11.55	2.31	1.41	1.62	2.94
San Diego	78.00	9.93	3.35	1.81	1.84	5.06
St. Louis	84.24	8.18	1.70	1.17	1.02	3.68
Washington DC	65.21	10.69	15.01	3.01	1.50	4.58
Average	**75.51**	**9.44**	**6.72**	**2.53**	**1.70**	**4.11**
Third Quartile	**82.46**	**10.64**	**5.28**	**2.58**	**1.95**	**4.56**

Note: Highlighted values result in a point towards recommendation.

4.1.4 Current Transportation Demand Management Practices and Future Plans

The transportation demand management practices are shown below in Table 13. The various strategies and practices for parking management, commute options, and transit system expansion are shown for each city. Due to the absolute nature of either planning congestion pricing or not, the options for this criterion are simply yes or no. Because every region has a focus on improving bicycle and pedestrian facilities, the various practices were not shown in detail. For every scenario where a strategy is apparent, the city was given a point toward recommendation for an activity-based model.

Table 13 - Findings for Transportation Demand Management Measures

City	Current Strategies			Future Plans	
	Parking Management	Bike/Ped Focus	Commute Options	Congestion Pricing	Transit System Expansion
Atlanta	no	yes	Clean Air Campaign carpool/vanpool telecommute	yes	yes
Boston	parking freeze zones no minimum parking requirements parking caps in CBD	yes	MassRIDES carpool telecommute encourage off-peak travel	no	yes
Buffalo	no	yes	Good Going carpool	no	yes
Chicago	parking strategies	yes	carpool/vanpool guaranteed ride home	yes	maintenance upgrades
Cleveland	no	yes	Ohio Rideshare carpool	no	maintenance upgrades
Dallas	no	yes	TryParkingIt carpool/vanpool telecommute	yes	yes
Detroit	no	yes	MiRideshare carpool	no	yes
Hartford	no	yes	CTrides carpool/vanpool telecommute guaranteed ride home	no	yes
Houston	no	yes	Commute Solutions carpool/vanpool telecommute	yes	yes
Jacksonville	no	yes	Cool to Pool carpool/vanpool telecommute	yes	yes
Kansas City	Potential Strategies: preferential spaces for carpools on-street parking restrictions	yes	RideShare Connection carpool/vanpool telecommute guaranteed ride home	no	yes
Las Vegas	relocate free employee parking	yes	Club Ride carpool/vanpool guaranteed ride home	no	increase service
Los Angeles	demand-responsive parking zone	yes	carpool/vanpool telecommute guaranteed ride home alternative work hours	yes	yes
Louisville	Potential Strategies: location-specific parking ordinances preferential spaces for carpools on-street parking restrictions	yes	Ticket to Ride carpool/vanpool guaranteed ride home	no	improve connectivity
Minneapolis	no	yes	Rideshare carpool/vanpool guaranteed ride home	yes	yes
Philadelphia	charge for currently free parking "cash out" program preferential spaces for carpools	yes	Share-A-Ride carpool/vanpool	no	yes maintenance first
Phoenix	no	yes	carpool/vanpool telecommute alternative work hours	no	yes
Portland	parking freeze zones no minimum parking requirements parking caps in CBD	yes	carpool/vanpool	no	yes
Salt Lake City	no	yes	UTA Rideshare carpool/vanpool telecommute alternative work hours	yes	yes
San Antonio	on-street parking pricing policies	yes	Clean Air Drive carpool/vanpool	yes	yes
San Diego	charge for current free parking preferential spaces for carpools	yes	iCommute carpool/vanpool telecommute	yes	yes
St Louis	no	yes	carpool/vanpool	no	maintenance
Washington, DC	no	yes	Commuter Connections carpool/vanpool telecommute	yes	yes

4.2 Recommendations for Converting to an Activity-Based Model

Table 14 provides the final results based on the convention of this thesis. For all of the conditions, the measure was given a value of one if the criterion was met and zero if it was not. The values for the metrics relating to environmental issues, model specifics, and the interest of the MPO were either yes or no and so were not previously shown. The final recommendation table shows a value of one for these scenarios if the answer to the criterion was yes. If the tally was found to be 12 points or greater, an affirmative recommendation was given to the MPO. The cities that are currently using an activity-based model were omitted from these recommendations. For clarity, the cities where an activity-based model was decided to be beneficial are highlighted blue. These regions are Atlanta, GA; Boston, MA; Chicago, IL; Houston, TX; Los Angeles, CA; Philadelphia, PA; Phoenix, AZ; Portland, OR; San Diego, CA; and Washington, DC.

Much of the literature suggests that many MPOs are still hesitant to adopt an activity-based model because of the costs associated with acquiring more detailed data and running the advanced model. Other concerns are that the activity-based models do not provide results superior enough to warrant converting from the conventional model. From the questionnaire provided to the modelers, the major concerns across the board were costs, the lack of experience that the modeling staff has with activity-based models, and the time it takes to create the model and then run the model once a working prototype is constructed. These concerns are further discussed in the following Discussion chapter. However, even with all of these concerns, it was found that three MPOs are currently using an activity-based model, 14 are interested in converting, and 11 are in the process of developing an advanced model.

After realizing that so many regions are starting to look at activity-based models more seriously, it seemed important to weigh this rubric against reality. A comparison of the recommendations that were provided from this tool to the actual usage of activity-based models is shown in Table 15. The eight cities that are currently building an activity-based model and that were given a recommendation to convert to an advanced model are highlighted in green. These eight cities are Atlanta, GA; Chicago, IL; Houston, TX; Los Angeles, CA; Philadelphia, PA; Phoenix, AZ; Portland, OR; and San Diego, CA. Three cities are currently developing an activity-based model but were not given a recommendation to do so and these are highlighted in pink. These three cities are Cleveland, OH; Jacksonville, FL; and Minneapolis, MN. The remaining two cities that were given a recommendation to switch to an activity-based model but are not currently in the process of doing so are Boston, MA and Washington, DC and are highlighted in orange. These comparisons are important to analyze because they determine the accuracy of this assessment tool. It is a concern that of the 23 cities evaluated, three were not given a recommendation to convert to an activity-based model even though these cities are in the process of building an advanced model. This could mean that the rubric has a tendency to provide a false negative recommendation. More analysis of this discrepancy is presented in the following Discussion chapter.

Table 14 - Recommendations for Converting to an Activity-Based Model

City	Population Characteristics				Highway Network			Environmental	Model Specs	MPO Attitude		Work Mode Share				Current TDM Practices			Future Plans		Recommendation	
	Children	Workers	Growth	0 Cars Available	Congestion Index	Peak Hour	Freight Congestion	Nonattainment	Nonmotor	Interest	Building	Carpool	Transit	Walk	Work at Home	Parking Management	Bike/Ped Focus	Commute Options	Congestion Pricing	Transit System Expansion	Tally	Y/N
Atlanta	1	0	1	0	1	1	1	1	1	1	1	0	0	0	1	0	1	1	1	1	14	YES
Boston	0	0	0	1	1	1	1	0	1	1	0	0	1	1	0	1	1	1	0	1	12	YES
Buffalo	0	1	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	1	0	1	7	NO
Chicago	0	0	0	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	1	0	13	YES
Cleveland	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	1	0	0	6	NO
Dallas	1	0	1	0	1	1	1	0	0	1	0	1	0	0	0	0	1	1	1	1	11	NO
Detroit	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	1	1	0	1	8	NO
Hartford	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	3	NO
Houston	1	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	1	1	12	YES
Jacksonville	0	1	1	0	1	0	0	0	0	1	1	0	0	0	0	0	1	1	1	1	9	NO
Kansas City	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1	0	1	6	NO
Las Vegas	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	4	NO
Los Angeles	1	0	0	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	15	YES
Louisville	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	0	1	7	NO
Minneapolis	0	0	0	0	1	1	1	0	1	1	1	0	0	0	0	0	1	1	1	1	10	NO
Philadelphia	0	0	0	1	1	1	0	1	1	1	1	0	1	1	0	1	1	1	0	1	13	YES
Phoenix	1	1	1	0	1	1	0	0	1	1	1	1	0	0	1	0	1	1	0	1	13	YES
Portland	0	0	1	1	1	1	0	0	1	1	1	0	0	1	1	1	1	1	0	1	13	YES
Salt Lake City	1	0	1	0	0	0	0	1	1	0	0	1	0	0	0	0	1	1	1	1	9	NO
San Antonio	1	1	1	0	1	0	0	0	1	0	0	1	0	0	0	1	1	1	1	1	11	NO
San Diego	0	1	1	0	1	1	0	0	1	1	1	0	0	0	1	1	1	1	1	1	13	YES
St. Louis	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	1	0	0	4	NO
Washington DC	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	0	1	1	1	1	15	YES

Table 15 - Comparison of Results from Rubric and Current MPO Implementation

City	Population Characteristics				Highway Network			Environmental	Model Specs	MPO Attitude		Work Mode Share				Current TDM Practices			Future Plans		Recommendation	
	Children	Workers	Growth	0 Cars Available	Congestion Index	Peak Hour	Freight Congestion	Nonattainment	Nonmotor	Interest	Building	Carpool	Transit	Walk	Work at Home	Parking Management	Bike/Ped Focus	Commute Options	Congestion Pricing	Transit System Expansion	Tally	Y/N
Atlanta	1	0	1	0	1	1	1	1	1	1	1	0	0	0	1	0	1	1	1	1	14	YES
Boston	0	0	0	1	1	1	1	0	1	1	0	0	1	1	0	1	1	1	0	1	12	YES
Buffalo	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	1	6	NO
Chicago	0	0	0	1	1	1	1	1	0	1	1	0	1	0	0	1	1	1	1	0	12	YES
Cleveland	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	1	0	0	6	NO
Dallas	1	0	1	0	1	1	1	0	0	1	0	1	0	0	0	0	1	1	1	1	11	NO
Detroit	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	1	1	0	1	8	NO
Hartford	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	3	NO
Houston	1	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	1	1	12	YES
Jacksonville	0	1	1	0	1	0	0	0	0	1	1	0	0	0	0	0	1	1	1	1	9	NO
Kansas City	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1	0	1	6	NO
Las Vegas	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	4	NO
Los Angeles	1	0	0	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	15	YES
Louisville	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	0	1	7	NO
Minneapolis	0	0	0	0	1	1	1	0	1	1	1	0	0	0	0	0	1	1	1	1	10	NO
Philadelphia	0	0	0	1	1	1	0	1	1	1	1	0	1	1	0	1	1	1	0	1	13	YES
Phoenix	1	1	1	0	1	1	0	0	1	1	1	1	0	0	1	0	1	1	0	1	13	YES
Portland	0	0	1	1	1	1	0	0	1	1	1	0	0	1	1	1	1	1	0	1	13	YES
Salt Lake City	1	0	1	0	0	0	0	1	1	0	0	1	0	0	0	0	1	1	1	1	9	NO
San Antonio	1	1	1	0	1	0	0	0	1	0	0	1	0	0	0	1	1	1	1	1	11	NO
San Diego	0	1	1	0	1	1	0	0	1	1	1	0	0	0	1	1	1	1	1	1	13	YES
St. Louis	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	1	0	0	4	NO
Washington DC	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	0	1	1	1	1	15	YES

CHAPTER 5

DISCUSSION

The purpose of this thesis was to assess the use of activity-based models across the United States and then to develop a tool to use to assess whether a model region might benefit from an activity-based model in lieu of the traditional trip-based model. The rubric that was developed consists of criteria that relate to the factors that lead to the activity-based model as being a potentially better system to predict trips across the model area because of the concentration on the underlying reasons for travel. This chapter presents a review of the results that were explained in the previous chapter and explains how they relate to the principles of activity-based models that have been discussed throughout this thesis.

5.1 Factors That Promote the Use of Activity-Bases Models

Activity-based models are touted for their ability to take into account traveler behavior because they can factor personal preferences and environmental conditions that would affect an individual's decision to travel. These models are also expected to be more sensitive to transportation policies related to reducing single-passenger automobile usage to combat congestion mitigate air quality impacts. The following provides an account of how the inclusion of the major factors that contribute to the desirability of an advanced model that were introduced in the literature affected the outcome of the recommendations given from the rubric.

The parameters used in the rubric focused on population characteristics, the state of the highway network with respect to congestion, environmental concerns, mode share, and transportation policies. The attitude of the MPO was included to provide a metric that takes into account the current state of the practice for each region. Table 16 shows all of the regions that were given a recommendation to convert to an activity-based model along with the result for each criterion. In an effort to evaluate which criteria seemed to be integral in influencing a positive recommendation, Table 16 was developed to visualize any trends. The results are varied, but there are two criteria, a congestion index greater than 1.0 and peak hour greater than 2, that were met for every city. The commute option and bicycle and pedestrian focus parameters were omitted from this analysis because all of the 26 cities surveyed were implementing these policies and would therefore not be a factor that would sway the recommendation. The metrics in Table 16 highlighted in blue are those where at least six out of the ten cities met these criteria. The population characteristics and the work mode share parameters that were given a cut point at the third quartile did not seem to have an impact on the positive recommendation, except for the growth rate and work at home metrics. This could be due to the fact that a maximum of seven regions could meet this measure, given the nature of using the third quartile for the parameters; therefore, unless all but one of the regions that received a positive recommendation, this metric would not be highlight in Table 16. It should also be noted that the zero cars available and walk metrics resulted in the same regions meeting these criteria. This indicates a direct correlation between these two measures.

Table 16 - Positive Recommendation City Parameters

City	Population Characteristics				Highway Network			Environmental	Model Specs	MPO Attitude		Work Mode Share				Current TDM Practices	Future Plans	
	Children	Workers	Growth	0 Cars Available	Congestion Index	Peak Hour	Freight Congestion	Nonattainment	Nonmotor	Interest	Building	Carpool	Transit	Walk	Work at Home	Parking Management	Congestion Pricing	Transit System Expansion
Atlanta	1	0	1	0	1	1	1	1	1	1	1	0	0	0	1	0	1	1
Boston	0	0	0	1	1	1	1	0	1	1	0	0	1	1	0	1	0	1
Chicago	0	0	0	1	1	1	1	1	0	1	1	0	1	1	0	1	1	0
Houston	1	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1
Los Angeles	1	0	0	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1
Philadelphia	0	0	0	1	1	1	0	1	1	1	1	0	1	1	0	1	0	1
Phoenix	1	1	1	0	1	1	0	0	1	1	1	1	0	0	1	0	0	1
Portland	0	0	1	1	1	1	0	0	1	1	1	0	0	1	1	1	0	1
San Diego	0	1	1	0	1	1	0	0	1	1	1	0	0	0	1	1	1	1
Washington DC	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	0	1	1
Total Conditions Met	**4**	**3**	**6**	**5**	**10**	**10**	**6**	**5**	**7**	**9**	**8**	**4**	**4**	**5**	**6**	**6**	**6**	**9**

The cities that were not given recommendations to convert to an activity-based model are shown in Table 17. This table was developed to provide a comparison of the parameters that were overwhelmingly met by the cities that were given a recommendation to how often they were met by the remaining cities.

Table 17 - Negative Recommendation City Parameters

City	Population Characteristics				Highway Network			Environmental	Model Specs	MPO Attitude		Work Mode Share				Current TDM Practices	Future Plans	
	Children	Workers	Growth	0 Cars Available	Congestion Index	Peak Hour	Freight Congestion	Nonattainment	Nonmotor	Interest	Building	Carpool	Transit	Walk	Work at Home	Parking Management	Congestion Pricing	Transit System Expansion
Buffalo	0	1	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1
Cleveland	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0
Dallas	1	0	1	0	1	1	1	0	0	1	0	1	0	0	0	0	1	1
Detroit	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	1
Hartford	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Jacksonville	0	1	1	0	1	0	0	0	0	1	1	0	0	0	0	0	1	1
Kansas City	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1
Las Vegas	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0
Louisville	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	1	0	1
Minneapolis	0	0	0	0	1	1	1	0	1	1	1	0	0	0	0	0	1	1
Salt Lake City	1	0	1	0	0	0	0	1	1	0	0	1	0	0	0	0	1	1
San Antonio	1	1	1	0	1	0	0	0	1	0	0	1	0	0	0	1	1	1
St. Louis	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
Total Conditions Met	**3**	**4**	**6**	**1**	**7**	**3**	**2**	**5**	**7**	**5**	**3**	**3**	**0**	**1**	**0**	**4**	**5**	**10**

The criteria in Table 17 that are highlighted in blue represent at least six out of the thirteen cities that met these measures. The growth rate, congestion index, use of nonmotorized modes in the current model, and transit system enhancement parameters each show that a majority of both the cities with recommendations and those without met these criteria. These metrics could be considered nonfactors because a large portion of the cities met them, but the final recommendations were not decisive upon these criteria.

Another observation about these criteria is that some of the parameters are correlated. The problem with having correlated metrics is that some issues will be accounted for multiple times. This will be discussed further in the Weaknesses of This Approach section at the end of this chapter.

5.2 Testimony of Benefits of Activity-Based Models

The three regions that responded to the initial survey that are currently utilizing activity-based models were not included in the assessment tool because of their current involvement. New York, Denver, and Columbus provided feedback concerning the decision to invest in the advanced model and the benefits they have experienced from doing so.

The New York City model was the first activity-based model to be developed in the United States. Before they developed the activity-based model, there was not even a four-step model in place. Due to being in severe nonattainment, they were required to develop a model that would reflect future growth and travel across the entire transportation network. They developed the activity-based model because they thought that this would be the preferred method of the future, so instead of developing a trip-based model and then converting in the future, they decided to take the time and effort to develop the activity-based model immediately. The model is very complex and there is a steep learning curve to learning how to operate it, but it provides the necessary results to account for transportation policy and the unique travel patterns in the New York region. So although it was expensive to develop and requires expertise to operate, they have experienced advantages that make the model a huge asset.

The Columbus model was one of the first activity-based models to be used in practice in the United States. This model was developed to focus on travel growth, not congestion management, in the future, which is especially important given the number of large distribution centers in the Columbus area that have an impact on overall travel [3]. The model also incorporates household interactions, which is important because the unique relationships between household members dictate travel patterns for families. The Columbus MPO initially developed the activity-based model when a consulting firm enticed them with the deal that they could give them the activity-based model for the same cost and in the same amount of time as they could an aggregate trip-based model. In recent years, the Columbus MPO has updated their trip-based model to directly compare the results that each model produces. Their analysis presented that both models have similar predictive abilities but the activity-based model has the ability to provide decision makers with better information on travel behavior [45].

In Denver, the MPO was facing criticism because the trip-based models were not providing answers to policy questions when they began expanding their transit system. Since they have been operating the activity-based model, they have been able to answer the complicated questions that they were once not able to and the outputs of the model have exceeded their expectations. One of the weaknesses of the trip-based model is that trips are predicted over an entire analysis zone and are subject to aggregation biases. The ability to model travel at the parcel level with the advanced model was seen as especially beneficial.

5.3 Concerns About Adopting Activity-Based Models

The parameters used in the assessment rubric all relate to the fundamental advantages of activity-based models that have been discussed throughout this paper. However, there are external facts that affect whether an MPO would choose to convert to an activity-based model that were not presented in the tallied results that dictated which regions were given a recommendation to use an advanced model. Several MPOs provided concerns they had about investing in an activity-based model and these concerns are presented below in Table 18.

Most of the MPOs that were surveyed expressed similar concerns about converting to an activity-based model. These general concerns consist of the cost it takes to develop and maintain the advanced model, the lack of experience that in-house staff has with using activity-based models, and the availability of the detailed data that the activity-based models require. Salt Lake City and St. Louis expressed that they are yet to be convinced that the activity-based models provide superior enough results to warrant the added costs associated with developing an activity-based model. Dallas pointed out that the activity-based models should only be used if there are specific needs for the region that the trip-based model cannot explain.

Table 18 - MPO Concerns About Implementing Activity-Based Models

City	Concerns
Boston	lack of staff expertise cost of using a consultant
Buffalo	lack of data storage learning curve to operate
Cleveland	cost lack of in-house experience
Dallas	data availability cost to build only useful if trip-based model cannot mode specific needs
Jacksonville	data availability lack of in-house experience
Kansas City	funding
Las Vegas	want to take an incremental approach
Los Angeles	inconsistent results with trip-based model model run time knowledge transfer and training
Louisville	lack of in-house experience
Philadelphia	in-house technical experience
Phoenix	data availability cost lack of experience
Portland	need educated staff more potential for misinformation (lack of experience with results)
Salt Lake City	marginal benefits
San Diego	typical unknowns
St. Louis	data availability marginal benefits cost of development and maintenance
Washington DC	limited staff limited funding to dedicate to this effort

Of the 16 cities listed in Table 18, seven are currently building activity-based models. The popularity of activity-based models has grown in recent years because of the results that have been seen in practice for those agencies that were at the forefront of using the advanced models. Before now, most MPOs were hesitant to extend resources to develop the activity-based models because they had only been discussed in research efforts with theoretical advantages. However, the majority of modeling agencies are satisfied with maintaining their trip-based models for the time being. "The widespread use of the four-step model does not imply its superior efficacy, but that it is simply the most economical option, with respect both to data requirements and simplicity of operation" [17].

5.4 Discrepancies Between Results and Reality

There were three instances where a false negative error was seen in the results – Cleveland, Ohio; Jacksonville, Florida; and Minneapolis, Minnesota. There were also two cases in which a recommendation was made to convert to the activity-based model but the region has elected to not use activity-based models at this time – Boston, Massachusetts and Washington, DC. Possible explanations for these discrepancies are presented below:

5.4.1 Boston, Massachusetts

According to the rubric assessment, the Boston region would benefit from an activity-based model. However, they responded with concerns that the activity-based model would be very expensive to implement because they lack the in-house experience it would take to develop the advanced model and would need to hire a consultant to build the model.

5.4.2 Cleveland, Ohio

Cleveland is currently developing an activity-based model but the rubric did not suggest that an activity-based model would be beneficial. This is a prime example of how the unique characteristics of a model region dictate the necessity to implement an activity-based model because the Cleveland region did not indicate congestion problems or a high usage of alternative transportation modes based on the methodology used in this research effort to gather this information. The Cleveland MPO has an advantage in creating an activity-based model because there is statewide support for advanced modeling, as evidenced by the Ohio Department of Transportation's statewide travel demand model. In addition, Columbus can provide assistance with the experience that they have had with their activity-based model.

5.4.3 Jacksonville, Florida

According to the survey, Jacksonville has a high reliance on the automobile and did not meet the criteria for any of the alternative transportation metrics. After further research, it was found that there are two other cities in Florida that are pursuing activity-based models that did not respond to the initial questionnaire that was sent out to MPOs – Tampa and Miami. Similar to Ohio, the Florida Department of Transportation operates a statewide travel demand model, indicating statewide support for advanced travel demand modeling efforts. This could help explain why Jacksonville is currently pursuing an activity-based model but was not recommended to do so based on the rubric assessment.

5.4.4 Minneapolis, Minnesota

The assessment tool provided another false negative error for Minneapolis. Minneapolis has proven to be progressive with implementing transportation policies related to reducing single-occupancy vehicle trips, which could be attributed to the encouragement of innovative research from the Center for Transportation Studies at the University of Minnesota. Although the rubric provides metrics for various transportation policies, the rubric was not able to account for the fact that there is such a heavy focus on these policies, as is the case in Minneapolis.

5.4.5 Washington, DC

Washington, DC was another city that the rubric assessment deemed would be a good candidate for an activity-based model but the MPO is not currently building one. Like Boston, they expressed concerns with the lack of funding that the MPO has to dedicate to converting to the advanced model, especially since the current model would need to be maintained alongside the advanced model until the activity-based model is fully functional.

5.5 Weaknesses of This Approach

The assessment tool developed in this thesis functions by looking at a range of characteristics for a given model area and awarding a point for each criteria where they meet the predetermined value for that metric. This method recommended the use of activity-based models to ten regions. When the results were compared to actual MPO implementation, eight of the ten recommended regions are in the process of building activity-based modes; however, there were five discrepancies in the results when compared to actual implementation of these advanced models. These inconsistencies were inevitable because the nature of this rubric is to use generalized data for many of the performance metrics. Travel demand modeling is a sophisticated practice that uses unique area statistics and characteristics to provide travel forecasts. Every model region has different transportation needs and should be reviewed on a case-by-case basis in order to fully assess the need to convert to an activity-based model. Other factors that could influence a region to develop an activity-based model are the presence of local experts in the field of activity-based models, key stakeholders who are advocates for the advanced modeling practices, or the availability of the necessary data is abundant.

To provide an assessment tool that could easily be used across all model regions, the criteria that was used needed to be generalized. This simplification of some of the measures made the rubric insensitive to how much focus is placed on certain policies or demand management strategies; such was the case with Minneapolis. The rubric also weighted each measure equally, so it was difficult to assess which factors contributed the most to the recommendations. Some of the factors were also correlated, which allowed for some issues to be accounted for multiple times. An example of this was the percent of walk trips taken to work and the percentage of households with zero vehicles available. The same cities met the criteria for each of these metrics, which can be seen in Table 16 and Table 17. Other factors that are correlated are the congestion index and the peak hour variable. Though the results were not exactly the same for these metrics like the previous example, it can be assumed that areas with more congestion will likely have a longer peak period due to the sheer volume of people that must travel at similar times of day.

One subject area that was excluded from the rubric was the effect of land use. Future land use patterns will dictate travel demand and should be incorporated when attempting to decide if a model area would benefit from an activity-based measure. However, because of the need to use the same assessment tool across many unique model regions, it was difficult to provide a land use metric that could translate across an entire model region. For example, if two transit-oriented developments had been built in one area within a model region, then it would not be accurate to say that the entire region is a proponent of transit-oriented developments.

In the Results chapter of this thesis, the response rate of MPOs that provided answers to the questionnaire was given. Some respondents provided very detailed information, but other respondents were brief with their answers. The survey that was presented to them provided too much room for answers that did not fully explain the details that the survey was meant to attain. This lack of detail led to the inability to understand the true nature of the city's transportation issues. This assessment tool was never meant to definitively predict whether a region needs an activity-based model. This tool should be used as an introductory approach to attempt to identify certain transportation issues and policies in a model region that would traditionally benefit from the use of an activity-based model and make a recommendation as to whether the area should take the next steps toward converting to an advanced model.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

The purpose of this endeavor was twofold. The first goal was to become familiar with the modeling efforts of the major cities in the United States to gain greater understanding of how the activity-based model can be advantageous to use over the traditional four-step model. The second venture was to create a system to assess whether an MPO should consider transitioning to an activity-based model based on a set of variables that the traditional models have difficultly accounting for because of the inherent weaknesses of those models. The weaknesses of the trip-based models and the strengths of the activity-based models were discussed in the literature review to provide the reader with integral information about how the activity-based model can provide MPOs with better traveler information to use in the forecasts that are vital for regions to grow efficiently.

The review of modeling practices showed that although many MPOs are still very hesitant to implement an activity-based model, there is a large presence of proponents for activity-based models. In California, the MPOs for four of the major cities are using activity-based models now because they need to produce forecasts that are sensitive to environmental policies. Other cities are becoming interested in activity-based models because they have seen the positive effects the advanced models have on answering policy questions in the regions that are already using them. Twenty-six MPOs responded to the questionnaire that was sent to them as a way to determine the modeling techniques that are currently in use. Of these 26 MPOs, three are currently using an activity-based model (Columbus, Ohio; Denver, Colorado; and New York, New York) and 11 are in the process of creating an activity-based model. This research effort is not comprehensive of the entire United States, but it is evident from this surge in popularity of converting to an activity-based model in recent years that more cities across the country are beginning to accept that the advanced model may be beneficial to their modeling programs for use in policy analysis.

In regard to the validity of the rubric that was developed to assess if an activity-based model would be beneficial to a region, it cannot be concluded that this method provided definitive results as to the necessity of improving region's travel demand modeling techniques. Of the 11 cities that are developing an activity-based model currently, the tool recommended converting to the advanced model to 8 of them. Three regions that are currently building activity-based models were not recognized to benefit from the advanced model and two cities that were given the recommendation to convert to activity-based models are not currently pursuing an advanced model. Overall, 10 cities were given recommendations to move toward an activity-based model, which could mean that the rubric is conservative or that because only large MPO regions were evaluated that these cities are more apt to benefit from advanced modeling practices. This approach was beneficial to begin the conversation about switching to activity-based models, but MPOs would need to take the recommendations from this investigation and continue with more in-depth cost/benefit analyses to determine what is best for their region. Further research into why the regions currently moving toward activity-based models would prove beneficial in evaluating the circumstances that led to these areas deciding to switch to the more sophisticated model

One major concern with the rubric is the use of broad subjects for evaluation. Though the criteria used are important to distinguish where a model region would need more advanced models to provide realistic results, the questions posed to get the feedback were very general and did not allow for a true understanding of the specifics of the city in question. Finally, it is unknown whether this rubric would prove to be useful for medium or small cities. New measures based on the benefits experienced users of the activity-based models would need to be evaluated if this tool were to be used for other cities across the country.

APPENDIX A.

MPO ACTIVITY-BASED MODEL QUESTIONNAIRE

I. Census Data

1. Where may I obtain census data that reflects the following household characteristics:
    a. Percentage of households with 1 or more children
    b. Number of working adults and adults within households
    c. Number of licensed adult drivers and number of automobiles available within households

II. Survey Methods

2. Did you use a survey for Trip Generation purposes along with census data?
    a. May I retain a copy of the latest survey?
    b. Does the current survey include a time of day element?
    c. Does the current survey ask in detail what purposes trips are made for?

3. If you did not use a survey, how was travel information estimated?

III. Congestion Issues and Planning

4. Does the peak hour last for more than one hour on a regular basis?

5. Do future congestion mitigation plans include congestion pricing techniques?

6. Are there currently incentive programs available to encourage taking transit or carpooling?

IV. Model Specifics

7. What entity/entities is/are responsible for the use of the model across the region?

8. What modeling software package is used for the travel demand model?

9. Does the current mode choice model include motorized and non-motorized (bike/walk) trips?

10. What is the average trip length determined by the travel demand model?

11. Is the model trip-based or activity-based?

12. If it is trip-based, are there plans to convert to an activity-based model?

13. Do you foresee any problems with converting to an activity-based model? (data collection problems, lack of data storage, in-house technical experience, etc.)

14. What were some drawbacks or limitations to this model that need to be addressed in future models?

REFERENCES

[1] Cambridge Systematics Inc., Vanasse Hangen Brustlin Inc., Gallop Corporation, C. R. Bhat, L. Shapiro Transportation Consulting, and P. Martin/Alexion/Bryson, "NCHRP Report 716 - Travel Demand Forecasting: Parameters and Techniques," Transportation Research Board, Washington, D.C., 2012.

[2] Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting, *Special Report 288 - Metropolitan Travel Forecasting: Current Practice and Future Direction*. Washington, D.C.: Transportation Research Board, 2007.

[3] Cambridge Systematics Inc. and Federal Highway Administration, "A Snapshot of Travel Modeling Activities: Atlanta Regional Commission (ARC), Mid-Ohio Regional Planning Commission (MORPC), North Central Texas Council of Governments (NCTCOG), Puget Sound Regional Council (PSRC), Sacramento Area Council of Governments (S," 2008.

[4] M. M. Fischer, "Travel Demand," in *Analytical Transport Economics: An International Perspective*, J. B. Polak and A. Heertje, Eds. Edward Elgar, 2000.

[5] R. Kitamura, S. Fujii, and E. I. Pas, "Time-use data, analysis and modeling: toward the next generation of transportation planning methodologies," *Transport Policy*, vol. 4, no. 4, pp. 225–235, 1997.

[6] M. D. Meyer and E. J. Miller, “Demand Analysis,” in *Urban Transportation Planning*, Second Edi., McGraw-Hill, 2000.

[7] M. G. McNally, “The Four-Step Model,” in *Handbook of Transport Modelling*, D. A. Hensher and K. J. Button, Eds. Pergamon, 2000.

[8] J. de D. Ortuzar and L. G. Willumsen, *Modelling Transport*, Fourth Edi. John Wiley & Sons, 2011, p. Chapter 4.

[9] Atlanta Regional Commission, “The Travel Forecasting Model Set For the Atlanta Region 2010 Documentation,” 2011.

[10] Cambridge Systematics Inc., “PSRC Travel Model Documentation,” 2007.

[11] M. D. Rooij, “The analysis of change, Newton’s law of gravity and association models,” *Journal of the Royal Statistical Society: Series A (Statistics in Society)*. Royal Statistical Society, 18-Sep-2008.

[12] L. N. Duffus, A. Sule Alfa, and A. H. Soliman, “The reliability of using the gravity model for forecasting trip distribution,” *Transportation*, vol. 14, no. 3, pp. 175–192, 1987.

[13] K. Watkins, “Introduction to Mode Choice.” 2012.

[14] F. S. Koppelman and C. Bhat, “A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models,” 2006.

[15] Resource Systems Group and White River Junction, “WFRC & MAG Transportation Model Documentation,” 2011.

[16] M. G. McNally, “An Activity-Based Micro-Simulation Model for Travel Demand Forecasting,” in *Activity-Based Approaches to Travel Analysis*, D. Ettema and H. Timmermans, Eds. Pergamon, 1997.

[17] Virginia Department of Transportation, “Implementing Activity-Based Models in Virginia,” 2009.

[18] R. Donnelly, G. D. Erhardt, R. Moeckel, and W. A. Davidson, “NCHRP Synthesis 406 - Advanced Practices in Travel Forecastin,” Washington, D.C., 2010.

[19] M. Bradley and J. L. Bowman, “Design Features of Activity-Based Microsimulation Models for US Metropolitan Planning Organizations,” in *Innovations in Travel Demand Modeling May 21-23, 2006*, 2008.

[20] M. Lee and M. G. McNally, “An empirical investigation on the dynamic processes of activity scheduling and trip chaining,” *Transportation*, vol. 33, pp. 553–565, Sep. 2006.

[21] F. Primerano, M. a. P. Taylor, L. Pitaksringkarn, and P. Tisato, “Defining and understanding trip chaining behaviour,” *Transportation*, vol. 35, pp. 55–72, Jul. 2008.

[22] J. L. Bowman and M. E. Ben-Akiva, “Activity-based disaggregate travel demand model system with activity schedules.” Pergamon, 2000.

[23] M. Ben-Akiva and J. L. Bowman, "Integration of an Activity-based Model System and a Residential Location Model," *Urban Studies*, vol. 35, no. 7, pp. 1131–1154, 1998.

[24] P. Vovsha, M. Bradley, and J. L. Bowman, "Activity-Based Travel Forecasting Models in the United States: Progress Since 1995 and Prospects for the Future," in *Progress in Activity-Based Analysis*, H. Timmermans, Ed. Elsevier, 2005.

[25] K. G. Goulias and R. Kitamura, "Recursive Model System for Trip Generation and Trip Chaining," *Transportation Research Record*, vol. 1236, pp. 59–66, 1991.

[26] J.-C. Thill and I. Thomas, "Toward Conceptualizing Trip-Chaining Behavior: A Review," *Geographical Analysis*, vol. 19, no. 1, pp. 1–17, 1987.

[27] M. E. Ben-akiva and J. L. Bowman, "Activity based travel demand model systems."

[28] T. Hagerstrand, "What About People in Regional Science," *Regional Science Association Papers*, vol. 24, pp. 7–21, 1970.

[29] Y.-C. Chiu, J. Bottom, M. Mahut, A. Paz, R. Balakrishna, T. Waller, and J. Hicks, "Dynamic Traffic Assignment: A Primer," *Transportation Research Circular*, vol. E-C153, no. June, 2011.

[30] M. G. McNally, "The Activity-Based Approach," in *Handbook of Transport Modelling*, D. A. Hensher and K. J. Button, Eds. Pergamon, 2000.

[31] J. L. Bowman, “Activity Based Travel Demand Model System with Daily Activity Schedules,” Massachusetts Institute of Technology, 1995.

[32] R. Cervero and K. Kockelman, “TRAVEL DEMAND AND THE 3Ds: DENSITY, DIVERSITY, AND DESIGN,” *Transp Res.*, vol. 2, no. 3, pp. 199–219, 1997.

[33] R. Kitamura, “Applications of Models of Activity Behavior for Activity Based Demand Forecasting,” 1996.

[34] J. D. Lemp, L. B. McWethy, and K. M. Kockelman, “From Aggregate Methods to Microsimulation: Assessing the Benefits of Microscopic Activity-Based Models of Travel Demand,” *Transportation Research Record*, vol. 1994, pp. 80–88, 2007.

[35] A. Anas, “A unified theory of consumption, travel and trip chaining,” *Journal of Urban Economics*, vol. 62, pp. 162–186, Sep. 2007.

[36] L. Wang, P. Waddell, and M. L. Outwater, “Incremental Integration of Land Use and Activity-Based Travel Modeling,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2255, pp. 1–10, Dec. 2011.

[37] TMIP, “Activity-Based Modeling Resources At a Glance,” 2012.

[38] Vanasse Hangen Brustlin Inc., Resource Systems Group, Shapiro Transportation Consulting Inc., and Urban Analytics, “Advanced Travel Modeling Study,” Washington, D.C., 2011.

[39] P. Vovsha and K.-A. Chiao, “Development of New York Metropolitan Transportation Council Tour-Based Model,” in *Innovations in Travel Demand Modeling May 21-23, 2006*, 2006.

[40] R. S. Anderson, “Development of Mid-Ohio Regional Planning Commission Tour-Based Model,” in *Innovations in Travel Demand Modeling May 21-23, 2006*, 2008.

[41] J. G. Strathman, K. J. Dueker, and J. S. Davis, “Effects of household structure and selected travel characteristics on trip chaining,” *Transportation*, vol. 21, pp. 23–45, Feb. 1994.

[42] “American FactFinder,” *Profile of General Population and Housing Characteristics: 2010 Census*, 2012. [Online]. Available: http://factfinder2.census.gov/faces/tableservices/.

[43] “American FactFinder,” *Means of Transportation to Work by Vehicles Available: ACS 2010*, 2012. [Online]. Available: http://factfinder2.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_10_1YR_B08141&prodType=table.

[44] P. Vovsha and M. Bradley, “Advanced Activity-Based Models in Context of Planning Decisions,” *Transportation Research Record*, vol. 1981, pp. 34–41, Jan. 2006.

[45] Y. Shiftan and M. Ben-Akiva, “A practical policy-sensitive, activity-based, travel-demand model,” *The Annals of Regional Science*, vol. 47, pp. 517–541, Jun. 2010.

[46] Texas Transportation Institute, “National Congestion Tables,” *Annual Urban Mobility Report*, 2012. [Online]. Available: http://mobility.tamu.edu/ums/congestion-data/.

[47] American Transportation Research Institute and Federal Highway Administration, “FPM Congestion Monitoring at 250 Freight Significant Highway Locations,” 2011. [Online]. Available: http://atri-online.org/2011/10/01/fpm-congestion-monitoring-at-250-freight-significant-highway-locations/.

[48] R. Weinberger, J. Kaehny, and M. Rufo, “U.S. Parking Policies: An Overview of Management Strategies,” New York, 2010.

[49] N. Ferdous, C. Bhat, L. Vana, D. Schmitt, J. L. Bowman, M. Bradley, and R. Pendyala, “Comparison of Four-Step Versus Tour-Based Models in Predicting Travel Behavior Before and After Transportation System Changes – Results Interpretation and Recommendations,” 2010.