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Martin O'Malley, *Governor*
Anthony G. Brown, *Lt. Governor*

James T. Smith, Jr., *Secretary*
Melinda B. Peters, *Administrator*

STATE HIGHWAY ADMINISTRATION

RESEARCH REPORT

INCORPORATING RELIABILITY AND PEAK SPREADING INTO MARYLAND STATEWIDE TRANSPORTATION MODEL

LEI ZHANG
SABYASACHEE MISHRA
PRINCIPAL INVESTIGATORS

GRADUATE RESEARCH ASSISTANTS:
SEPEHR GHADER
KHADEMUL HAQUE
LIANG TANG

UNIVERSITY OF MARYLAND

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16. Abstract

Maryland Statewide Transportation Model (MSTM) is a four step transportation model developed by Maryland State Highway Administration (MSHA) to perform a robust, consistent, and reliable assessment of the future developments on key measures of transportation performance. This study proposes two sub-components in MSTM to incorporate more advanced methods in travel demand modeling. The first sub-component addresses travel time reliability; which can affect various steps of a traditional travel models. Reliability plays a crucial role in economic evaluation of projects, and describes the performance of the network. This study proposes a method to measure the value, to forecast, and to incorporate reliability in transportation planning process. Various studies have tried to measure the reliability and its value, but they usually focus on a specific corridor, and measure reliability based on SP surveys. This study uses empirically observed travel time as a source of RP data to measure reliability. Empirically observed reliability data is used to find the value of reliability for a specific mode choice problem. The reliability data is also combined with travel time data to establish the relationship between travel time and travel time reliability in order to forecast the reliability. These finding are combined with MSTM to find the economic benefits of improving the network in a case study. The second sub-component addresses the spread of peak travel because of changes in supply and demand. In MSTM four pre-defined time periods are used to account for time-of-day component. The current method is not sensitive to congestion, any policy, or geographical and temporal changes. In this study discrete choice models are combined with MSTM to model departure time choice. This study introduces a method to estimate preferred arrival time of travelers, which cannot be observed, based on skim values; and estimates a departure time model in a proposed iterative framework. Empirically observed reliability data is also combined in the framework to make the choices sensitive to reliability. This framework can be applied to any trip based four step model with readily available data like skim matrices and household surveys. Another iterative framework is proposed to forecast the demand distribution of any given scenario using the estimated model. The results are also validated with the observed demand distributions.

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EXECUTIVE SUMMARY

Maryland Statewide Transportation Model (MSTM) is a transportation model developed by Maryland State Highway Administration (MSHA) to perform a robust, consistent, and reliable assessment of the effects of future developments on key measures of transportation performance. The architecture of MSTM consists of traditional five steps including trip generation, destination choice, mode choice, time-of-day distribution, and trip assignment. MSTM is used as an evaluation tool to assess the effects of future investments and corresponding changes in travel patterns in MD. A first version of MSTM (MSTM Version 1.0) is now available which is well calibrated and validated with 2007 and 2030 as the base and future years. MSTM is a reliable tool to design, analyze, and assist the implementation of various land use, transportation planning, demand management, and other transportation-related policies in Maryland. This study proposes two sub-components in MSTM to incorporate state-of-the art practices and recent developments in travel demand modeling.

The first sub-component addresses travel time reliability in MSTM. Reliability can affect various steps of a traditional travel models, like mode choice and trip assignment. Reliability plays a crucial role in economic evaluation of projects and describes the performance of a transportation network. When existing condition of the network is being monitored reliability should be among performance measures, because travelers consider value of reliability in travel choices. In addition, when benefits and costs of future or existing projects are being evaluated, reliability should be considered, since value of reliability savings can affect the results.

This study proposes a method to measure the value, to forecast, and to incorporate reliability in the transportation planning process. Travel time data for one year is obtained and processed to obtain reliability between some origin-destination (OD) pairs. A method is introduced to measure OD travel time based on link travel times. Standard deviation is used to measure travel time reliability using between daily variations of the data. Thereafter, this reliability data is used to estimate a mode choice model between two competing alternatives (auto and rail) with reliability as an independent variable. Estimating coefficient of reliability makes it possible to find reliability ratio (RR) and value of travel time reliability (VoTR). The reliability data is also combined with travel time data to establish the relationship between travel time and travel time reliability. A nonlinear regression is used to obtain the relationship of travel time reliability on travel time. This regression is useful to forecast reliability when travel time is available. These findings are combined with MSTM in four different scenarios to find the economic benefits of a build versus no-build scenario for base year, and some more extensive network improvements in the future year. Value of reliability savings by these improvements is calculated and presented in four different levels; State, County, Zone, and corridor level.

The findings shows considerable amount of reliability savings (while considering a build versus a no-build) that should not be neglected. State level findings show that reliability savings are about 10 percent of travel time savings. The constrained long range plan shows that proposed future year improvements will result in larger value of reliability savings. County level results show that counties that benefit from network improvements also have higher reliability savings. Counties having the highest reliability savings are showed to be different between base year and future year due to the geographical pattern of network improvements. Zone level results display that future savings are more spread out in the state. Corridor level findings demonstrate considerable value of reliability savings per traveler for some major corridors. The results in different levels suggest that reliability should not be neglected in planning process because it can have significant effect on a vast geographical area. The framework used in this study can help any planning agency to incorporate reliability in their planning process by using available local data.

The second sub-component addresses the spread of peak travel because of changes in supply and demand. In MSTM four pre-defined time periods are used to account for time-of-day component. The current method is not sensitive to congestion, any policy, or geographical and temporal changes. A more appropriate model should be more disaggregated to demonstrate shifts of demand between smaller time periods. The perspective method is expected to be sensitive to congestion, policies, and changes in behavior to more realistically demonstrate the distribution of demand in a typical modeled 24 hours. Such model will predict demand shifts from hour to shoulders of the peak when roadways become more congested. The phenomenon is known as peak spreading and addressed as a second sub-component in this project as an addition to MSTM.

In this study discrete choice models are combined with MSTM to model departure time choice (to account for peak spreading) of the travelers inside Montgomery County in Maryland. 12 time intervals (five one hour intervals for peak, and off peak; and one hour interval of mid-day, and night) are assumed as alternatives. Skim value, travel time reliability and scheduling delay penalties are considered as attributes. Separate models are estimated for different trip purposes (HBW, HBS, HBO, HBSch, NHBW, and NHBO). An iterative framework is proposed for model estimation, and results of one iteration are presented. The first step for the modeling is to create the input database: (1) to extract the Montgomery County as a sub-area from MSTM, and to obtain skim matrices for the sub-area for 12 intervals. The skim matrices were obtained by using static hourly factors for the first iteration. The hourly skims are combined with TPB-BMC Household Travel survey data to estimate a departure time choice model. No data existed about preferred arrival time of travelers and it is estimated using skim matrices. The estimated models show negative effect of longer travel time, unreliability, and scheduling delay as expected. Scheduling delays show to be less important for travelers in HBS and HBO trips in comparison with HBW trips. Estimated models are used to predict demand distribution for two scenarios, base year (2007) and future year (2030). Another iterative method is proposed for forecasting and results of one iteration are presented. Prediction results are compared and slight changes in demand distribution are observed. It is shown that trips shift from peak hour to shoulders of the peak, specifically 6am and 2pm. While HBW shows more significant shift in the morning peak, other trip purposes have their major shift in the afternoon.

In summary, both reliability and peak spreading are two important sub-components addressed in this project demonstrate state-of-the-practice in travel demand modeling. The application illustration in MSTM suggests that reliability and peak spreading should be considered while analyzing existing, future, and proposed supply-demand changes to realistically reflect travel behavior in transportation planning and applications.

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RELIABILITY CHAPTER 1: INTRODUCTION

Value of Travel Time (VoT) and Value of Travel Time Reliability (VoTR) are two most important parameters used in transportation planning and travel demand studies. VoT refers to the monetary value travelers place on reducing their travel time or savings. In contrast, VoTR denotes the monetary value travelers place on reducing the variability of their travel time or improving the predictability. Over the years VoT has a long established history through the formulation of time allocation models from a consumer theory background (Jara-Díaz, 2007) (Small and Verhoef, 2007) Various models and their review in the mainstream of travel demand modeling are thoroughly discussed in the literature (Abrantes and Wardman, 2011) (Shires and De Jong, 2009) (Zamparini and Reggiani, 2007). In contrast, VoTR has been gaining significant attention in the field. However, despite of increased attention, the procedures for quantifying it are still a topic of debate, and number of researchers and practitioners have proposed numerous aspects such as: experimental design (e.g. presentation of reliability to the public in stated preference (SP) investigations); theoretical framework (e.g. scheduling vs. centrality-dispersion); variability (unreliability) measures (e.g. interquartile range, standard deviation; a requirement in the centrality-dispersion framework); setting (or estimating) the preferred arrival time (e.g. assuming work start time as preferred arrival time in the scheduling approach); data source (e.g. revealed preference(RP) vs. (SP)); and others (Carrion and Levinson, 2012) (Koppelman, 2013) (Mahmassani *et al.*, 2013). As a consequence, VoTR estimates exhibit a significant variation across studies.

It is clear that reliability is an important measure of the health of the transportation system in a region, as state Departments of Transportation (DOTs) and Metropolitan Planning Organizations (MPOs) prepare to manage, operate and plan for future improvements. Travel time reliability, depicted in the form of descriptive statistics derived from the distribution of travel times, is an additional and critical indication of the operating conditions of any road network as when interfaced with other performance metrics such as network travel time or average travel time along key routes (Pu, 2011). Considering its importance, transportation planners are inclined to include reliability as a performance measure to alleviate congestion. To investigate the use of travel time reliability in transportation planning, Lyman and Bertini (Lyman and Bertini, 2008) analyzed twenty Regional Transportation Plans (RTPs) of metropolitan planning organizations (MPOs) in the U.S. None of the RTPs used reliability in a comprehensive way, though a few mentioned goals of improving regional travel time reliability.

To date a number of studies and research papers have been published, where value of reliability was measured using SP survey, RP survey, corridor travel times, and assessing the impact of reliability in demand (trip based or activity based) and supply (network simulation) models. The reviewed literature related to this study can be classified in two groups (1) various measures of travel time reliability and their measurement, (2) integration of travel time reliability in transportation planning process.

Travel Time Reliability Measures

Over the years researchers and practitioners have measured and calibrated reliability measures in various ways, and VoTR estimation can be described in two groups: performance-driven reliability measures, and travelers' response (or, value of) (un-)reliability (Pu, 2011). Performance-driven measures (such as congestion, safety delay, reliability, etc.) are largely utilized for practical application purposes in the transportation systems. Performance-driven measures are mostly derived from observed data and are utilized for immediate planning purposes. Response measures, on the other hand, are often researched to incorporate uncertainty in travel demand or economic modeling in order to accurately reflect travelers' choice behavior; well-defined traditional statistics are typically preferred as reliability measures to enable mathematical or statistical modeling. Response measures require significant time and resources to develop, and often require caution to develop; thereby planning agencies are more oriented towards utilizing the performance driven reliability measures.

Some of the initial performance measures of reliability were percent variation, misery index and buffer time index (Lomax *et al.*, 2003). In subsequent studies by Federal Highway Administration (FHWA) and in the National Cooperative Highway Research Program (NCHRP), 90th or 95th percentile travel time, buffer index, planning time index, percent variation, percent on-time arrival and misery index are recommended as travel time reliability measures (FHA, 2010) (Systematics). Recent Strategic Highway Research Program (SHRP2) research recommended a list of five reliability measures similar to those found in the NCHRP report, with skew statistic replacing the percent variation (Systematics, 2013). Standard deviation is often considered as a measure of reliability, and is not recommended by USDOT for planning purposes (Dong and Mahmassani,

2009) (Dowling *et al.*, 2009). In a comparison of multiple measures proposed over the years, coefficient of variation proved to be a better measure of reliability (Pu, 2011).

Travel Time Reliability in Transportation Planning Context

A number of studies have attempted to empirically measure behavioral responses to changes in travel time variability (Noland and Polak, 2002). But their application to transportation planning context is limited. It is found in the literature that a number of factors such as destination, departure time, and mode choice affect travel time reliability (Ben-Akiva *et al.*, 1989) (Bhat and Sardesai, 2006) (Lam and Small, 2001). Similarly studies were done for understanding reliability of specific routes (Chen *et al.*, 2000) (Levinson, 2003) (Liu *et al.*, 2004) (Tilahun and Levinson, 2010). Specifically, reliability measures are studied for freeway corridors through empirical analysis and simulation approaches (Chen *et al.*, 2000) (Chen *et al.*, 2003) (Levinson *et al.*, 2004) (Rakha *et al.*, 2006) (Sumalee and Watling, 2008) (Zhang, 2012). Day-to-day variability of route travel times for freeway corridors is generally considered for measuring reliability (Van Lint and Van Zuylen, 2005). However, freeway corridors only encompass portion of a real life multimodal transportation network. A planning agency trying to evaluate the effect of various policies (other than freeways) may not be able to fully utilize such information to estimate value of travel time reliability savings on overall network level. In the planning stage, agencies often are not ready to collect new data but would like to utilize available resources to estimate travel time reliability using existing tools such as using the travel demand model. Usually there is limited publicly available data to measure travel time reliability in a large scale network for planning purposes (Bates *et al.*, 2001). Recently, few SHRP2 projects are underway to create suitable tools for the evaluation of projects, and design policies that are expected to improve reliability. Incorporating reliability into transportation planning models is still an evolving area of research.

The objective of this study is to develop a framework for planning agencies (DOTs and MPOs) to estimate VoTR for their respective regions for managing existing travel demand and to estimate the benefits of future improvements. The study discusses various steps on how to consider reliability as a performance measure in planning and decision making process by making the best utilization of available data sources and planning models. The study includes systematic framework for transportation planning agencies to (1) measure travel time reliability, (2) determine value of reliability, (3) incorporate reliability in transportation planning models, and (4) estimate changes in reliability because of new or proposed transportation infrastructure investments. In this study a framework that can be integrated with planning models for estimating travel time reliability savings is proposed and demonstrated in a real world case study.

The next chapter explains the methodology used in details which can be easily adapted by planning agencies. Chapter 3 discusses the details of estimating value of reliability through a mode choice model based on utility maximization theory. Chapter 4 explains how origin-destination reliability data is obtained, and how this data is used to estimate reliability based on congestion measures by a regression model to forecast reliability situation in any given scenario. The case study chapter describes application of the proposed methodology in a real world planning model and discusses the importance of considering VoTR in the planning process. The conclusion chapter summarizes the proposed research and discusses future directions.

RELIABILITY CHAPTER 2: METHODOLOGY

2-1 FRAMEWORK

A step by step process to integrate reliability in a transportation planning model is shown in the Figure 1. The methodology is categorized into three parts. The first part contains development of a random utility model (an example could be mode choice) with travel time reliability as an independent variables among others. This model will be used to calculate VoTR. VoTR can be estimated using any random utility model with a variable indicating reliability and travel time or travel cost. In this study mode choice model is used as an example. From the mode choice estimation VoTR can be determined as the ratio of coefficient of reliability and travel cost. Details of calculating VoTR can be found in chapter 3. The second part of the figure contains calculating OD-based travel time reliability measure and developing relationship between reliability and travel time. In a planning model the path travel times are static. To capture variation and to obtain reliability of each route a relationship between reliability and travel time is useful. For each O-D pair, reliability measure can be determined using the regression relationship between mean travel time and reliability. O-D specific shortest path travel time is usually available from a number of sources, But OD specific travel time reliability data is not available readily and the second step helps obtaining it. OD specific reliability data is used in random utility model estimation. It is also used in estimating the relationship between congestion and reliability to forecast future reliabilities. Chapter 4 talks about OD based travel time reliability and reliability forecasting in detail. The third part of flowchart discusses how to obtain travel time reliability savings in a transportation planning or travel demand model. Once the reliability of the OD is known for before and after improvement, then the savings in reliability can be computed by the value of reliability as the demand is known for before and after scenario. The improvement because of travel time reliability can be captured at system, county, zone, and corridor level as desired by the user. These are all demonstrated in chapter 5.

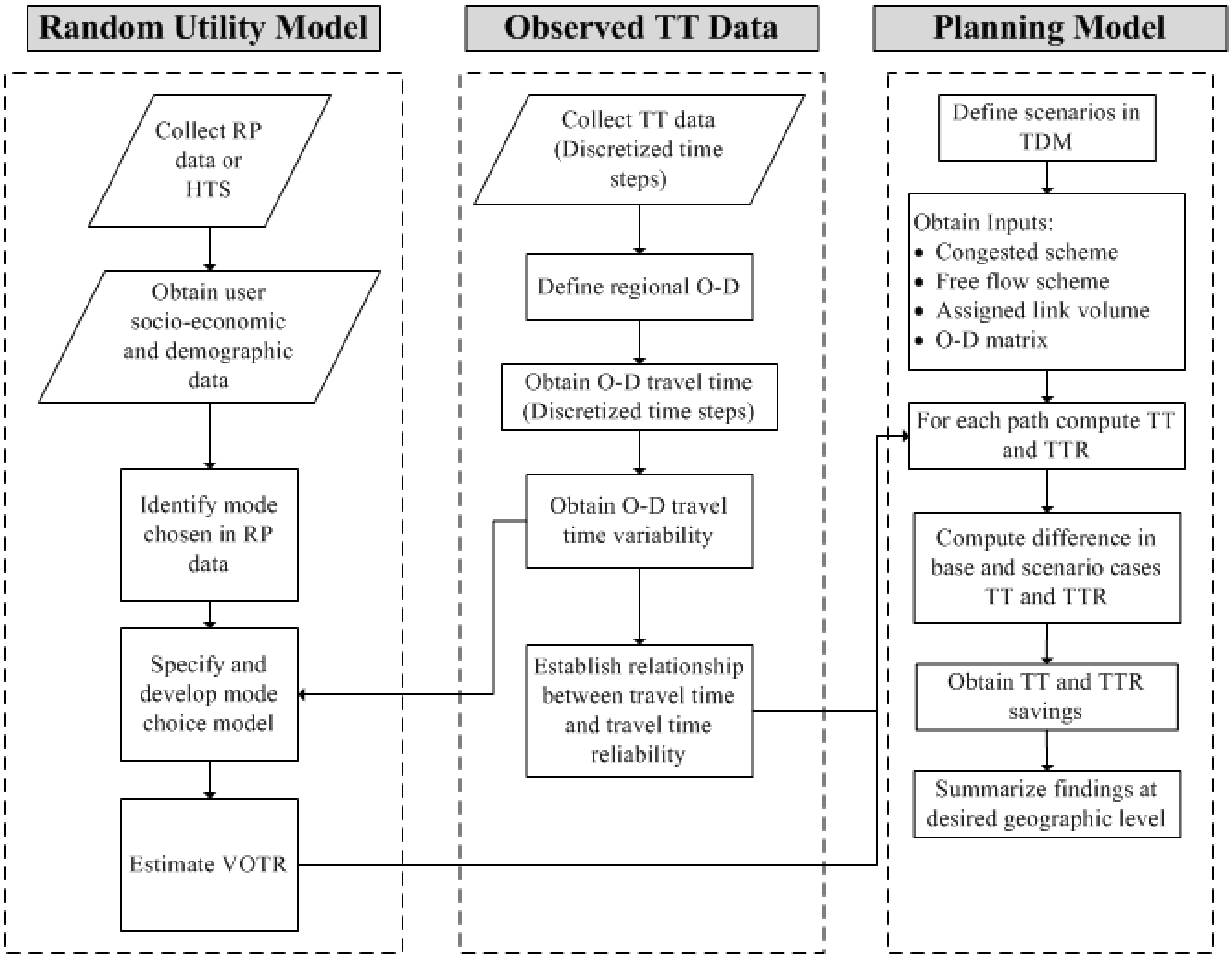

Figure 1 Proposed methodology for VoTR estimation and integration in planning models

2-2 DATA

The following datasets are used in this framework:

2-2-1 2007-2008 TPB-BMC Household Travel Survey

2007-2008 Household Travel Survey data conducted by Metropolitan Washington Council of Governments (MWCOG) and Baltimore Metropolitan Council (BMC) is used in the study to capture changes in daily travel patterns, and gather information on demographics, socio-economics, and trip making characteristics of residents. This survey contains four main parts which include Person characteristics, Household Characteristics, Trip Characteristics and Vehicle characteristics. This dataset contains 108,111 trips and their details. In this study, trips reported in the dataset are used in mode choice model estimation. Trip start time, trip distance, experienced travel time of the trip, and reported mode, along with socio-economic and demographics are attributes extracted from the dataset. Start time is used for getting the reliability of the trip. Distance is used to calculate the monetary cost of each trip, such as fuel cost for auto trips and transit fare for transit trip.

2-2-2 INRIX historical travel time data

INRIX provides real-time and historical travel time data to users. INRIX collects traffic data from more than 100 million vehicles in more than 32 countries. The data is obtained from different sources such as sensors on the network, local transport authorities, delivery vans, trucks, taxis and also users of INRIX traffic App. INRIX gathers these raw sets of data and converts them to easy-to-understand real-time and historical data. Travel time data for various paths are obtained from INRIX. TMCs (Traffic Message Channels) are the spatial units of INRIX data. In this study, INRIX historical data is obtained for a whole year in five minute increments, for specific paths and aggregated together for every hour. Different reliability measures like standard deviation and coefficient of variation between the values of travel time for each hour of the day are calculated from one year data using between day variations, as a measure of unreliability. After being processed, this data is used in both mode choice model estimation and reliability regression. INRIX does not cover all the functional classes of roadways, but it contains most of the major and minor arterials, along with full representation of freeways, interstates, and expressways.

2-2-3 MSTM outputs

Maryland Statewide Transportation Model (MSTM) is considered as the travel demand model to demonstrate the benefits of VoTR from new infrastructure investment. MSTM is the first statewide travel demand model developed for the Washington-Baltimore region and its primary development has occurred through the course of 2009-2014. MSTM is a traditional four step travel demand model which is well calibrated and validated, and currently being used for various policy and planning applications. The novelty of the MSTM is the use of a three-layer structure. The first layer includes macro scale travel patterns from the entire U.S. and the third layer includes travel patterns at a finer urban level detail. The second layer is statewide in scope and is an amalgamation of the first and third layer. The trip-based model consists of eighteen trip purposes that are cross-classified by five income categories, eleven modes of travel, and four time-of-day periods. Details of the model structure is presented in the literature (Mishra *et al.*, 2011) (Mishra *et al.*, 2013).

Figure 2 shows the full study area including the state of Maryland, Delaware, Washington DC., and portions of Pennsylvania, Virginia, West Virginia. The base year network consists of more than 167,000 links, and contains sixteen functional classifications including all highway, transit, walk access, and transfer links.

For external travels all the freeways are included outside the modeling region. The toll roads and Highway Occupancy Vehicle (HOV) lanes are coded in the network with the current user charges.
Outputs of the MSTM for predefined scenarios are used in case study chapter to calculate travel time savings. In addition, the estimated reliability-travel time relation is used with skim values to estimate the OD based reliability matrices to calculate reliability savings.

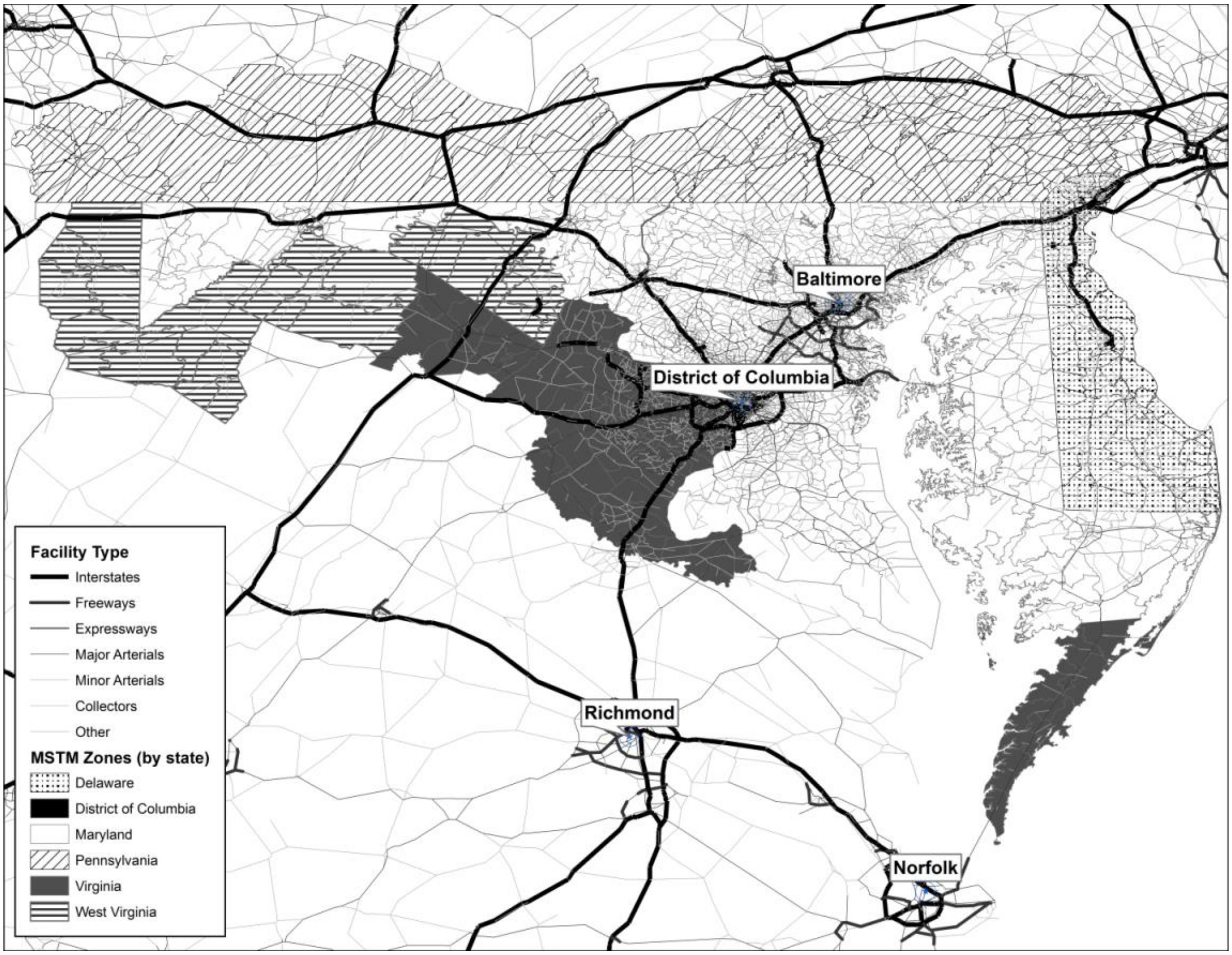

Figure 2 Topological map showing zone system and network of MSTM study area

2-2-4 MWCOG travel model skim matrices

Mode choice model estimation needs travel time information for all the alternatives. Household travel survey only contains travel time information for the chosen alternatives; hence another data source should be used for travel time information. MWCOG model is a travel model developed my Washington DC metropolitan area planning organization to model travels inside Washington DC metropolitan area, and it includes parts of Maryland and Virginia. This model provides travel time information between Traffic Analysis Zones in skim matrices. The reason MWCOG matrices are preferred to MSTM skim matrices for mode choice estimation is because MWCOG model is more consistent with TPB HHTS and they have the same zoning structure.

RELIABILITY CHAPTER 3: VALUE OF RELIABILITY

As described in Chapter 2, one major step is to develop a random utility model, which can be mode choice model, departure time choice model or route choice model based on data availability. Mode choice model is used to estimate value of reliability as an example in this study to demonstrate how local data can be used to obtain localized value of reliability. The first task would be to identify population of travelers with desired origins, destinations, socio-economics information, demographics information, mode choice and recognize network of links and nodes representing the study area. Typically this information is obtained from a Regional Household Travel Survey or any RP survey. The survey would provide trip information like origin, destination, time, and mode in addition to household and traveler information.

A key behavioral assumption for the mode choice decision is that in a random utility maximization framework, each traveler chooses a mode that maximizes his or her perceived utility. With no loss of generality, the utility function of mode m for traveler i can be given by:

$$U(mi) = \alpha * TT_{mi} + \beta * TC_{mi} + \gamma * \ TTR_{mi} + \theta_i DC_i + \ \varepsilon$$

Where,

TT = path travel time

TC = Travel cost

TTR = Travel time reliability (example: coefficient of variation)

DC_i = Decision maker's ith characteristics

α = coefficient of travel time

β = coefficient of travel cost

γ = coefficient of reliability

ε = error term

θ_i = coefficient of decision maker's ith characteristic

α / β = value of time

γ / β = value of travel time reliability

γ / α =reliability ratio

The mode choice model provides the relative fractions of users of different modes. The main features of the problem addressed here entail the response of users not only to attributes of the travel time, but also to the prices or tolls encountered and the reliability of travel time. Accordingly, users are assumed to choose a mode that minimizes a generalized cost or disutility that includes three main attributes: travel time, monetary cost, and a measure of variability to capture reliability of travel.

The specific mode choice model here is designed to find the mode share between rail and auto, because the data was available for these two modes. As a result, the OD pairs that these two modes were the only option were selected. The TPB-BMC Household Travel Survey (HHTS) data, and INRIX travel time data are used for developing a mode choice model. The HHTS contained 108,111 trips between different origins and destinations, but for considering mode choice, only those OD pairs which had both auto and rail trips were considered. This consideration resulted in 159 OD pairs. The following steps were followed:

1) More than one path may exist between an OD pair. To calculate the reliability, it is assumed that users use the shortest path that connects the origin to the destination, The INRIX data for this path is gathered and processed, and the measure of reliability is calculated for this shortest path. More details of OD based reliability calculation is available in chapter 4.At this step shortest path between origin and destination is selected visually based on the different routes that Google Maps suggests.
2) Regional skim matrices are used for the travel time of both rail and auto alternative.
3) The HHTS and regional skim matrices were combined together. Reliability measure is also added to this combination for auto mode. Rail is assumed to be 100 percent reliable because it follows schedule.

Model specification is shown in Table 1. Biogeme software (Bierlaire, 2003) is used to build the mode choice model. Variable Veh describes if the traveler owns a vehicle on not. Age is traveler's age, and discretionary is a binary variable describing if a trip is for a discretionary purpose. In this model rail is the reference category. The model resulted in expected magnitude and sign of the variables. VoTR can be calculated:

$$VoTR = (-0.122)/ (-0.0013) = 93.85 cent/min = 56.31\$/h$$

However, since the coefficient of travel time is not significant, VoT cannot be calculated directly. Based on the Maryland Statewide Transportation Model (MSTM), the average value of time in Maryland is 14$/h. The RR can then be estimated using VOR divided by VOT:

$$RR = 56.31/14 = 4.02$$

The estimated RR is large than RRs in the previous literature which usually varies from 0.10~ 2.51 (Carrion and Levinson, 2012). This may be caused by several reasons. First of all, the mode choice model in this study only considers rail and driving, while other modes exist in reality, like bus, carpool, bike, etc. Secondly, TTR in this study is calculated by user experienced data in Washington DC area. Instead, most of previous studies used SP survey to collect reliability information. Use of SP and RP data often cause different estimations. Moreover, use of different time intervals will lead to different travel time variations. Since a 1 hour time interval is used in this study, the TTR measures estimated will be much lower than using smaller time intervals, thus leads to a higher estimation of reliability ratio. Finally, different reliability measures will lead to different RR estimations. Because of these reasons, RR value may vary a lot when using different reliability measures or different estimation methods. In the following parts of this study, RR value suggested by State Highway Administration is used. When more data is available, specific logit models for the study area can be estimated to get a localized RR estimation.

Table 1 Logit model estimation results for mode choice with reliability

Variable	**Coefficient**	**P-value**
Constant (Auto)	-1.660	0.00
Veh	0.757	0.00
Age	0.203	0.00
Discretionary	0.869	0.00
Travel Time	-0.007	0.12
Travel Cost	-0.001	0.00
Reliability	-0.122	0.01
Number of observations	521	
Log likelihood at convergence	125.51	
ρ^2	0.174	

Note: Rail is the reference category

RELIABILITY CHAPTER 4: ESTIMATING RELIABILITY

The first task would be to obtain travel time data for a region on selected origin-destination pairs. The travel time data could be of two types: (1) designed path travel times, (2) variation on travel times. The travel time variation should capture the actual travel times taken by the vehicles. A relationship between travel time and travel time reliability must be developed. This relationship is needed, as in regional planning models a typical day path travel time is reported and variation cannot be captured. Standard deviation is considered here as the reliability measure as it is suggested to be the robust estimate (Pu, 2011). While establishing reliability measure, it would be important to describe all origins and destinations and enumerate all the shortest paths to estimate ideal travel times. For capturing travel time variation, one year (or similar time frame) travel time data for the study region should be collected. An appropriate time period should be defined (say minute by minute travel times in AM or PM hour), and the times on pre-defined paths need to be estimated. A relationship (such as multiple regression or similar technique) between mean travel time and travel time variation can be established.

INRIX historical data on travel time is used for the regression. INRIX data is based on Traffic Management Channels (TMCs). Linking TMC with defined O-D pairs is a challenging task. In this study, 159 OD pairs that contained higher number of rail and auto trips were obtained for the mode choice estimation part. Same data is used to find the relationship between travel time and travel time reliability. The whole year 2012 travel time data is used. As stated earlier, INRIX gives travel time information for any TMC, but OD based reliability is needed in this study. To calculate OD-based reliability, it is assumed that travelers use the shortest path between each OD pairs. Afterward, all TMC segments along the shortest path were identified, and one year data was requested for them. Subsequently travel times were added for all TMC segments along the shortest path to find the path travel times. INRIX does not cover all the path, so methods were designed to calculate entire path travel times using available freeway and non-freeway data. This method assumes the missing freeway segments are being driven with the average speed of available freeway segments. The same assumption is made for non-freeway segments. The requested data is processed and standard deviation is calculated using between day variations of 157 days data, for each hour of the day. The result of this step is the measure of auto reliability for each OD pair, for each hour of day. Figure 3 summarizes the procedure used to obtain OD based reliability measures:

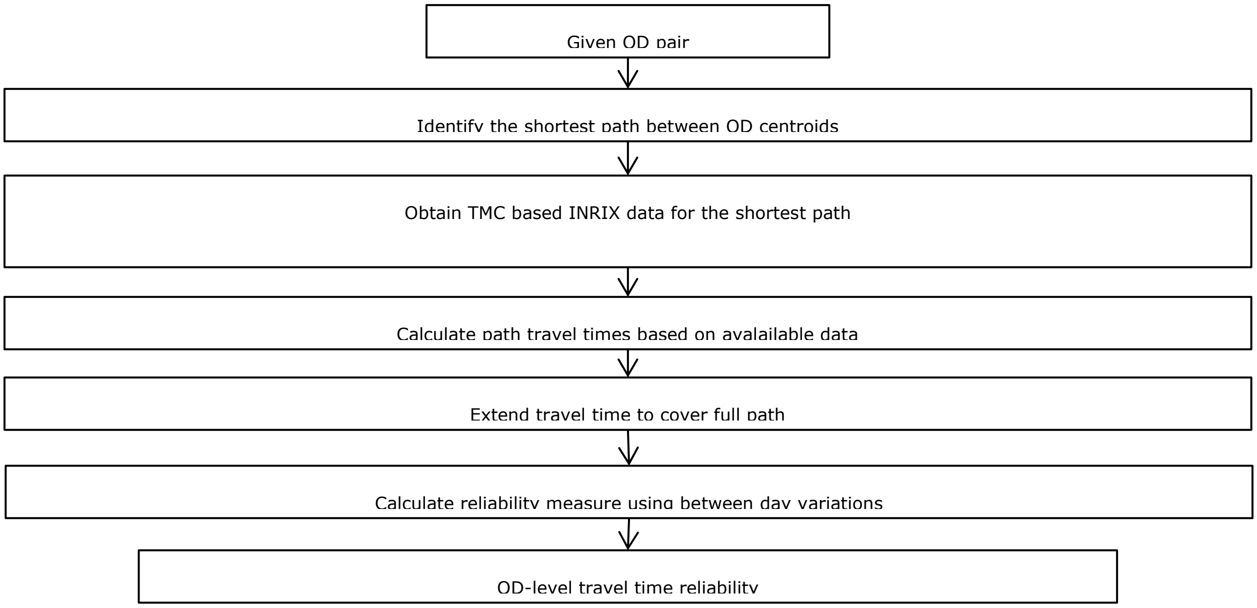

Figure 3 Procedure for obtaining OD-level reliability measures

Various types of regression using different reliability measures as dependent variable, different travel time and congestion measures as independent variable, and different forms of regression were tried. Finally standard deviation is regressed with percent deviation of congested travel time from free flow travel time. The result is shown in Figure 3. A number of outliers are removed from the regression estimation. The Logarithmic relationship is found to provide the best goodness of fit. The resulted r-square is 0.7675. This relationship will be used to find the change in reliability for any two given scenarios to calculate reliability savings.

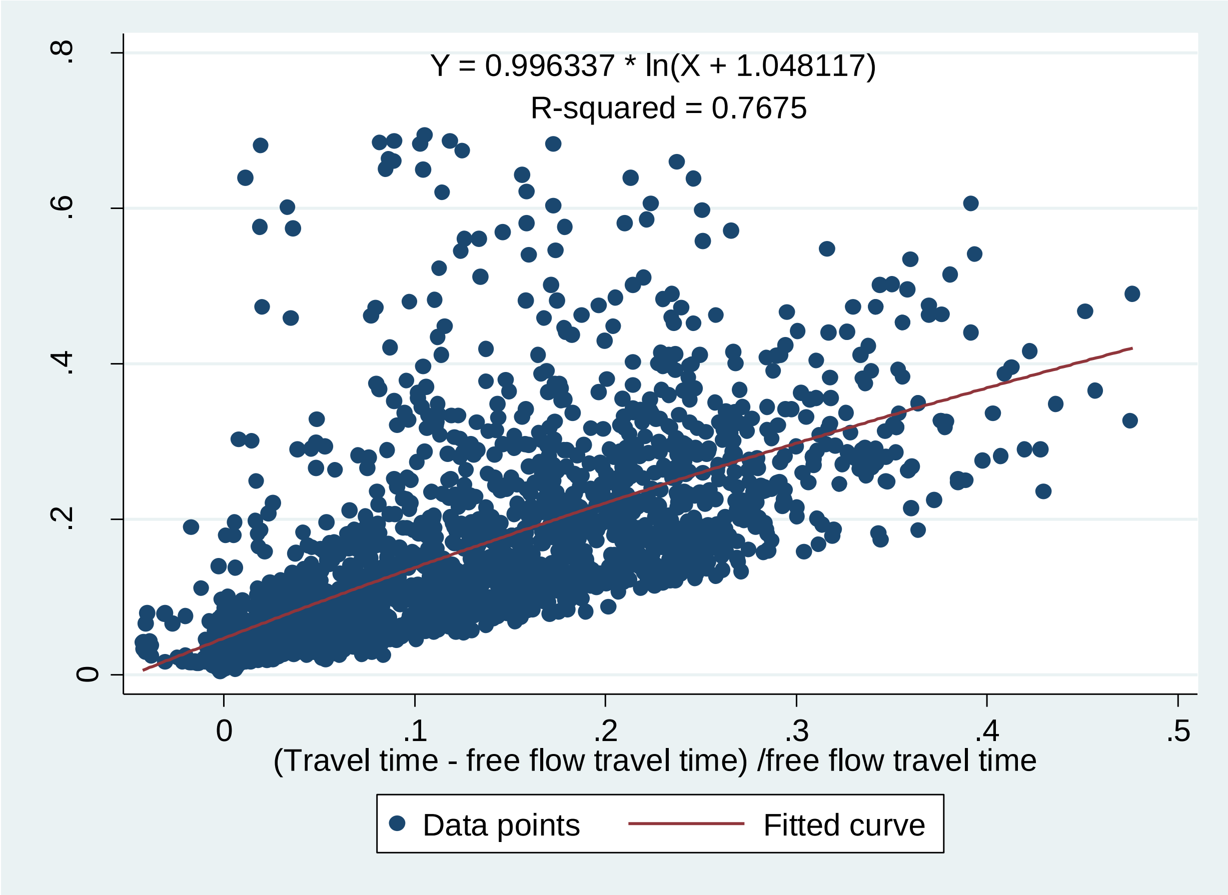

Figure 4 Regression of standard deviation per mile on a percent deviation from free flow time travel time

RELIABILITY CHAPTER 5: CASE STUDY

To estimate reliability savings because of recent network investment Inter County Connector (ICC) is considered as a part of the case study. For the base year, reliability saving is analyzed by considering scenarios with and without ICC. Figure 4 shows a detailed view of ICC along with other major facilities in the southern Maryland. ICC is one of the most significant and high-profile highway projects in Maryland since the completion of the existing Interstate freeway system several decades ago. The ICC connects existing and proposed development areas between the I-270/I-370 and I-95/US-1 corridors within central and eastern Montgomery County and northwestern Prince George's County (two most populous counties in Maryland). ICC is opened to traffic in the year 2011. One of the goals of the study will be to evaluate the reliability savings on other major facilities because of ICC.

To demonstrate the value of reliability savings, four scenarios are defined in MSTM: Base year build, base year no build, future year build, and future year no build. The base year build and no-build scenarios are different in ICC and minor other network improvements between 2007 and 2013. The future year build scenario consists of improvements as reported in the constrained long range plan. In the future year build scenario a number of improvements are considered such as the I-270 expansion, the I-695 expansion, the network of toll roads, the purple line and the red line. The future year no-build scenario includes the base year network with future year demand (socioeconomic and demographic). The base and future years are 2010 and 2030 respectively.

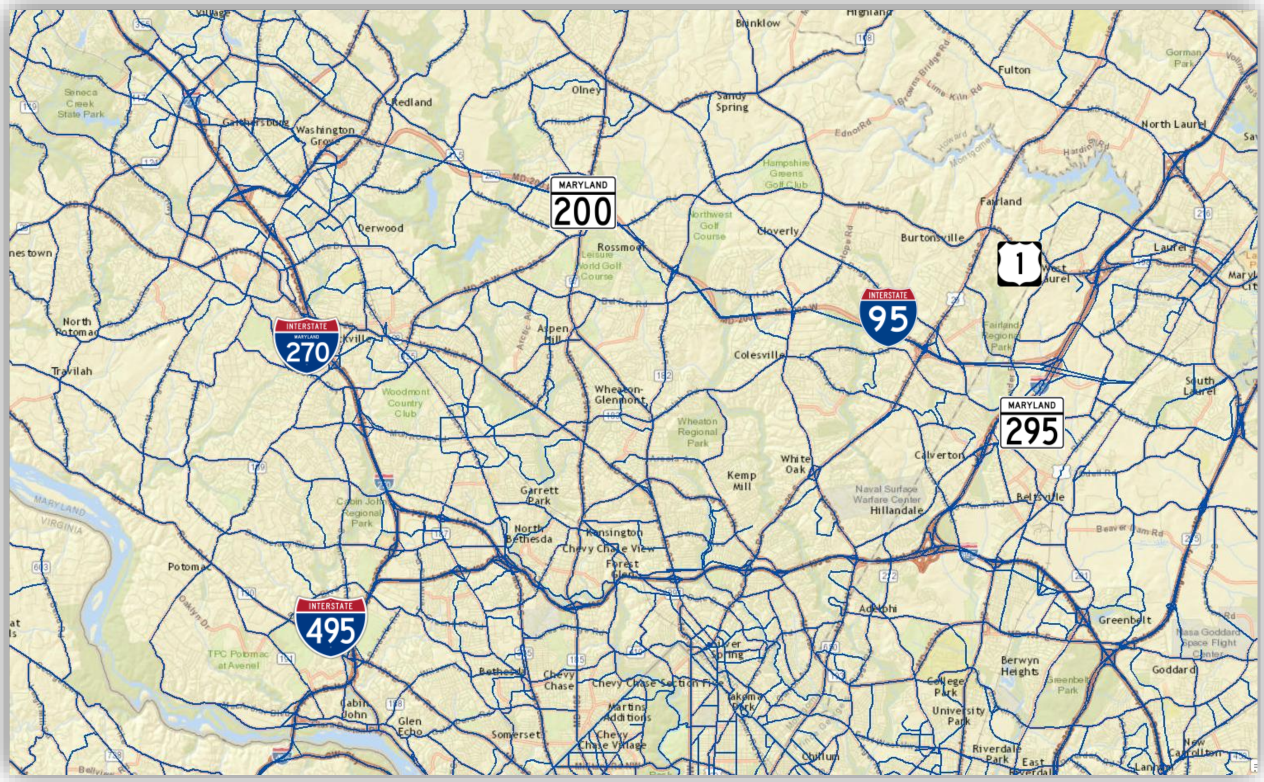

Figure 5 ICC and I-270

The first task was to prepare necessary input files to run MSTM. Input files for four scenarios were created. The four scenarios constructed are: Base year build, base year no build, future year build, and future year no build. The next task was to complete the model run and summarize the results. In model summary congested skim matrix needed to be developed to represent congested travel times for each O-D pair. Similarly, corresponding trip matrices needed to be obtained. Reliability matrices were obtained using the relationship described in chapter 4. Travel time savings and travel time reliability savings were computed for base year and future year using the reliability ratio equal to 0.75 as suggested by State Highway Administration. In chapter 3 it was explained in details how this value can be obtained using local data by a simple random utility model to obtain localized VoTR.

For comparison purposes, average travel times by OD pair and by time of day before and after system enhancement were captured. Then the system benefits were estimated resulting from improved travel reliability. The base year comparison shows benefits because of ICC, and the future year comparison shows benefits resulted from the projects included in constrained long range plan. The findings are summarized at varying geographic levels: statewide, county, zone and corridor. Both travel time savings and travel time reliability savings were computed at these geographic levels. Analysis is conducted for AM peak period only and by considering all the trips as medium income group. However, the results can be summarized for other peak periods and by considering five income classes in MSTM.

5-1 STATEWIDE FINDINGS

Statewide findings were estimated by taking travel time improvements for all O-D pairs when multiplied by corresponding trips. Findings suggest that both base and future year cases receive savings when compared to their no-build counterparts. Future year savings are higher than base year as expected. At statewide level travel time reliability savings are approximately ten percent of that of travel time for base year. Table 2 shows statewide travel time and travel time reliability savings for a typical AM peak hour. It is expected that the future year will have larger savings because greater number of new projects are introduced in the CLRP.

Table 2 Statewide peak hour savings for base and future year

Year	Total Savings	Travel Time Savings (Minutes)	Travel Time Savings ($)
Base Year	Travel Time	1,434,002	334,552
	Travel Time Reliability	144,255	33,774
Future Year	Travel Time	4,512,147	1,052,682
	Travel Time Reliability	454,639	106,214

5-2 COUNTY LEVEL FINDINGS

Travel time savings for the base and future years are shown in Figure 5, and travel time reliability savings are plotted at county level in Figure 6. County level savings are shown for a typical day in AM peak period. In the base year, Montgomery and Prince George's county received higher savings. These savings are because of ICC in the base year- build scenario. In the future year, Ann Arundel and Baltimore counties will receive higher savings as justified by constrained long range plan projects in these counties.

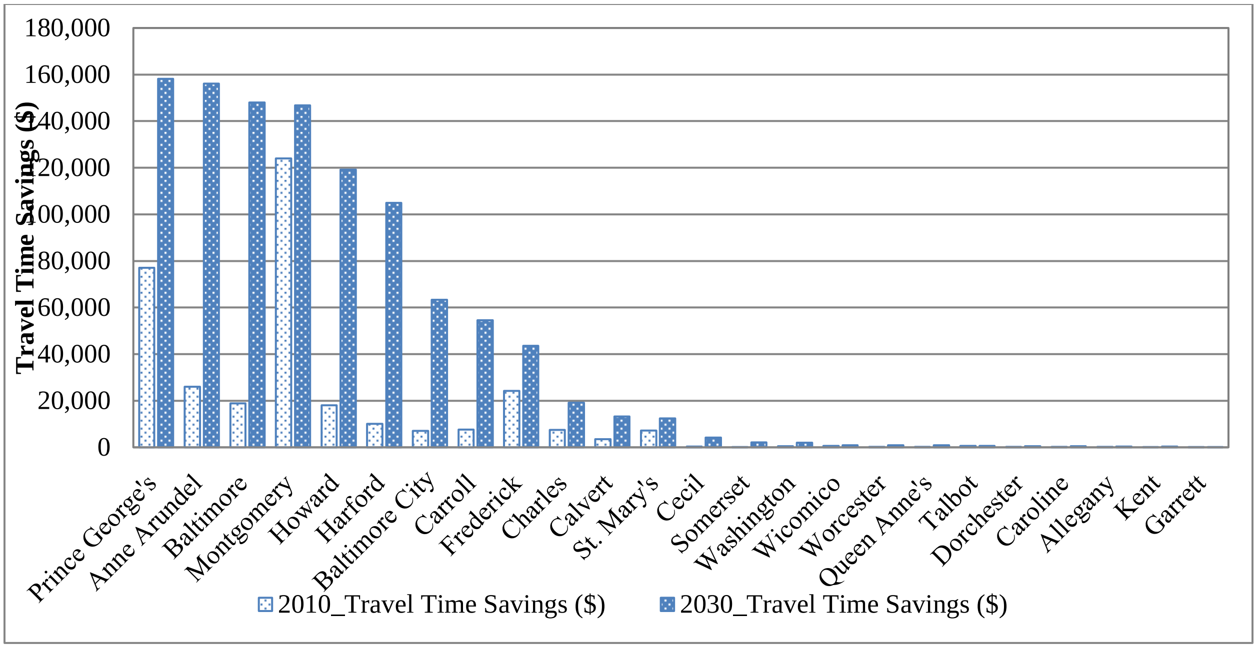

Figure 6 County level travel time savings comparing build and no-build scenarios

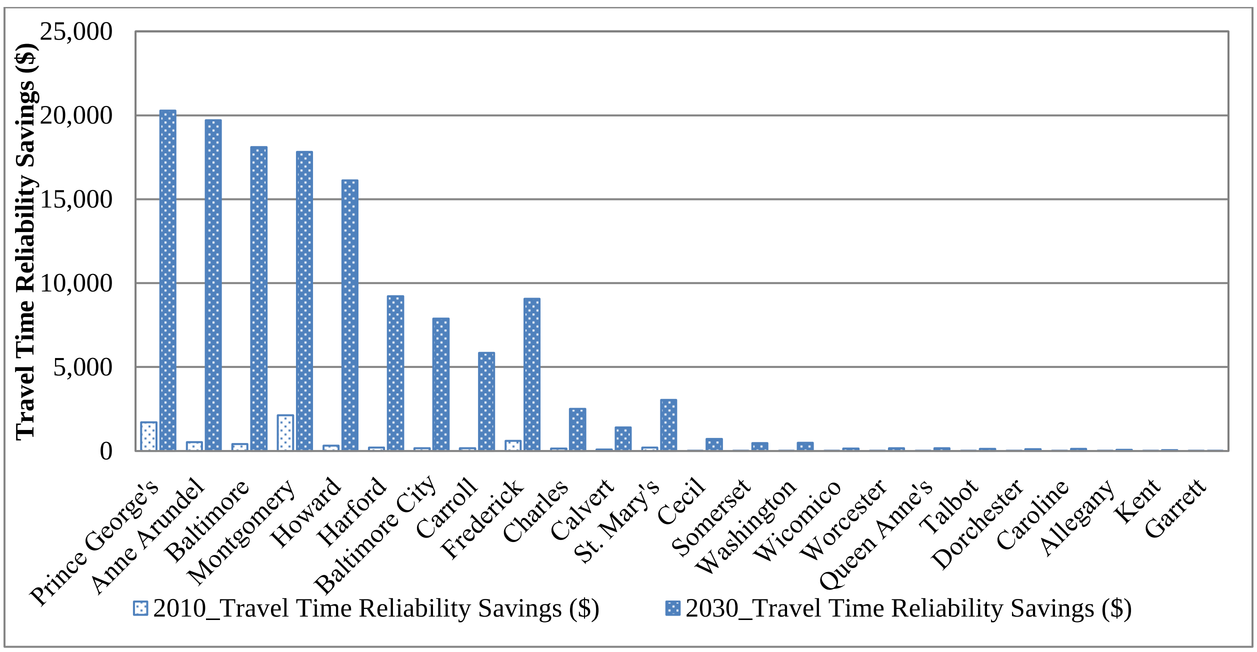

Figure 7 County level travel time reliability savings comparing build and no-build scenarios

5-3 TAZ LEVEL FINDINGS

TAZ level findings are shown in Figure 7 through 10. Base year findings suggest that zones cloze to ICC have higher travel time and travel time reliability savings. Future year findings suggest that the savings are spread over major urban and suburban areas. Figures 7 and 9 represent travel time savings in minutes for zones in three categories: less than one minute, between one to five minutes, and more than five minutes. Figures 8 and 10 represent travel time reliability savings in dollars for zones in three categories: less than \$0.25, between \$0.25 and \$1, and more than \$1.

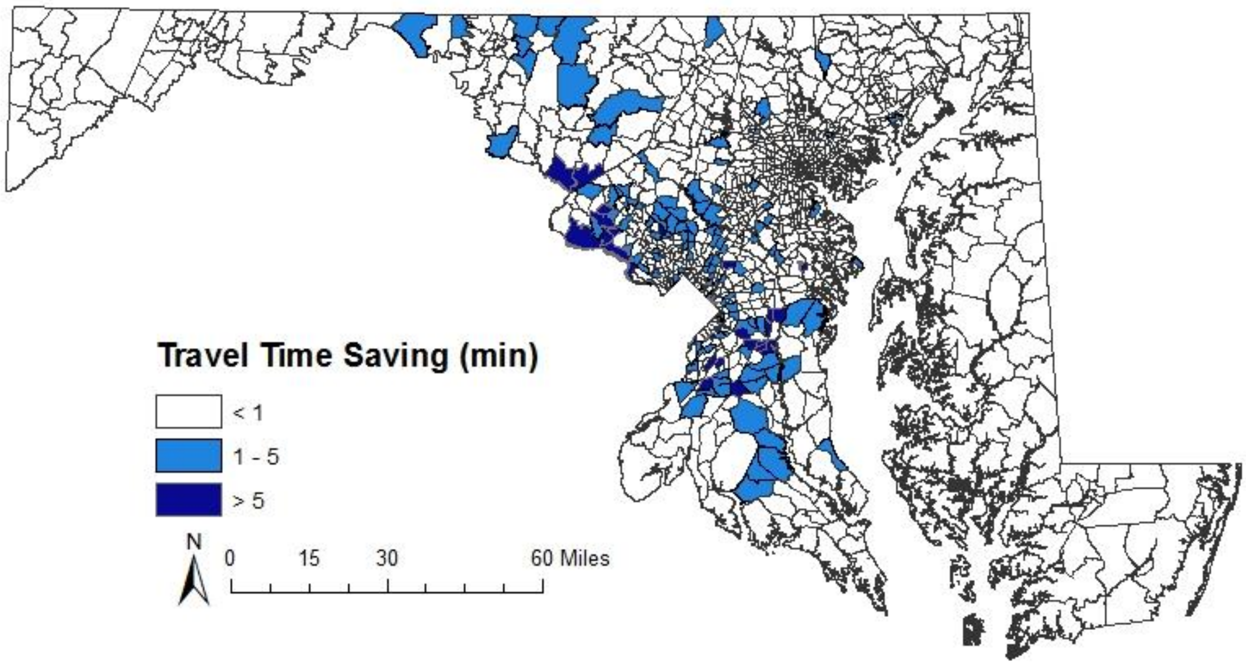

Figure 8 Travel time saving per trip comparing base year build with base year no-build

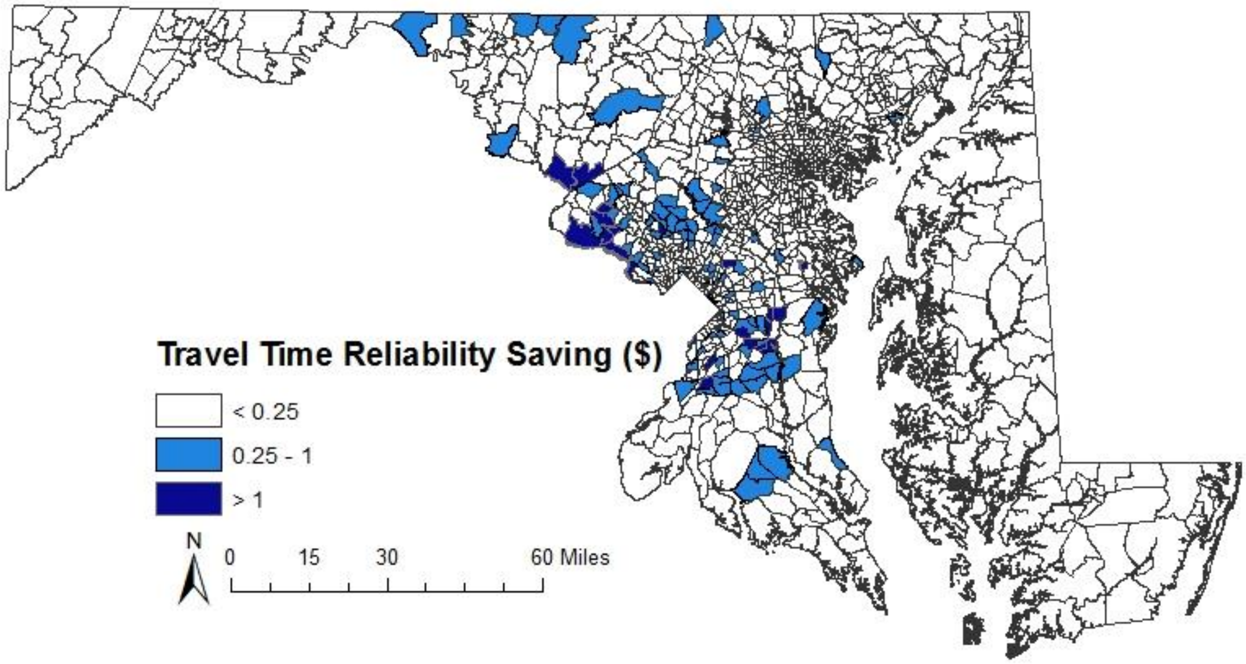

Figure 9 Travel time reliability savings per trip comparing base year build with base year no-build

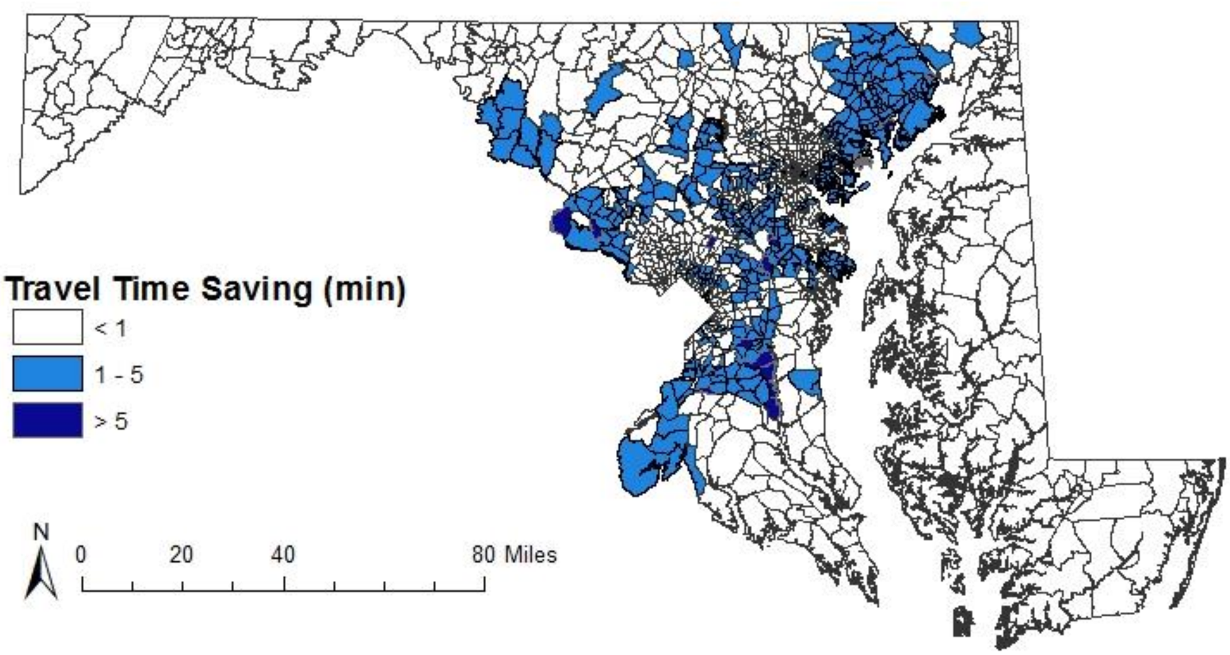

Figure 10 Travel time savings per trip comparing future year build with future year no-build

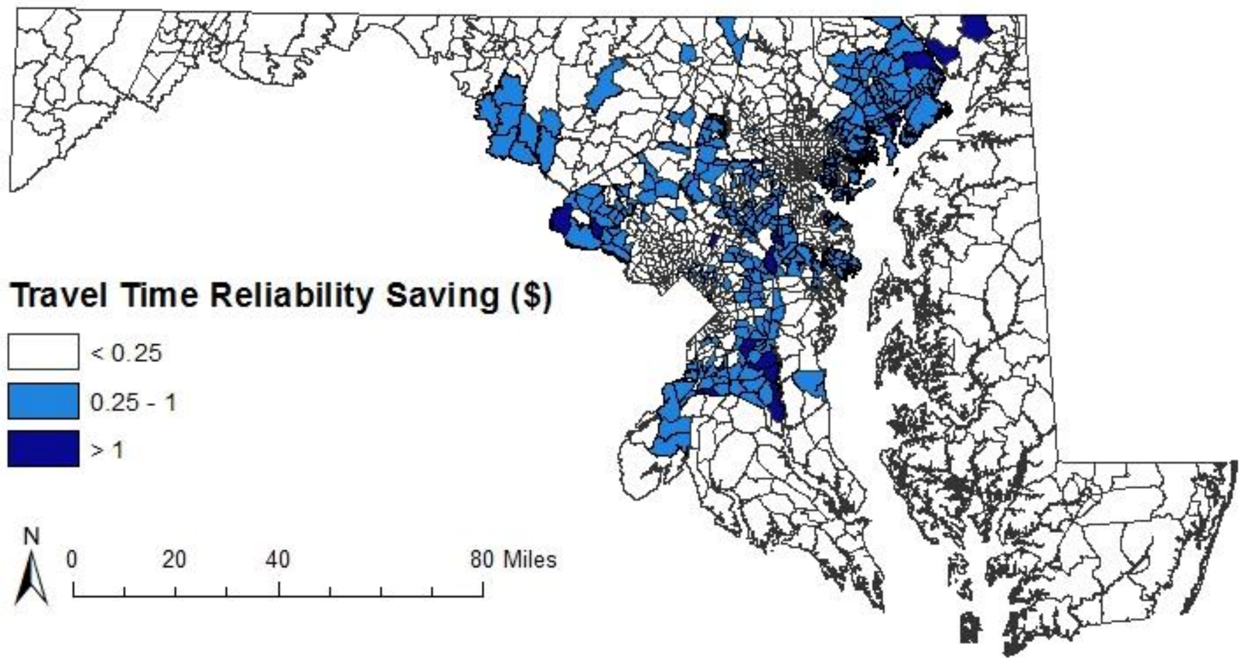

Figure 11 Travel time reliability savings per trip comparing future year build with future year no-build

5-4 CORRIDOR LEVEL FINDINGS

Travel time and travel time reliability savings are estimated for I-270 corridor using link level congested travel times for each scenario. Table 3 shows that for I-270 corridor travel time savings are achieved for both base and future case when compared with their respective no build scenarios. Similarly future year's reliability savings per traveler for other major interstates in the states are shown in Figure 11. Among all corridors interstate I-270 shows higher reliability savings. When reliability savings are computed for all the travelers using these corridors for all time periods of the day and for a planning period of 20 to 30 years such savings should not be neglected in the decision making process.

Table 3 I-270 travel time and travel time reliability savings results for different scenarios

Scenario	I-270 Travel Time (Min)		I-270 TT Savings (min/ Traveler)		I-270 TTR Savings ($ / Traveler)	
	NB	SB	NB	SB	NB	SB
Base-No Build	20.2	23.8	1.6	1.9	0.19	0.21
Base-Build	18.6	21.8				
Future-No Build	21.6	25.7	1.8	2.0	0.22	0.20
Future-Build	19.8	23.7				

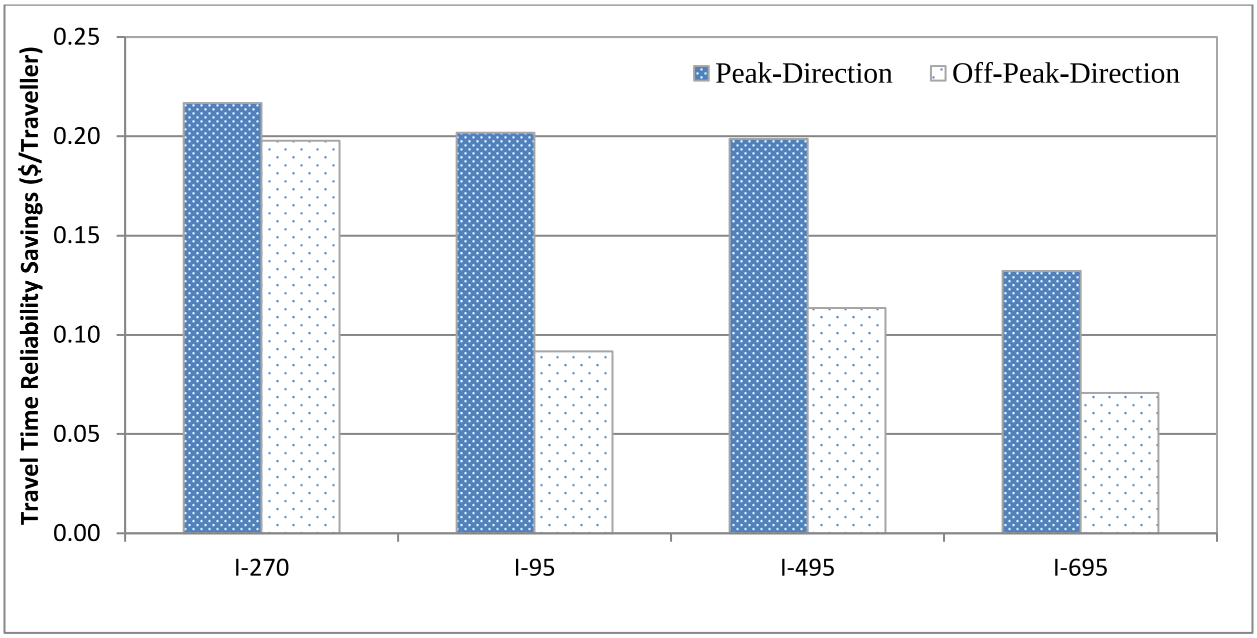

Figure 12 Travel time reliability savings for sample interstate corridors comparing future year build and future year no-build

RELIABILITY CHAPTER 6: SUMMARY AND CONCLUSION

Reliability is one of the major parameters that describe the performance of transportation network. When current condition of the network is being monitored, reliability should be among performance measures, because travelers value reliability, and consider it in their choices. In addition, when benefits and costs of proposed or current projects are being evaluated, reliability should not be neglected, since value of reliability savings can affect the results. In this study a framework was proposed to measure value, to forecast, and to incorporate reliability in the transportation planning process. Measuring reliability of trips between origin destination pairs was done using historical data. Some assumptions made it possible to convert link travel times into OD travel times, and standard deviation of travel time was calculated using between day variations of the data as a reliability measure. Afterward, this data was used to estimate a mode choice model between two competing alternatives with reliability as an independent variable. Estimated coefficient of reliability made it possible to find reliability ratio and value of travel time reliability (RR and VoTR). The reliability data was also combined with travel time data to probe the relationship between travel time and travel time reliability. A nonlinear regression was used to regress travel time reliability on travel time. This regression is useful to obtain reliability matrices when travel time matrices are available. These findings were combined with MSTM in four different scenarios to find the economic benefits of building ICC in the base year, and some more extensive network improvements in the future year. Value of reliability savings by these improvements was calculated and presented in four different levels; State, County, Zone, and corridor level.

The findings showed considerable amount of reliability saving that should not be neglected. State level findings showed that reliability savings were about 10 percent of travel time savings. It also showed that more comprehensive improvements in year 2030 will result in larger value of reliability savings. County level results showed that counties that benefit from network improvements also have higher reliability savings. Counties having the highest reliability savings showed to be different between base year and future year due to the geographical pattern of network improvements. Zone level results displayed that future savings are more spread out in the state. Corridor level findings demonstrated considerable value of reliability savings per traveler for some major corridors.

The results in different levels suggested that reliability should not be neglected in planning process because it can have significant effect on a vast geographical area. The framework used in this study can help any planning agency to incorporate reliability in their planning process by using available local data.

This work can be improved in many aspects for future. The mode choice model can be substituted with any other type of choice model based on utility maximization. Results from different choice models can be compared, to see how value of reliability differs in different choices. Besides, other reliability measures can be used instead of standard deviation to analyze how it affects the results. One hour intervals for reliability data can also be changed with smaller intervals to see the effect. The reliability forecasting part can be improved by adding weather or crash data to the regression. This study uses reliability value of reliability as a post processor of MSTM to calculate reliability savings. One major future work is to incorporate reliability inside MSTM by making some of the four steps sensitive to reliability. For instance, mode choice model of MSTM can consider reliability. This requires huge amount of reliability data for model estimation and calibration, but eventually it can improve the models significantly.

PEAK SPREADING CHAPTER 1: INTRODUCTION

Peak spreading is defined as expansion of peak period traffic from the traditional height of the peak outward to the shoulders of the peak. It happens when number of travelers and the level of congestion increase on a roadway. It affects average daily peak period traffic profile by making it wider and flatter. In definition, same amount of traffic spread over larger period of time, which results in lower peak, but in reality peak spreading is a result of growth in traffic, and lower peak would never be observed.

Two primary reasons mentioned in the literature for peak spreading phenomenon are, active and passive peak spreading. In active peak spreading travelers purposely retime their journey to avoid all or part of the peak period. They might do it by beginning their trips earlier to arrive at the same time, or might retime their trips completely. Active peak spreading has behavioral basis, and models that are not sensitive to travel behavior cannot capture it. Passive peak spreading occurs when journeys extend beyond the height of the peak as a result of increased delay due to the congestion, with no change in demand profile. As congestion increases, so do travel times; thus the peak period becomes more spread out because travelers are spending more time on the network. Passive peak spreading can be modeled through traffic assignment in any travel model.

Any transportation model should be able to capture peak spreading, because failure to do so may result in overestimation of traffic volumes in peak hour, and accordingly underestimation of traffic volumes in the shoulders of the peak. In addition, polices such as variable road pricing (and other pricing mechanisms) that stimulate effective use of the existing network and becoming increasingly popular are often aimed at changing temporal distribution of traffic. Therefore any model aiming to work with such policy measures should be able to produce temporal distribution of demand, and be sensitive to travel behavior changes. Understanding the factors effecting travels' departure time choice (to model peak spreading) is a necessary pre-requisite to examine the potential effectiveness of policy measures aimed at alleviating traffic congestion, reducing emission, and achieving other transportation system measures. Unfortunately, there is no step for time of day choice inside four step models with static traffic assignment. Many of the four step models lack temporal component, or suffer from weak temporal modeling.

Temporal component is usually modeled by one of the following methods (Barnes, 1998):

1. Post processing technique applying hourly factors
2. Link based or trip based adjustments which address the problem of projected demand exceeding capacity
3. Equilibrium scheduling theory
4. Discrete or continuous choice models
5. Rule based models

Hourly factors are the most basic approach to estimate volumes for hourly analysis. These factors can be varied by facility or area type. They can be applied after mode choice, which allows different peaking characteristics for different purposes. This method is widely used because of its simplicity, and is able to provide a rough estimate of peak hour traffic volume; however, it is only a static process, so it is not able to allow any type of temporal or geographical changes. Besides, it is not sensitive to policy changes, congestion level or capacity constraints. Maryland State wide Transportation Model (MSTM), like many other four-step models, currently uses this method (Costinett *et al.*, 2009) with four time periods; namely morning peak, midday, afternoon peak, and night.

Link based, or trip based methods are other ways of considering peak spreading. They use the capacity of the links, and do not allow the demand to exceed the capacity during the peak hour by shifting the demand to the shoulders of the peak. Link based methods mainly use a function of some congestion measures to calculate V/C ratio, and try to keep it below 1. An example can be seen in Arizona DOT model (Loudon *et al.*, 1988). This model assumes that while trips may shift outside the peak hour, they will occur in a 3 hour peak period, and formulates the relationship between the peak hour and peak period volumes as a function of peak period V/C ratio and facility type. Link based methods are more realistic than hourly factors, and they are sensitive to congestion; however they lack behavioral assumption. Continuity of flow is not guaranteed. Besides, they fail to consider spreading resulted from somewhere else in the network or shifts outside the peak period. Trips based methods are preferred to link based, since they can keep the continuity of flow. They revise trip tables in order to reduce trips on the links in which demand exceeds capacity. An example is Tri-valley model in California (Cambridge Systematics). In this model hourly factors are used at the beginning to calculate peak hour demand matrices, and then this demand is assigned to the network to calculate V/C ratio. For links where demand exceeds capacity, a mathematical approach is used to adjust trip tables to make V/C ratio equal to 1. Revised trip tables are assigned to the network again, and then V/C ratio is checked. The process is repeated till a close match between desired and obtained volume is met.

Equilibrium scheduling theory (EST) (Hyman, 1997) uses direct equilibration of simple models of demand and network. These models are based on Vickrey's bottleneck model (Vickrey, 1969) where homogeneous users traveling from one origin to one destination use one link. Vickery argues that a system of a simple utility function for demand and a simple queue function for network leads to an equilibrium such that no traveler can reduce their cost by changing departure time.

$$V(t) = \alpha\, C(t) + \beta\, Max(0, (PAT - t - C(t))) + \gamma\, Max(0, (t + C(t) - PAT))$$

$$L(t) = \int_{t1}^{t} q(w)dw - h * (t - t1)$$

In equilibrium scheduling theory Vickrey's model is extended in number of aspects like considering heterogeneous users. It can be generalized to transportation networks or even dynamic traffic assignment. One major issue with EST is modelling preferred arrival time. The positive aspect of EST is modeling in continuous time, and the biggest negative feature is being deterministic. It has the strong assumption that there is no unmeasured interpersonal variation. The other negative issue is that effect of socio-economics and demographics can only be seen in PAT estimation. One example of EST is HADES (Heterogeneous Arrival and Departure time based on Equilibrium Scheduling theory) discussed by van-Vuren (van Vuren *et al.*, 1999) . In this study PAT is modeled by regression on socio-economic and journey related variables. SATURN and CONTRAM are used as assignment models to implement EST. The conclusion of this study states that HADES is the final stage of EST development, and further research should be toward discrete choice models.

Discrete choice models are followed by Small (Small, 1982), are based on random utility theory. Such models categorize the time span into discrete intervals, and usually assume similar specification as Vickrey's utility with an added error term. Socio-economics or demographics effect can be easily included to the utility function. Many types of discrete choice models are introduced by researchers for variety of purposes. The primary difference of these models is their assumption about the error term. Some of the widely used models are multinomial logit, nested or cross nested logit, ordered generalized extreme values, multinomial probit, and mixed logit. Correlation among unobserved factors is one of the issues that different types of models try to solve by assuming specific structure for the error term. Except multinomial logit, all mentioned discrete choice models consider error correlation to some extent. Both observed and unobserved heterogeneity can be considered in discrete choice models by adding person-specific terms to deterministic or probabilistic part of the utility function.

Many types of discrete choice models can be categorized under a class of random utility models known as Generalized Extreme Value (GEV) models introduced by Mcfadden (McFadden, 1978) For instance multinomial logit (MNL)is simple type of GEV models that assumes error terms are iid gumble, which results in no correlation between error terms. An example can be seen in (Zeid *et al.*, 2006). Zeid et. al. (2006) followed FHWA research project which designed a procedure to be applied within activity or tour-based models, and they used household travel survey data from San Francisco bay area to estimate and test a MNL model for time of day with 36 alternatives. Capturing scheduling delays by using continuous time functions and predicting travel times based on regression using travel times in the survey are among some interesting ideas they used in their work. Nested logit is another type of GEV models, which is usually used when two choices are being modeled together. Nests may represent different choice dimensions, or they may also refer to different categories on just one choice. Error terms of alternatives in the same nest have correlation among each other, while alternatives in different nests have independent error terms. Another GEV model similar to nested logit is Ordered Generalized Extreme Value model introduced by (Small, 1987) which is used with ordered alternatives. Nests have overlap that provides more flexibility to the correlation pattern. Covariance between any two alternatives receives a contribution from each subset they share together. Correlation in OGEV model depends on distant, while correlation between distant alternatives is sometimes needed. One example of OGEV is in (Bhat, 1998b) where he estimated joint choice of mode and departure time in a nested structure with mode choice at the higher level of hierarchy, using MNL for mode choice and OGEV for time of day choice. The model is used to estimate shopping trips, and is applied to data from 1990 San Francisco travel survey. Results show that the model performs better than MNL and NL models.

Another widely used type of discrete choice models is multinomial probit, which assumes normal distribution for error terms. It is able to compute complete variance covariance matrix and correlation between each two alternatives, but at the expense of evaluating very high dimensional multivariate normal integral for the choice probabilities. Another impediment is having large number of parameters to estimate. Methodological developments suggest approximating these high-dimensional integrals with smooth, unbiased and efficient simulators. MNP has been used to some extent in the literature, like work by Liu and Mahmassani (Liu and Mahmassani, 1998), by exposing constraints on covariance matrix, but it still needs powerful computers.

The last aforementioned type of discrete choice models is mixed logit, which has been known since (Cardell and Dunbar, 1980) (Bolduc and Ben-Akiva, 1991) as highly flexible yet practical model type. It is not less general than MNP, and it is able to estimate complete variance covariance matrix. In the literature, mixed logit models are in two forms, error components (ECL) and random coefficient (RCL). According to (McFadden and Train, 2000) ECL can approximate as closely as one pleases, any type of discrete choice model based on random utility maximization. In mixed logit models, the choice probabilities of alternatives conditional on error components or random coefficients take the familiar multinomial logit form. The unconditional probabilities are obtained by integrating the MNL form over the distribution of random parameters. In terms of estimation, the log-likelihood function cannot be evaluated analytically, because it does not have a closed form solution, simulation techniques are used to approximate the choice probabilities in the log-likelihood function. One example of mixed logit is (Bhat, 1998a) that uses error component mixed multinomial logit for the analysis of travel mode and departure time choice for home based social-recreational trips using data from 1990 San Francisco bay area. Another example is an error component logit model for the joint choice of mode and time of day, using stated preference data in Netherland for LMS tour based model by (De Jong *et al.*, 2003). General form of error component considered is $\sum_s \sum_t \boldsymbol{\eta}_s \boldsymbol{w}_{st} \mathcal{E}_t + \boldsymbol{\varepsilon}$ where $\mathcal{E}_t$ is the error component vector distributed $\boldsymbol{f}\,(\mathbf{0}, \mathbf{1})$, $\boldsymbol{\eta}_s$ is vector of parameters to be estimated, and $\boldsymbol{w}_{st}$ is a general weighting matrix based on data or fixed by the analyst. They tested different component, proportional to shift in departure time, change in cost, change in travel time, and component for mode shift, and estimated different models for different tours and trip purposes. One RCL mixed logit model example is (Börjesson, 2008) that estimated a mixed logit model by random coefficient, using both RP and SP data for Stockholm area morning peak hour. Mode choice is jointly considered by modeling the propensity of shift from driving. Reliability is also considered in the utility function. In the SP data, reliability is presented by intervals, whereas it is obtained from traffic cameras in RP data. Travel times are simulated with CONTRAM.

Some of the more recent works treat time as a continuous variable. (Bhat and Steed, 2002) states the following disadvantages for discrete modeling of time: (1) setting interval boundaries is arbitrary, and different boundary assumption can change the model. (2) Points close to each other but in different intervals are perceived similar by the traveler, but the model considers them in different intervals. (3) Loss of temporal resolution. Usual approach in treating departure time as a continuous variable involves hazard functions like works by (Wang, 1996) (Bhat and Steed, 2002). The primary limitation of hazard models is that they are not based on random utility theory. (Lemp and Kockelman, 2010) uses continuous logit model that is based on random utility theory. They estimated their model with Bayesian estimation technique on work tour data from 2000 San Francisco bay area travel survey. Modeling time as a continuous variable requires having travel time and travel time variation as continuous functions of time during the day, which is done through OLS regression.

Most of the aforementioned choice models are based on rational behavior, assuming travelers are able to identify all their feasible alternatives, measure all their attributes, and choose accordingly to maximize their utility. Rule based models avoid this assumption of rationality, and try to model how travelers actually make decisions through learning, knowledge, searching, etc. One good example is the positive model (Zhang, 2007) of departure time choice by (Xiong and Zhang, 2013) that uses search cost and search gain concepts to model Bayesian learning of travelers, and tries to find some rules by which travelers actually choose their departure time.

In this study discrete choice models are selected as the best initial approach. Modeling continuous choice is a possible direction for the future studies. In the next chapter, the methodology is discussed in details. Chapter 3 explains how MSTM is used to obtain hourly skims as one of alternative attributes. Chapter 4 discusses how preferred arrival time is estimated using skim matrices, and chapter 5 presents departure time choice model estimation results separated by trip purpose. In chapter 6, estimated models are used to predict the demand distribution of the base and future year to show how peak spreading occurs. The peak spreading part finishes with summary and concluding remarks.

PEAK SPREADING CHAPTER 2: METHODOLOGY

Peak spreading is the result of travelers' departure time choice, when they try to choose a different time interval for their trips, considering conditions of network such as congestion and reliability in additions to scheduling preference. The need of a departure time choice model to model peak spreading appears pragmatic to assess realistically model traveler's preferences. Peak spreading can be observed by comparing distribution of travel demand for any two scenarios. This study compares travel demand distribution for base year (2007) and future year (2030) in the study area; Montgomery County, Maryland. Travel demand distributions are obtained by an estimated departure time choice model. Further, the model is validated to illustrate consistency and reasonableness. The departure time choice model predicts choice of travelers among the following 12 alternatives (proposed for this study):

1- 5 a.m. to 6 a.m.
2- 6 a.m. to 7 a.m.
3- 7 a.m. to 8 a.m.
4- 8 a.m. to 9 a.m.
5- 9 a.m. to 10 a.m.
6- Mid-day 10 a.m. to 3 p.m.
7- 3 p.m. to 4 p.m.
8- 4 p.m. to 5 p.m.
9- 5 p.m. to 6 p.m.
10- 6 p.m. to 7 p.m.
11- 7 p.m. to 8 p.m.
12- Night 8 p.m. to 5 a.m.

These alternatives are selected based on observed departure time choice of travelers in the study area. Most of the travels are made during morning peak (5 a.m. to 10 a.m.) which is divided to 5 one hour periods and afternoon peak (3 p.m. to 8 p.m.) which is again divided to 5 one hour periods. The rest of the day is separated into mid-day and night periods.

One of the principal characteristics of a trip is its purpose. Trips with different purposes may be different in terms of being discretionary or non-discretionary, having fixed or flexible schedule etc. Accordingly this study uses separate models for different trip purposes. These six purposes utilized in this study are as follows:

1- Home-based to work
2- Home-based to shopping
3- Home-based to school
4- Home-based to other
5- Non- home-based to work
6- Non-home-based to other

The data used in the model estimation and the steps of the framework are explained in the following sections.

2.1 DATA

The datasets used in this study contains household travel survey which forms the basis of the analyzing underlying behavior of various trips. Planning model skim matrices is combined with this dataset in order to form the attributes of alternatives. When the estimated model is used for forecasting, trip matrices from the planning model are used as a basis for number of trips between each origin and destination. These datasets are described here:

2.1.1 2007-2008 TPB-BMC Household Travel Survey

The Transportation Planning Board (TPB) from February 2007 to April 2008 conducted this survey in order to gather information about demographics, socioeconomic and trip making characteristics of residents in Washington and Baltimore metropolitan areas. 14,000 households (about 31,000 persons) participated in this survey, and the data is geocoded at the Traffic Analysis Zone (TAZ) level. The data contains four major components: household data, person data, vehicle data and trip data. This dataset is used to obtain information about trip origin, trip destination, trip purpose, trip distance and travelers' departure time choice. This dataset contains 15956 trips related to Montgomery County.

2.1.2 MSTM skim matrices

Maryland Statewide Transportation Model is developed by Maryland State Highway Administration (MSHA) to consistently, and reliably assess the effects of future developments on key measures of transportation performance. It can also be used as an evaluation tool to address effects of investments on development patterns. This model is a 4 step transportation model that includes, trip generation, trip distribution, mode choice and assignment. MSTM includes base year model (2007) and future year model (2030). Both demand and network parameters are different for these two scenarios.

Among principal output of MSTM are skim matrices. Skim values describe the general cost of travel between OD pairs, which may include travel time, travel cost, tolls and etc. Each origin or destination is a SMZ (Statewide Model Zone), and MSTM has 1607 SMZs which include all Maryland and some selected counties in adjacent states. In departure time choice model estimation of this work, it is assumed that skim values are among the utility parameters that formulate travelers' choice; therefore these skim values are combined with HHTS trip data to complement required trip information for model estimation. In addition, when estimated models are used for daily travel demand distribution prediction, trips are generated by their corresponding OD skims.

One main challenge of using MSTM skim values for this project is that MSTM currently has only 4 time periods; namely, morning peak, afternoon peak, midday and night. The current method to divide trips in these time periods is constant hourly factors. In order to model departure time choice among 12 previously described alternatives, having skim values for each of the alternatives is required. Chapter 3 describes the method used to obtain skim values corresponding to alternatives.

2.1.3 MSTM trip tables

Trip matrices are among other main outputs of MSTM. Trip matrices contain information about number of trips between OD pairs. When departure time choice model is used for prediction, trips are generated between OD pairs based on trip matrices. MSTM trip matrices are divided by trip purpose. These trip purposes are the same as described earlier for the model estimation.

2.2 FRAMEWORK

The framework for obtaining travel demand distribution for any given scenario contains two key parts. The first part is model estimation based on the base year data. The estimated model will be used afterward in the second part which is model prediction. Model prediction forecasts travel demand distribution of the given scenario.

2.2.1 Model estimation framework

Departure time choice model is estimated using the available trip data in the Household travel survey. This dataset contains information about the departure time choice of the traveler, and lacks the generalized cost information of the other alternatives the traveler could choose. MSTM skim matrices are used as a source for information about the other alternatives. The way MSTM's hourly skim matrices obtained will be explained in chapter 3. The estimation process cis summarized in Figure 12.

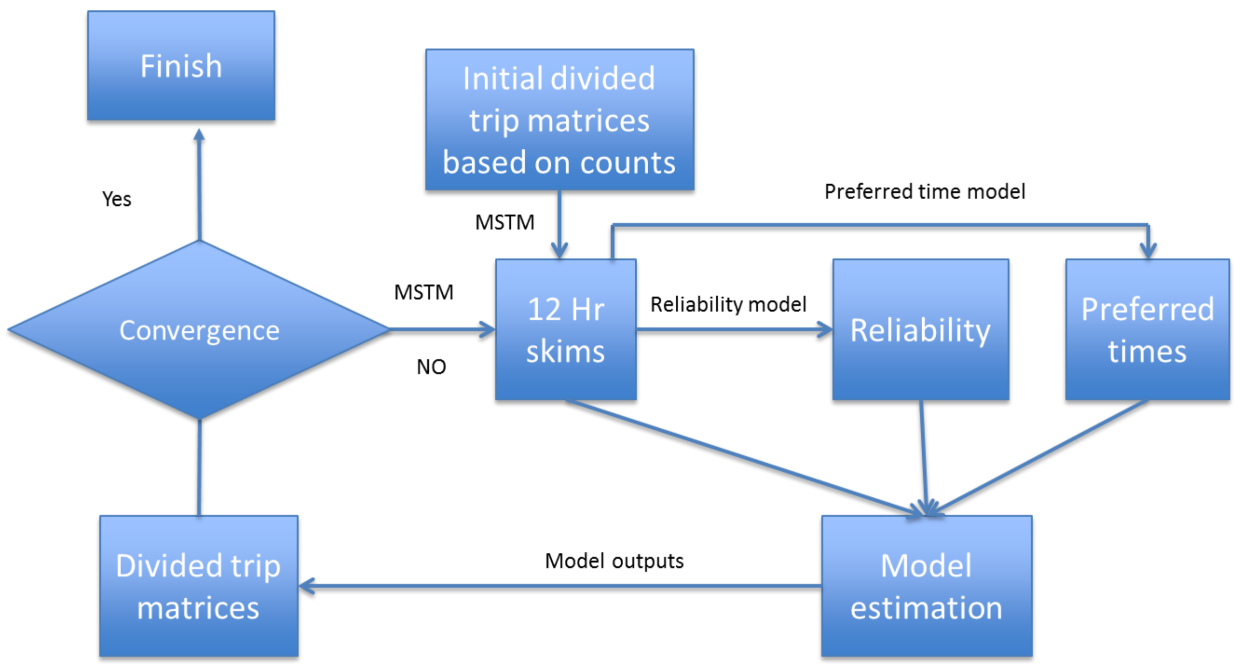

Figure 13 Departure time choice estimation framework

The process starts by dividing MSTM's four standard trip matrices into 12 trip matrices. These initial trip matrices are used in the first iteration, and they will be updated in each iteration. Twelve matrices represent the twelve alternatives previously described for this project. By doing so, MSTM can provides alternative specific skim matrices. This process will be explained in greater detail in chapter 3. In chapter 4 of the reliability part, regression of reliability based on the travel time is explained. Using the same method, reliability data can be derived from the skim matrices for each alternative. Another important data for model estimation is information about travelers' preferred arrival time. This data is not available in the household travel survey, and it is required to calculate scheduling terms of the departure time choice model. Chapter 4 describes how skim matrices are used to estimate preferred arrival time information. Afterward, generalized cost information, reliability information, and preferred time information are combined with household travel survey data to form the complete dataset required for model estimation.

The departure time choice model is a discrete choice and follows random utility theory. The form of the utility function is similar to the standard form introduced by (Small, 1982).

$$U_i = ASC_i + \beta_{skim} * skim_i + \beta_{late} * La_i + \beta_{early} * E_i + \beta_{dist-skim} * dist * skim_i + \beta_{reliability} * R_i$$

U_i: Utility of alternative i

ASC_i: alternative specific constant of alternative i

$Skim_i$: generalized cost of travel for alternative i

La_i: lateness penalty for alternative i

E_i: earliness penalty for alternative i

$Dist_i$: distance between origin and destination

R_i: travel time reliability of alternative i

β_{skim}: coefficient of the generalized cost

β_{late}: coefficient of the lateness penalty

β_{early}: coefficient of the earliness penalty

$\beta_{dist-skim}$: coefficient of the combination of distance and skim

$\beta_{reliability}$: coefficient of the reliability

The form described is the general form of the utility function that is tried for different trip purposes. Specific terms may show insignificant effect and be removed from some models. Scheduling disutility is usually modeled by shifts from the most preferred time; either preferred departure or preferred arrival time. Lateness penalty and earliness penalty in the model capture this disutility. They are formulated as below:

$$E_i = Max[\,preferred\ arrival\ time_i - arrival\ time_i, 0\,]$$

$$La_i = Max[arrival\ time_i - preferred\ arival\ time_i, o]$$

Different types of discrete choice models like Multinomial Logit, Nested Logit, and Mixed logit are estimated for each trip purpose and the best model is chosen. The main difference between these types of models is their assumption on random error term, which describes the correlation between alternatives.

The result of the model estimation is based on the initially divided trip tables. The model itself can be used to simulate the trips and distribute them between alternatives. This gives better estimation of the departure time choice of the travelers; thus the trips are divided based on the estimated model to get the new divided trip tables. New divided trip tables are used as the input of MSTM and another round of the loop is executed again. This process continues until the divided trip tables resulting from estimated model matches the previous step's divided trips by some convergence criteria. When convergence reached, the final model can describe the behavior of travelers, and it should be used to predict travelers' behavior in the future scenarios. In this project, only one iteration of the loop is performed, and continuing the same steps in additional iterations may lead to better results. More iterations can be conducted in the future to improve the model estimation part.

2.2.2 Model prediction framework

After estimating the departure time choice model using the local data, the model is used to predict the distribution of travel demand. In this study, departure time choice model is used to compare base year 2007 demand with future year 2030 demand. Each scenario is defined with its total demand and network inside MSTM. This project uses total trip tables and divides them into 12 separate trip matrices for 12 intervals. The prediction process is summarized in Figure 13.

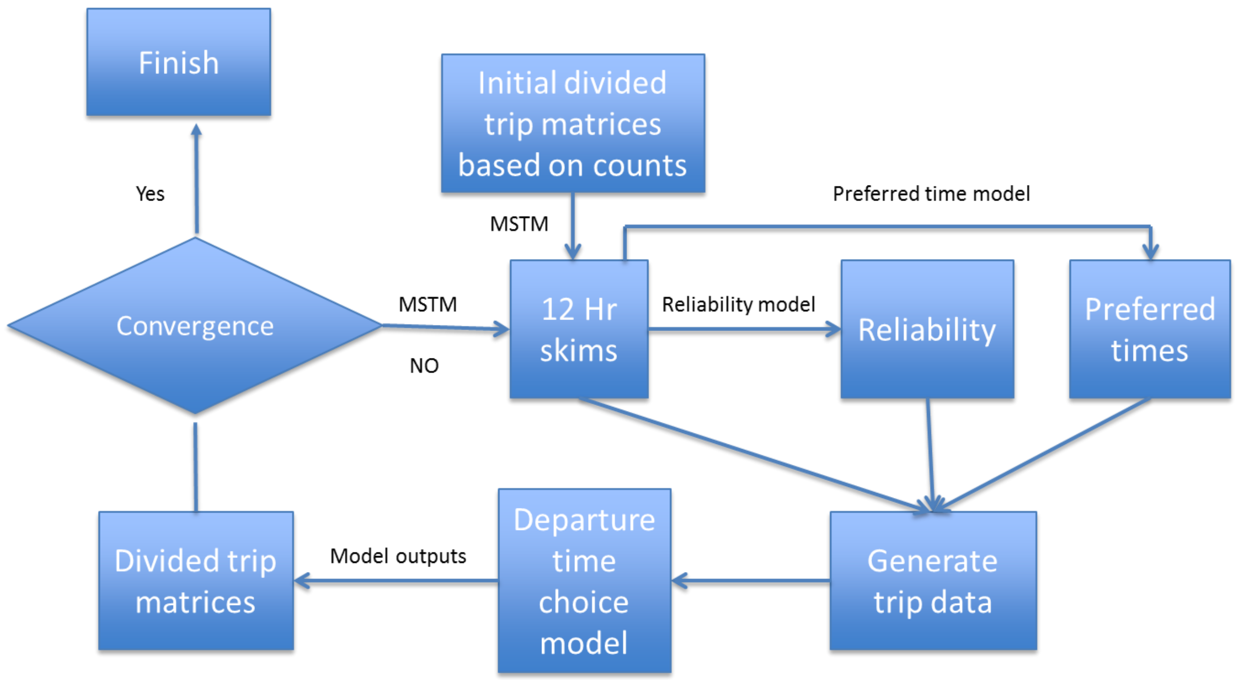

Figure 14 Framework to forecast demand distribution for any given scenario using estimated departure time choice model

In order to predict the demand distribution of any given scenario, an initial trip tables and skim matrices are needed. Chapter 3 describes how traffic counts data is utilized to obtain initial trip tables and skim matrices for 12 intervals. Trip data should be generated for the scenario based on the trip tables and skim matrices. Trip tables include number of trips between origins and destinations, and skim matrices complement this data by adding generalized cost data for each interval. In this project's modeling framework, each trip has a preferred arrival time, which should be generated. This is done by generating a random number from preferred arrival time distribution of each trip purpose.

It is assumed that the distribution of preferred arrival times stays the same for any scenario. This distribution is obtained from the model estimation data which preferred arrival time for each trip was previously estimated. The estimation of preferred arrival time is explained in detail in chapter 3. It is assumed that the same distribution applies to any other scenario, and preferred arrival time of trips are generated by generating random numbers from this distribution. This distribution varies by trip purpose. The same reliability model explained earlier is used again to obtain reliability of alternatives for all trips. Origin and destination of the trips from trip tables, generalized cost of alternatives from skim matrices, scheduling disutility from generated preferred arrival time, and reliability data are all combined together to form the dataset used for calculating probability of choosing each alternative. This dataset is inputted into the previously estimated departure time choice model, and the choices are simulated. The result of this simulation is the demand distribution and divided trip tables.

Divided trip tables are compared with the initial trip tables to check if they match by some convergence criteria. If the convergence criterion is not met, another iteration of the loop is run again until the input and output of the iteration match. Similar to the estimation, only one iteration of the loop is done at this step. Further iterations will be run in the future to improve the final distribution of the demand.

PEAK SPREADING CHAPTER 3: HOURLY SKIMS

The Figure 14 describes the step-by-step procedure of the data preparation for the peak spreading model development:

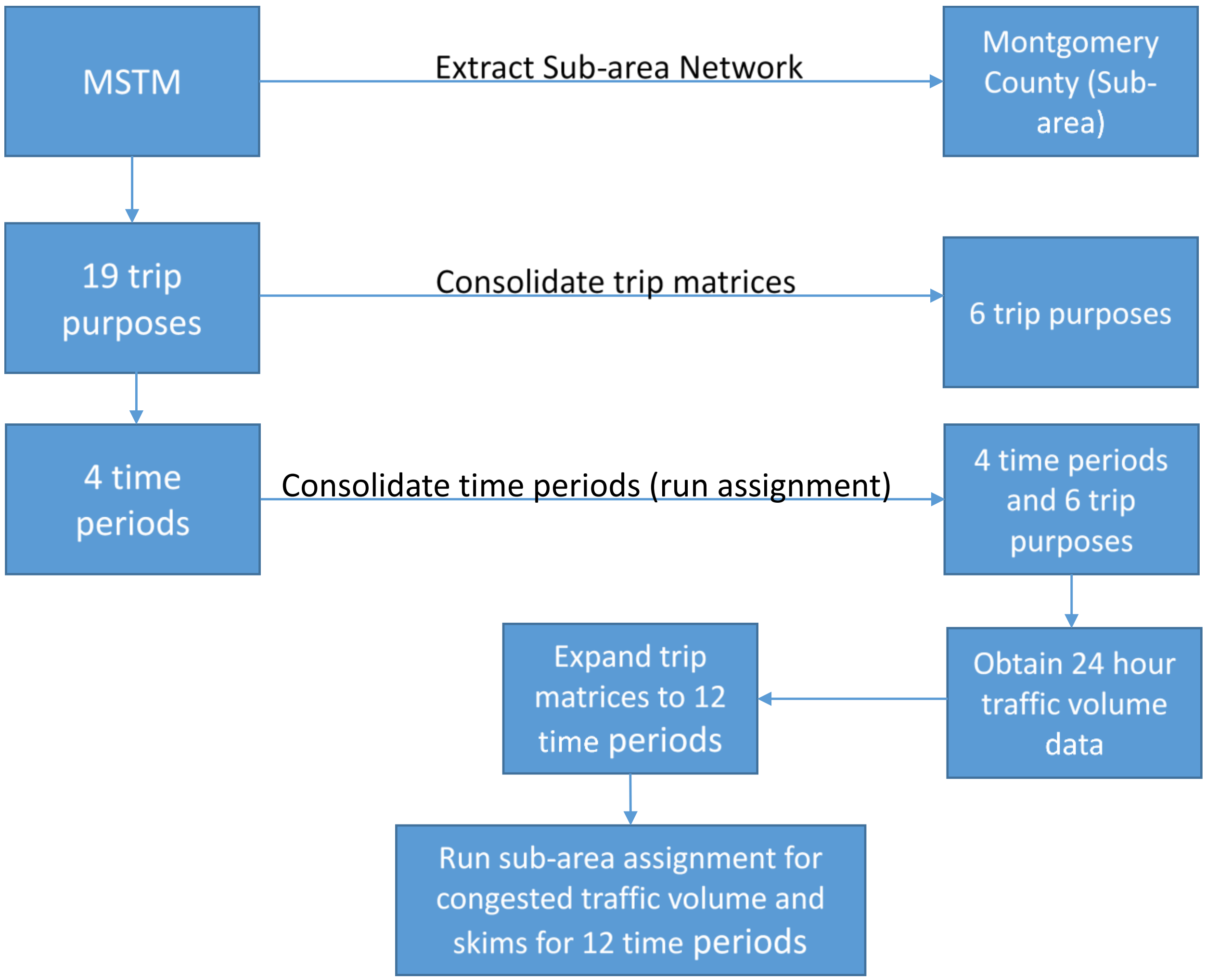

Figure 15 Step by step procedure to obtain trip tables and skim matrices for 12 alternatives

The first step in the data preparation is the extraction of sub-area network of Montgomery County from the Maryland Statewide Transportation Model (MSTM). MSTM is designed as a multi-layer model working at both statewide and regional levels. The model contains 1,739 traffic analysis zones, including 1,607 state model zones (SMZ) and 132 regional model zones (RMZ) (Ye X., 2009). MSTM executes the traditional four step travel demand model in the network: cross-classified model for trip generation, gravity model for trip distribution, nested-logit model for mode choice and time of day allocation model for traffic assignment. In this model, Frank Wolfe algorithm is employed for multi-class user equilibrium assignment. The algorithm repeatedly executes three major steps: shortest path generation, AON assignment and volume adjustment until the convergence criteria is satisfied.

The extraction of the sub-area of the Montgomery County was performed with the help of “Drawing Layer” tools in CUBE software using the shape-file of Montgomery County network and the MSTM. The shape-file was used as a layer on the full MSTM network and then the portion of the network consisting of Montgomery County was extracted and then saved. Once completed, the newly created sub area network could be opened in CUBE which confirmed that the extraction was successful. Figure 2 shows the extracted sub-area network of Montgomery County.

The second step was to extract the trip matrices from MSTM using the Montgomery County sub-area network over four daily time periods (i.e. AM peak, PM peak, Midday and Night). The trip matrices were extracted for 19 trip purposes which was later consolidated to 6 trip purposes over the 4 daily time periods, AM peak (5:00 am – 10:00 am), Midday (10:00 am – 3:00 pm), PM peak (3:00 pm – 8:00 pm) and Night (8:00 pm – 5:00 am). The trip matrices were extracted for the base scenario by running highway assignment using the extracted sub-area network as input. This script (Script I in Appendix) is needed to run overnight for the completion. The outputs of this process are the 6 trip matrices for each of the 4 time-periods. In this script, the following function is formulated to calculate the generalized link cost for all user classes:

$$cost = t + (toll/vot) + \pi \times distance$$

Where

t: link travel time (minutes), which is a function with respect to traffic volume assigned onto the link;

toll: toll charge in cents which differ in peak and off-peak period.

vot: value of time (cents/minutes), converting toll charge in cents into time in minutes.

distance: link distance in miles; the coefficient π converts distance in miles into time in minutes (taken as 0.25 in this study).

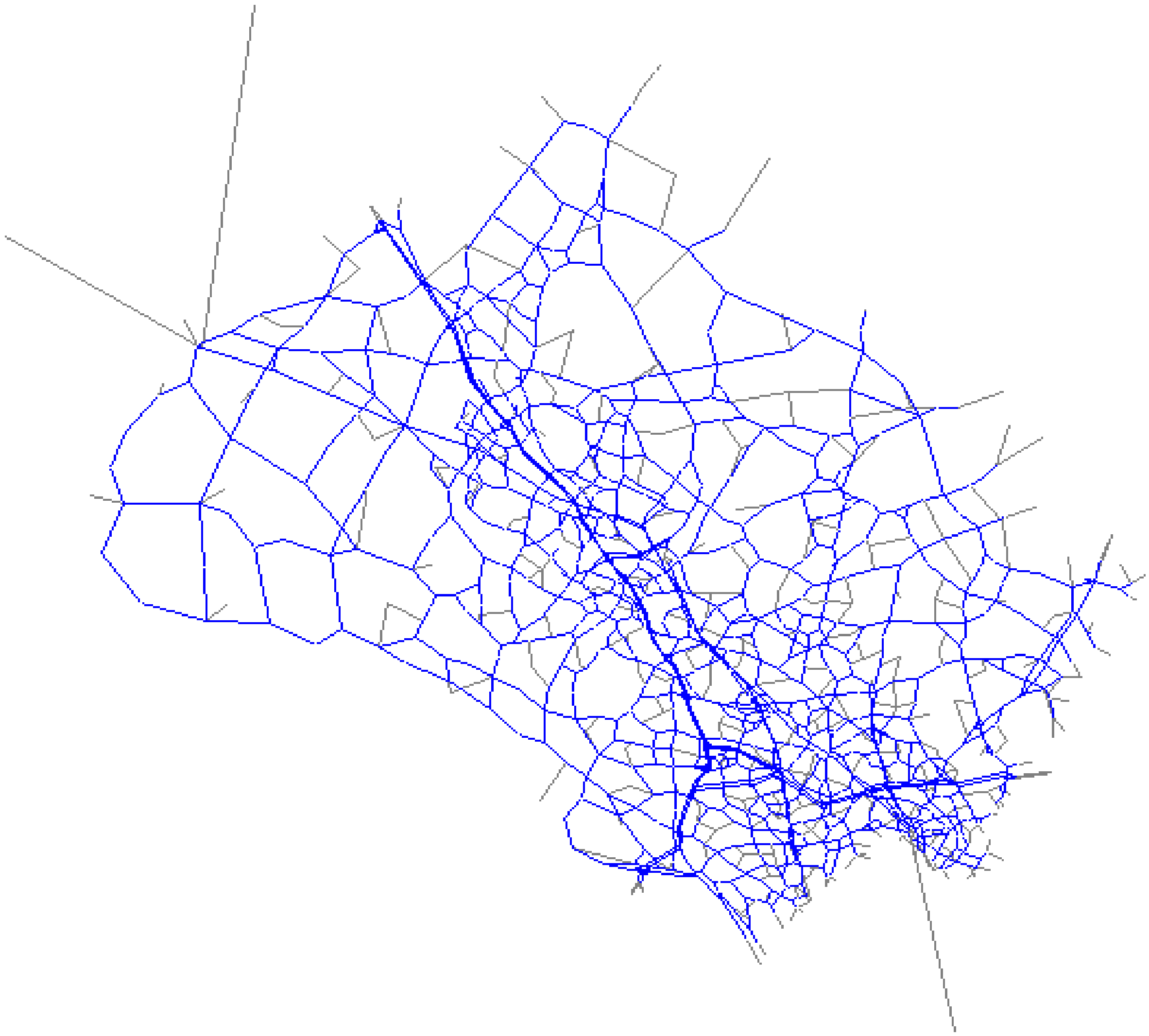

Figure 16 Extracted Montgomery County network from MSTM

The facilities, user class and restrictions are suitably coded and the standard BPR function is formulated for the link-cost function as:

$$t = t_0 [1 + \alpha (v/c) \beta]$$

Where

α and β are two coefficients which differ across link classes;

t_0 = 60 × distance (mile) / speed (mph);

v: the sum of total assigned traffic volumes of 20 user classes;

c: lane capacity (vehicles/hour) × the number of lanes / ConFac;

ConFac = 0.39 for AM peak period (3 hours), equivalent to expanding capacity by 2.56;

ConFac = 0.21 for Midday peak period (6 hours), equivalent to expanding capacity by 4.76;

ConFac = 0.34 for PM peak period (3 hours), equivalent to expanding capacity by 2.94;

ConFac = 0.22 for Night period (12 hours), equivalent to expanding capacity by 4.55

For the running of this script, a stamp.log file (See Appendix) has been used which contains various parameters required for model execution. This file contains various zone ranges, general parameters, highway skim parameters, trip generation parameters, trip distribution parameters, mode choice parameters, assignment parameters and other parameters needed to run all steps of the model. Finally, the volumes are added in the assigned matrices and the final trip matrices for the four time periods are formed.

The next step is to convert the four time-period matrices in to 12-time period matrices. The 12 time periods include the hourly trip matrices for the 5 hours AM and PM peak period respectively and for the Mid-day and Night, the whole period was considered as one time-period for each of them. In order to get the 12 time-period matrices, the trip matrices for the four periods, AM, MD, PM and NT were combined to form daily O-D trip matrices based on the respective trip purposes and then the hourly assignment of trip matrices was accomplished by multiplying the daily O-D trip matrices with the 12 time-period factors.

After the creation of the 12 time-period trip matrices, 12 Montgomery sub-area network files consisting of the congested speed of the links are created using the CUBE script (Script II in Appendix), Highway Assignment for sub-area analysis. For this process, ConFac values of 1 are used for AM and PM peak periods, 0.21 for MD period and 0.22 for NT period. The input data for this process are the 12 time period trip matrices for the 6 trip purposes and the sub-area network of Montgomery County that was extracted in step one. Stamp.log file as discussed above has also been used for running this script. The output of this process are the network files for the 12 time periods containing the congested speed of the links which, in turn, works as the input file for the generation of travel time matrices or Skims as explained in the next step.

The final step of the data preparation is the creation of travel time matrices for the links of the sub-area network. This process is also done using CUBE script (Script III in Appendix) in which the sub-area network for the 12 time periods containing the congested speeds works as the input file and the output is the 12 time period travel time matrices or skims. In this process the travel time is calculated using the following formula:

$$TT = 60*Distance/\ (CSPD)$$

Where,

TT = Travel time in Minutes

Distance = Distance or Length of the links in miles

CSPD = Congested speed of the links in miles/hr.

PEAK SPREADING CHAPTER 4: PREFERRED ARRIVAL TIME ESTIMATION

The departure time choice model used in this project is a type of discrete choice models which has scheduling delay penalties in its utility function. These penalties are formulated as the shift from preferred arrival or preferred departure time. As a result, information about preferred time is needed to estimate the model and using the model for forecasting.

Most revealed preference surveys like household travel surveys lack preferred time information. 2007-2008 TPB-BMC HHTS which is used as the primary data source in this study has the same deficiency; thus preferred time of the recorded travels need to be estimated.

Any assumption on preferred arrival times, strongly effects model estimation result. For instance, it can be assumed that preferred arrival time is equal to actual arrival time for the base case that is used for model estimation. This assumption results in estimating skim coefficient equal to zero, since it means travelers choose the alternative that makes their scheduling delay penalty equal to zero. Any assumption on preferred times should be considered carefully because it may completely change the model estimation results.

One reasonable approach is to estimate preferred arrival time based on actual arrival time. It can be assumed that the actual arrival time is the result of travelers' choice which maximizes their utility function. Travelers may choose less congested intervals instead of their preferred interval, if utility gained by smaller generalized cost dominates disutility of earliness or lateness. Therefore choice of any interval is based on the tradeoff between smaller generalized cost utility, and scheduling delay disutility. When actual arrival interval j is observed, the preferred arrival time may be any of the more congested periods that by shifting from there, the gained utility of smaller cost has dominated the disutility of earliness or lateness. The following function is assumed to calculate the probability that observed trip at interval j has PAT at interval i:

$$P(PAT = i|AAT = j) = \alpha/k * \frac{S_i - S_j}{|i-j|} \qquad If\ S_i > S_j$$

$$P(PAT = i|AAT = j) = 0 \qquad If\ S_i <= S_j$$

Si: skim value at interval i

α: Parameter to be estimated or assumed

k: scaling factor

This formulation states that travelers do not shift from their preferred time to a more congested interval. For less congested intervals, the probability of shift increases by the utility gain (S_i-S_j), and decreases by the utility loss (*i-j*). *P* indicates probability of shift from *i* to *j*, so sum the P values over all intervals should be 1. Or:

$$\mathbf{0} \leq \sum_{i \neq j} \boldsymbol{P(PAT = i \mid AAT = j)} \leq \mathbf{1}$$

The above sigma represents probability of the observed trip at *j* being shifted from any other preferred interval *i*. For instance, this sigma is 0 for the peak hour, because nobody shifts from their non-peak preferred interval to peak interval as it forces more congestion and more deviation from the preferred time. *K* is a scaling factor that corrects the probability values to make the above sigma between 0 and 1, and is calculated by the formula below:

$$\boldsymbol{k} = \frac{\boldsymbol{CDF}\left(\sum_{i \neq j} \boldsymbol{\alpha} * \frac{\boldsymbol{S_i - S_j}}{|\boldsymbol{i - j}|}\right)}{\sum_{i \neq j} \boldsymbol{\alpha} * \frac{\boldsymbol{S_i - S_j}}{|\boldsymbol{i - j}|}}$$

Cumulative density functions give a value between zero and 1, and they can be used to scale the shift probabilities. The chosen CDF should keep the small values nearly the same, but decrease the larger values into [0, 1] scale. Exponential CDF with $\lambda=1$ is used here to scale the probabilities.

The other parameter of the model, *α* can be estimated simultaneously with the departure time choice model parameters using maximum likelihood estimation. In order to do that, log likelihood function should be combined with the law of total probability:

$$\boldsymbol{LL} = \sum_{i\ osbervation} \sum_{j\ intervals} \boldsymbol{P(AAT_i | PAT = j) * P(PAT = j)}$$

For each observation in model estimation process, likelihood is substituted by conditional likelihood. *α* is estimated through maximum likelihood estimation. At this step, *α* is assumed to be one, and it will be estimated in the future works.

The method described can estimate the preferred arrival time for model estimation data. The distribution of preferred arrival times for each trip purpose can be obtained from the results of this estimation. When applying the departure time choice model for other scenarios for forecasting, this distribution is assumed to be fixed, and preferred time of travels are randomly drawn from the preferred arrival time distribution.

PEAK SPREADING CHAPTER 5: DEPARTURE TIME CHOICE MODEL ESTIMATION

Model estimation is done separately for each of the six trip purposes. Biogeme software (Bierlaire, 2003) is used to estimate different types of discrete choice models. The initial purpose of this study was to estimate random coefficient mixed logit models, but the results showed that the variance of random coefficient was not significant; meaning that the coefficients did not vary significantly among the sample, so assuming mixed logit structure did not improve the models. The reason can be the combination of the assumed alternatives. Mixed logit structure is designed to capture the correlation of the alternatives, and it seems that one hour intervals do not show that much correlations. It is possible that by decreasing the length of each alternative from one hour to 15 minutes or smaller, mixed logit structure show better performance.

The models described in this chapter are either multinomial logit or nested logit. If nested logit shows better performance than multinomial logit in terms of likelihood, and nest coefficients are significant, nested logit structure is preferred to multinomial logit.

One major difficulty in discrete choice models for departure time choice is to represent intervals by a single time-point. Usually, the midpoint is selected to represent the interval, but for midday and night intervals of this study which are 5, and 9 hours midpoint is not a good choice. Therefore, these intervals are divided into one hour intervals with the same skim value and alternative specific constant for modeling purposes.

5.1 HOME BASED WORK (HBW) TRIPS

For this trip purpose nested logit structure showed better performance than multinomial logit and it is preferred. The nests are morning peak containing alternatives 1 to 5, afternoon peak containing alternatives 7 to 11, midday containing 5 hours of alternative 6, and night containing 9 hours of alternative 12. Tables 4 to 6 summarize the results of model estimation:

Table 4 HBW model performance

Model:	Nested Logit
Number of estimated parameters:	18
Number of observations:	2928

Number of individuals:	2928
Null log-likelihood:	-9305.342
Constant log-likelihood:	-7655.392
Initial log-likelihood:	-9984.788
Final log-likelihood:	-2442.420
Likelihood ratio test:	13725.843
Rho-square:	0.738
Adjusted rho-square:	0.736

Table 5 HBW model parameter estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_1	0.554	0.308	1.80	0.07	0.315	1.76	0.08
ASC_10	0.732	0.243	3.01	0.00	0.264	2.77	0.01
ASC_11	0.637	0.250	2.54	0.01	0.268	2.37	0.02
ASC_12	0.00	fixed					
ASC_2	1.26	0.295	4.26	0.00	0.295	4.26	0.00
ASC_3	1.29	0.277	4.67	0.00	0.278	4.66	0.00
ASC_4	1.04	0.267	3.89	0.00	0.263	3.94	0.00
ASC_5	0.115	0.276	0.42	0.68	0.273	0.42	0.67
ASC_6	-1.07	0.271	-3.93	0.00	0.283	-3.77	0.00
ASC_7	-0.184	0.275	-0.67	0.50	0.280	-0.66	0.51
ASC_8	0.443	0.256	1.73	0.08	0.268	1.65	0.10
ASC_9	0.532	0.245	2.17	0.03	0.262	2.03	0.04
B_early	-0.0636	0.00206	-30.88	0.00	0.00197	-32.22	0.00
B_late	-0.0544	0.00176	-30.88	0.00	0.00171	-31.73	0.00
B_skim	-0.0458	0.00877	-5.22	0.00	0.0103	-4.45	0.00

Table 6 HBW model nest coefficients estimation results

Name ▼	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
afternoon_peak	0.915	0.0438	20.87	0.00	0.0402	22.74	0.00
mid_day	0.935	0.0752	12.43	0.00	0.0683	13.69	0.00
morning_peak	0.899	0.0418	21.52	0.00	0.0372	24.16	0.00
non_peak	1.28	0.140	9.14	0.00	0.134	9.58	0.00

The results show the correct sign for skim and scheduling delays, because they are all disutility, and they should have negative sign. The Rho-square is relatively large because of preferred arrival time estimation.

The model is estimated on 70 percent of the data, and the remaining 30 percent is used for validation purposes. The estimated share should be compared with real share for validation. Figure 16 shows the result of model validation:

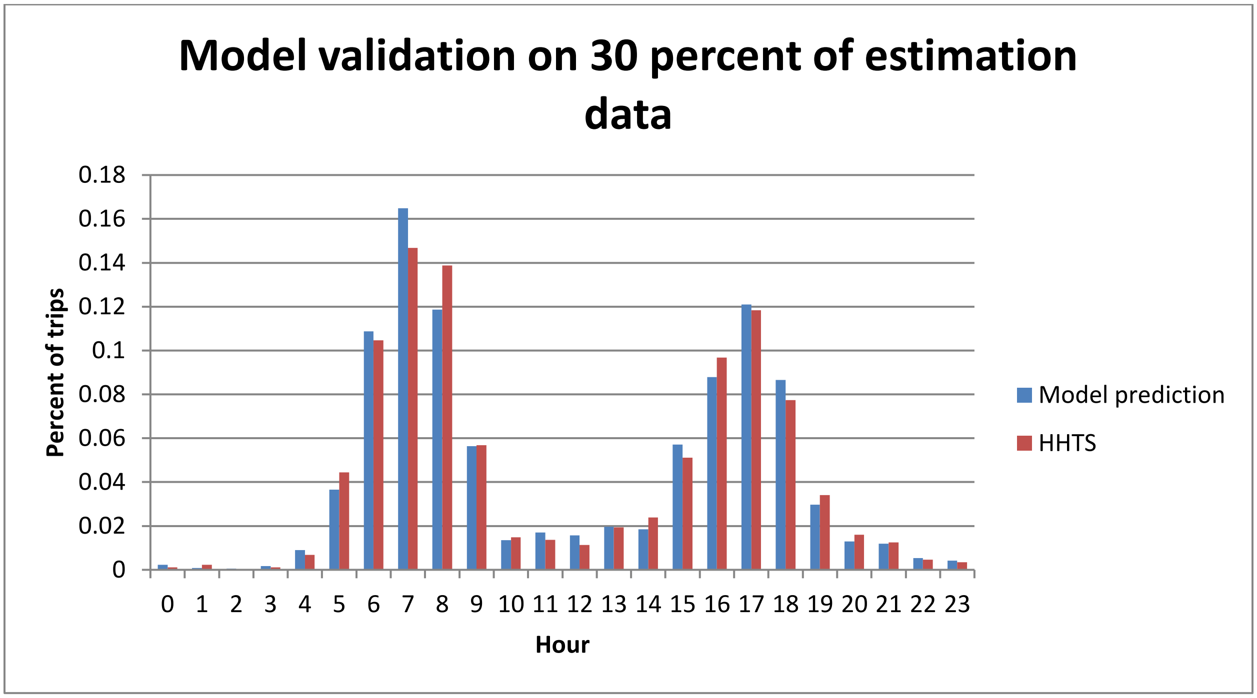

Figure 17 HBW model validation using 30 percent of data

Normalized root mean square error of this validation is 0.102 which is satisfying. It can be seen that work trips are primarily concentrated in morning peak and afternoon peak hours.

5.2 HOME BASED SHOPPING (HBS) TRIPS

Similar to HBW model, nested logit structure showed better performance than multinomial logit. The nests are morning peak containing alternatives 1 to 5, afternoon peak containing alternatives 7 to 11, midday containing 5 hours of alternative 6, and night containing 9 hours of alternative 12. Tables 7 to 10 summarize the results of model estimation:

Table 7 HBS model performance

Model:	Nested Logit
Number of estimated parameters:	19
Number of observations:	2260
Number of individuals:	2260
Null log-likelihood:	-7182.402
Constant log-likelihood:	-6147.558
Initial log-likelihood:	-7615.467
Final log-likelihood:	-1573.795
Likelihood ratio test:	11217.213
Rho-square:	0.781
Adjusted rho-square:	0.778

Table 8 HBS mode parameter estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_1	-1.48	0.628	-2.36	0.02	0.447	-3.32	0.00
ASC_10	0.531	0.212	2.51	0.01	0.220	2.41	0.02
ASC_11	0.778	0.180	4.32	0.00	0.192	4.05	0.00
ASC_12	0.00	fixed					
ASC_2	-0.251	0.448	-0.56	0.57	0.418	-0.60	0.55
ASC_3	0.0846	0.393	0.22	0.83	0.350	0.24	0.81
ASC_4	0.393	0.353	1.11	0.27	0.311	1.26	0.21
ASC_5	0.582	0.305	1.91	0.06	0.270	2.16	0.03
ASC_6	0.794	0.243	3.27	0.00	0.219	3.62	0.00
ASC_7	0.629	0.261	2.41	0.02	0.253	2.48	0.01
ASC_8	0.493	0.252	1.96	0.05	0.242	2.03	0.04

ASC_9	0.473	0.233	2.03	0.04	0.233	2.03	0.04
B_dist_skm	0.00448	0.00166	2.70	0.01	0.00166	2.70	0.01
B_early	-0.0593	0.00189	-31.41	0.00	0.00156	-37.95	0.00
B_late	-0.0590	0.00215	-27.45	0.00	0.00220	-26.74	0.00
B_skim	-0.185	0.0278	-6.65	0.00	0.0355	-5.21	0.00

Table 9 HBS model nest coefficients estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
afternoon_peak	0.958	0.0488	19.62	0.00	0.0415	23.08	0.00
mid_day	1.04	0.0596	17.48	0.00	0.0505	20.62	0.00
morning_peak	1.17	0.119	9.85	0.00	0.106	10.98	0.00
non_peak	0.987	0.0780	12.65	0.00	0.0665	14.84	0.00

All the signs are as expected, and rho square is relatively large because of preferred arrival time estimation. It can be seen that the ratio between skim coefficient and scheduling coefficient is considerably larger than this ratio for HBW model. It shows that scheduling is less important for HBS trips, and travelers prefer to have shorter travel times. The results of model validation are presented in the Figure 17:

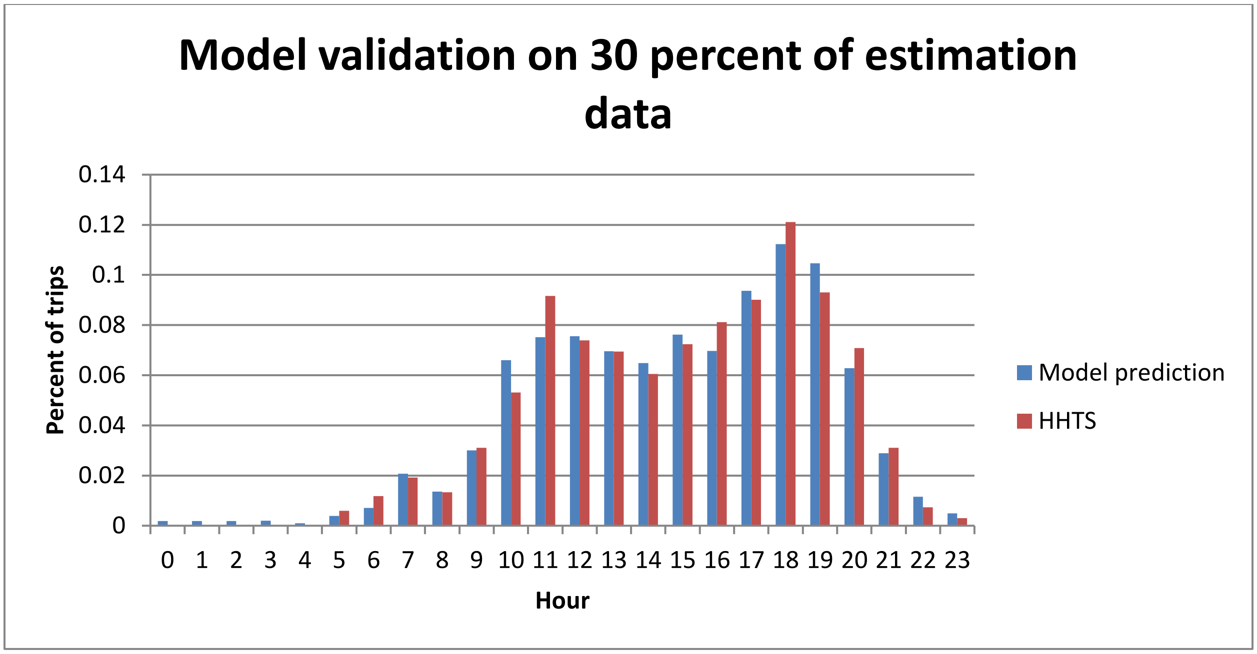

Figure 18 HBS model validation with 30 percent of data

Normalized root mean square error for this model is 0.252 which is still reasonable, but not as good as HBW model. The figure shows that shopping trips are not as concentrated as work trips and they are distributed along the day.

5.3 HOME BASED OTHER (HBO) TRIPS

Similar to HBW model, nested logit structure showed better performance than multinomial logit for HBO trips. The nests are morning peak containing alternatives 1 to 5, afternoon peak containing alternatives 7 to 11, midday containing 5 hours of alternative 6, and night containing 9 hours of alternative 12. Tables 10 to 12 summarize the results of model estimation:

Table 10 HBO model performance

Model:	Nested Logit
Number of estimated parameters:	19
Number of observations:	4911
Number of individuals:	4911
Null log-likelihood:	-15607.422

Constant log-likelihood:	-13923.690
Initial log-likelihood:	-16527.351
Final log-likelihood:	-3518.540
Likelihood ratio test:	24177.765
Rho-square:	0.775
Adjusted rho-square:	0.773

Table 11 HBO model parameters estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_1	-1.51	0.356	-4.25	0.00	0.290	-5.22	0.00
ASC_10	0.550	0.161	3.41	0.00	0.162	3.39	0.00
ASC_11	0.402	0.138	2.92	0.00	0.143	2.82	0.00
ASC_12	0.00	fixed					
ASC_2	-0.0511	0.281	-0.18	0.86	0.241	-0.21	0.83
ASC_3	0.576	0.235	2.45	0.01	0.205	2.80	0.01
ASC_4	0.845	0.213	3.97	0.00	0.182	4.65	0.00
ASC_5	0.439	0.202	2.17	0.03	0.186	2.36	0.02
ASC_6	0.217	0.181	1.20	0.23	0.167	1.30	0.19
ASC_7	0.255	0.195	1.31	0.19	0.191	1.34	0.18
ASC_8	0.244	0.190	1.29	0.20	0.184	1.33	0.18
ASC_9	0.595	0.175	3.41	0.00	0.172	3.45	0.00
B_dist_skm	0.00221	0.000590	3.75	0.00	0.000954	2.32	0.02
B_early	-0.0646	0.00145	-44.41	0.00	0.00120	-53.95	0.00
B_late	-0.0611	0.00153	-39.90	0.00	0.00148	-41.25	0.00
B_skim	-0.155	0.0141	-10.96	0.00	0.0206	-7.51	0.00

Table 12 HBO model nest coefficients estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
afternoon_peak	0.890	0.0325	27.35	0.00	0.0282	31.58	0.00
mid_day	0.963	0.0414	23.24	0.00	0.0353	27.26	0.00
morning_peak	0.856	0.0372	23.04	0.00	0.0332	25.81	0.00
non_peak	0.945	0.0513	18.40	0.00	0.0456	20.70	0.00

Signs are consistent with expectation, and Rho-square is high similar to previous models because of preferred arrival time estimation. Similar to HBS trips, the ratio of skim coefficient over penalty coefficient is larger than the ratio for HBW, showing that shorter travel time is more important for shopping and other trips.

Results of validation can be seen in the Figure 18:

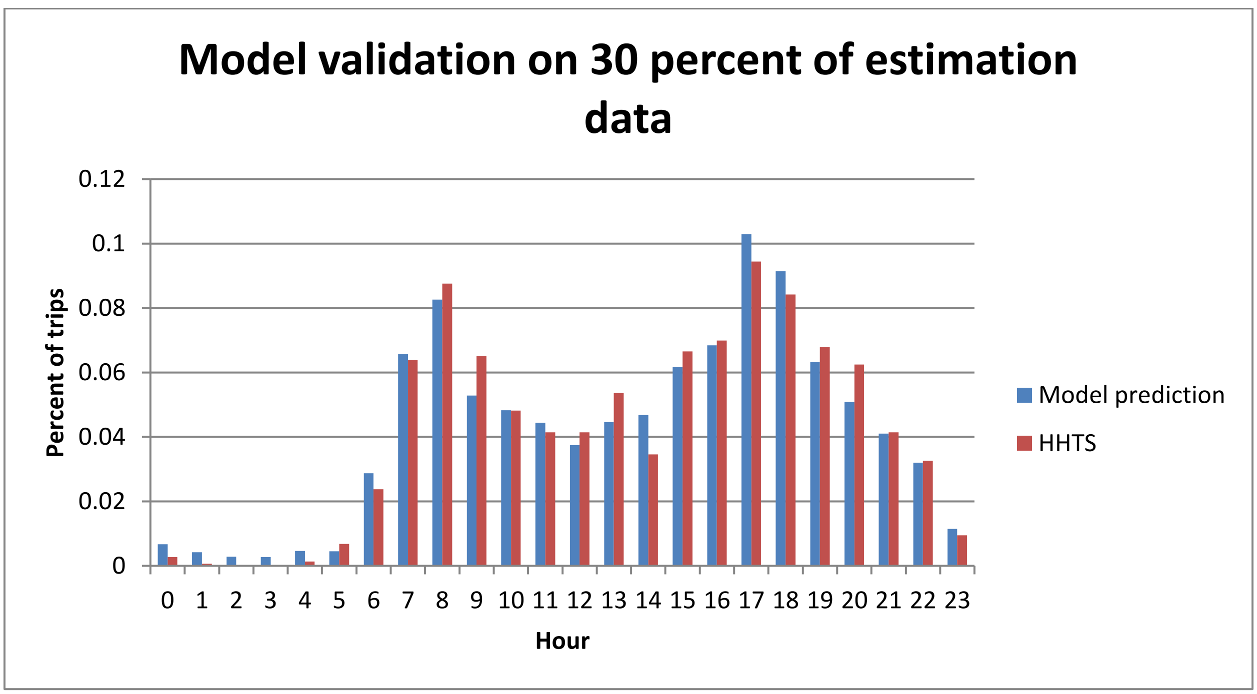

Figure 19 HBO model validation with 30 percent of data

The normalized root mean square error is 0.358 which is larger than two previous models, showing that other trips are harder to model. Similar to HBS trips are distributed during the day.

5.4 HOME BASED SCHOOL (HBSch)TRIPS

Similar to previous models, HBSch model follows nested logit structure with the same nests. Tables 13 to 15 summarize the estimation results:

Table 13 HBSch model performance

Model:	Nested Logit
Number of estimated parameters:	19
Number of observations:	957
Number of individuals:	957
Null log-likelihood:	-3041.398
Constant log-likelihood:	-2160.452
Initial log-likelihood:	-3281.312
Final log-likelihood:	-655.215
Likelihood ratio test:	4772.365
Rho-square:	0.785
Adjusted rho-square:	0.778
Final gradient norm:	+4.470e-003

Table 14 HBSch model parameters estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_1	0.854	0.946	0.90	0.37	0.815	1.05	0.30
ASC_10	0.00390	0.741	0.01	1.00	0.807	0.00	1.00
ASC_11	0.469	0.788	0.60	0.55	0.979	0.48	0.63
ASC_12	0.00	fixed					

ASC_2	4.27	0.784	5.44	0.00	0.798	5.34	0.00
ASC_3	4.08	0.734	5.56	0.00	0.745	5.47	0.00
ASC_4	3.42	0.698	4.90	0.00	0.707	4.84	0.00
ASC_5	0.945	0.706	1.34	0.18	0.714	1.32	0.19
ASC_6	2.37	0.667	3.56	0.00	0.692	3.43	0.00
ASC_7	1.80	0.648	2.77	0.01	0.675	2.66	0.01
ASC_8	0.820	0.676	1.21	0.23	0.713	1.15	0.25
ASC_9	1.21	0.696	1.73	0.08	0.749	1.61	0.11
B_dist_skm	0.00480	0.00394	1.22	0.22	0.00369	1.30	0.19
B_early	-0.0704	0.00469	-14.99	0.00	0.00453	-15.53	0.00
B_late	-0.0570	0.00364	-15.65	0.00	0.00351	-16.24	0.00
B_skim	-0.148	0.0336	-4.40	0.00	0.0374	-3.95	0.00

Table 15 HBSch model nest coefficients estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
afternoon_peak	0.990	0.114	8.69	0.00	0.0948	10.45	0.00
mid_day	1.24	0.158	7.87	0.00	0.170	7.29	0.00
morning_peak	0.812	0.0711	11.42	0.00	0.0632	12.86	0.00
non_peak	0.890	0.230	3.87	0.00	0.259	3.44	0.00

Signs are as expected, and rho square is high because of preferred arrival time estimation. The validation results are presented in the figure 19:

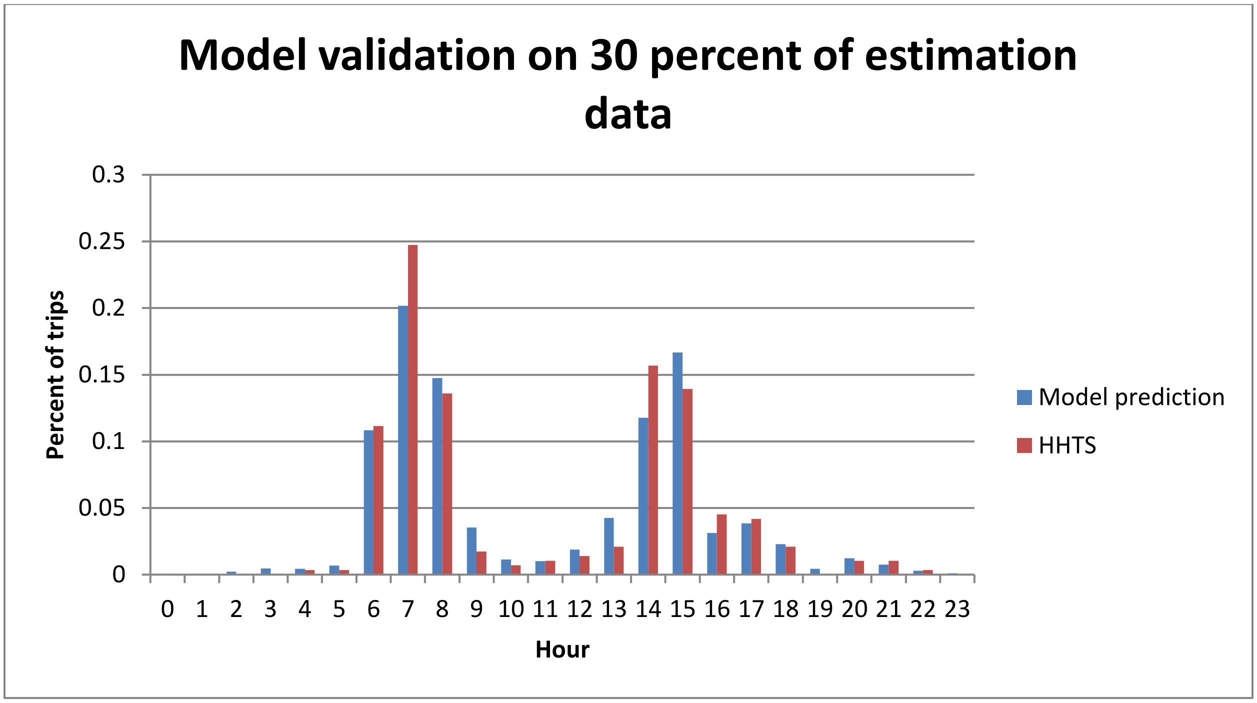

Figure 20 HBSch model validation with 30 percent of data

Normalized root mean square error is 0.050 for this model. Concentration of travels in morning and afternoon peaks is considerable.

5.5 NON-HOME BASED WORK (NHBW) TRIPS

This model has two main differences with the previous models. First, nested logit structure did not improve the model, and multinomial logit is preferred. Second, using reliability instead of skim improved the model. The distribution of NHBW trips shows considerable number of trips in midday. These trips are at the middle of the working hours, and they have to be reliable. This may be the reason why reliability performed better than skim. While putting both reliability and skim in the previous models made reliability insignificant because of correlation between skim and reliability, adding both terms in NHBW model made the skim insignificant. Both variable show significant effect if they are in the model alone, but the model with reliability had higher Rho-square and it was preferred. Tables 16 to 18 summarize the estimation results:

Table 16 NHBW model performance

Model:	Multinomial Logit

Number of estimated parameters:	14
Number of observations:	1401
Number of individuals:	1401
Null log-likelihood:	-4452.453
Constant log-likelihood:	-3653.126
Initial log-likelihood:	-4452.453
Final log-likelihood:	-899.234
Likelihood ratio test:	7106.438
Rho-square:	0.798
Adjusted rho-square:	0.795

Table 17 NHBW model parameter estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_1	0.273	0.704	0.39	0.70	0.636	0.43	0.67
ASC_10	2.50	0.445	5.62	0.00	0.492	5.08	0.00
ASC_11	1.83	0.448	4.08	0.00	0.473	3.86	0.00
ASC_12	0.00	fixed					
ASC_2	0.518	0.644	0.80	0.42	0.604	0.86	0.39
ASC_3	1.56	0.571	2.74	0.01	0.563	2.78	0.01
ASC_4	1.76	0.532	3.31	0.00	0.554	3.18	0.00
ASC_5	1.92	0.501	3.83	0.00	0.532	3.61	0.00
ASC_6	1.79	0.451	3.96	0.00	0.517	3.46	0.00
ASC_7	1.79	0.460	3.90	0.00	0.517	3.47	0.00
ASC_8	2.25	0.449	5.02	0.00	0.499	4.52	0.00
ASC_9	2.39	0.444	5.37	0.00	0.495	4.83	0.00

B_early	-0.0596	0.00175	-34.09	0.00	0.00153	-38.86	0.00
B_late	-0.0607	0.00214	-28.42	0.00	0.00201	-30.22	0.00
B_reliability	-0.0535	0.0211	-2.54	0.01	0.0149	-3.58	0.00

The sign of variables is as expected, and Rho-square is high because of preferred arrival time estimation. The result of model validation can be seen in the Figure 20:

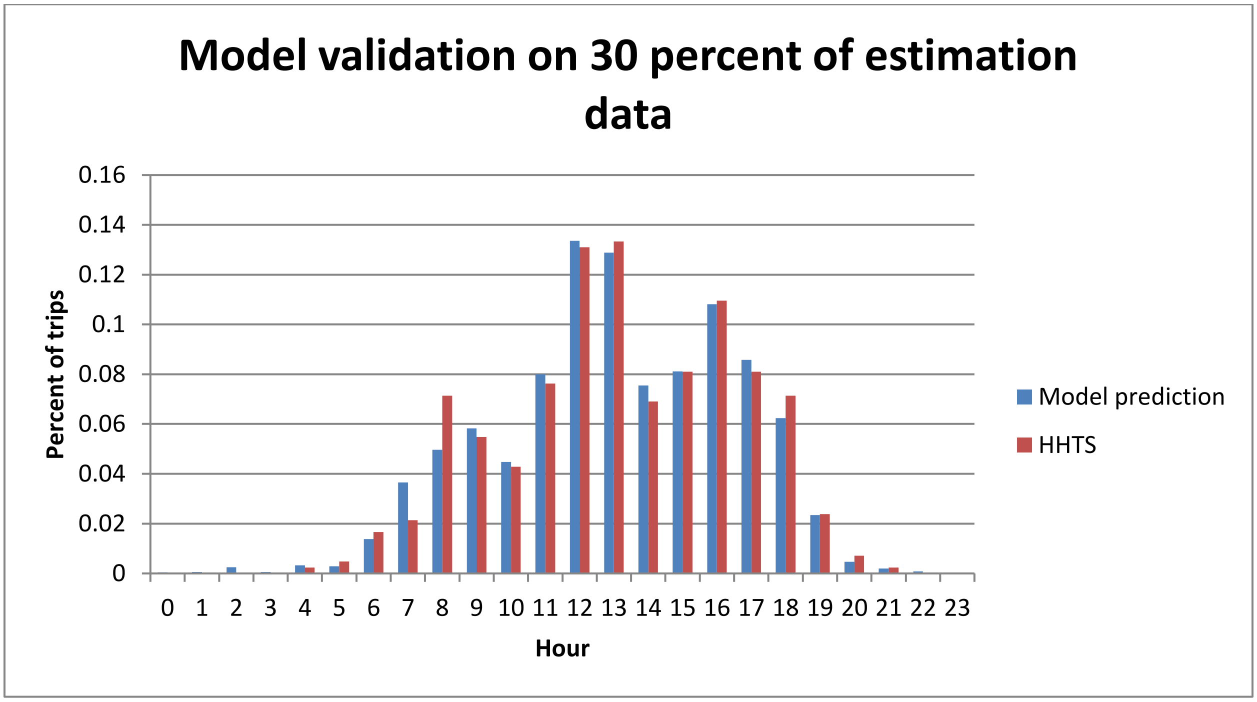

Figure 21 NHBW model validation with 30 percent of data

Normalized root mean square error for this model is 0.131. Considerable number of trips in the midday can be observed in the figure.

5.6 NON-HOME BASED OTHER (NHBO) TRIPS

Nested logit structure showed better performance than multinomial logit and it is preferred. The nests are morning peak containing alternatives 1 to 5, afternoon peak containing alternatives 7 to

11, midday containing 5 hours of alternative 6, and night containing 9 hours of alternative 12. Tables 18 to 20 summarize the results of model estimation:

Table 18 NHBO model performance

Model:	Nested Logit
Number of estimated parameters:	19
Number of observations:	2569
Number of individuals:	2569
Null log-likelihood:	-8164.420
Constant log-likelihood:	-6735.675
Initial log-likelihood:	-8756.732
Final log-likelihood:	-1572.398
Likelihood ratio test:	13184.045
Rho-square:	0.807
Adjusted rho-square:	0.805

Table 19 NHBO model parameters estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_1	-2.97	0.951	-3.12	0.00	0.782	-3.79	0.00
ASC_10	0.614	0.293	2.09	0.04	0.286	2.15	0.03
ASC_11	0.739	0.254	2.91	0.00	0.253	2.92	0.00
ASC_12	0.00	fixed					
ASC_2	-2.48	0.817	-3.03	0.00	0.644	-3.85	0.00
ASC_3	0.181	0.477	0.38	0.71	0.369	0.49	0.62
ASC_4	0.468	0.409	1.14	0.25	0.312	1.50	0.13
ASC_5	0.786	0.354	2.22	0.03	0.281	2.80	0.01
ASC_6	1.08	0.299	3.61	0.00	0.236	4.57	0.00

ASC_7	1.04	0.304	3.42	0.00	0.257	4.05	0.00
ASC_8	0.872	0.304	2.87	0.00	0.274	3.18	0.00
ASC_9	0.612	0.302	2.03	0.04	0.291	2.10	0.04
B_dist_skm	0.00584	0.00184	3.17	0.00	0.00180	3.24	0.00
B_early	-0.0623	0.00210	-29.70	0.00	0.00176	-35.44	0.00
B_late	-0.0637	0.00235	-27.04	0.00	0.00239	-26.68	0.00
B_skim	-0.206	0.0310	-6.65	0.00	0.0311	-6.63	0.00

Table 20 NHBO model nest coefficients estimation results

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
afternoon_peak	0.973	0.0541	17.96	0.00	0.0433	22.47	0.00
mid_day	0.958	0.0472	20.31	0.00	0.0401	23.89	0.00
morning_peak	0.829	0.0782	10.60	0.00	0.0654	12.67	0.00
non_peak	1.15	0.148	7.78	0.00	0.125	9.21	0.00

The signs are as expected, and Rho-square is high due to the preferred arrival time estimation. The result of model validation can be seen in the figure 21:

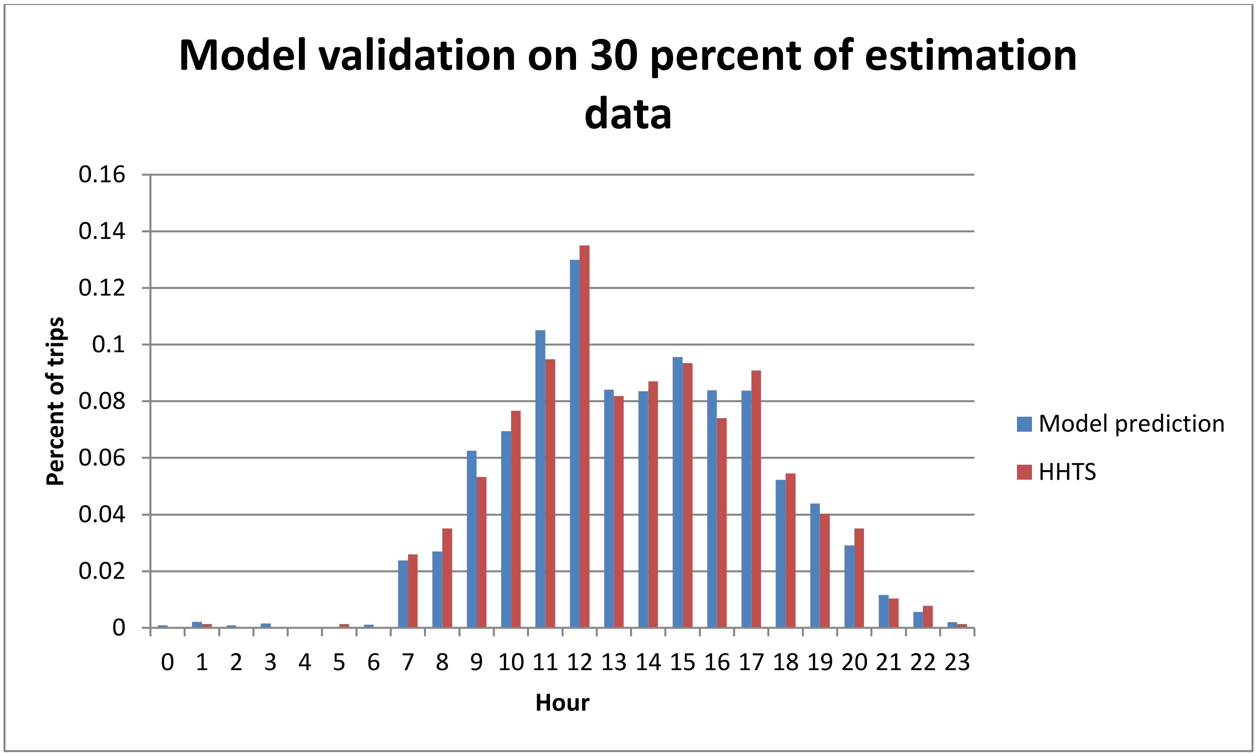

Figure 22 NHBO model validation with 30 percent of data

Normalized root mean square for this model is 0.415, which is the largest among all models, suggesting that this purpose is the hardest one to model. These trips are distributed along the day, and large number of trips can be seen in the midday alternative.

As another way of validating the work, estimated models are used to obtain total distribution of the demand, which is the sum of the demand distribution for all 6 trip purposes. Demand prediction results are described in detail in next chapter. The result is compared with the observed distribution of demand from household travel survey. Figure 22 shows this comparison:

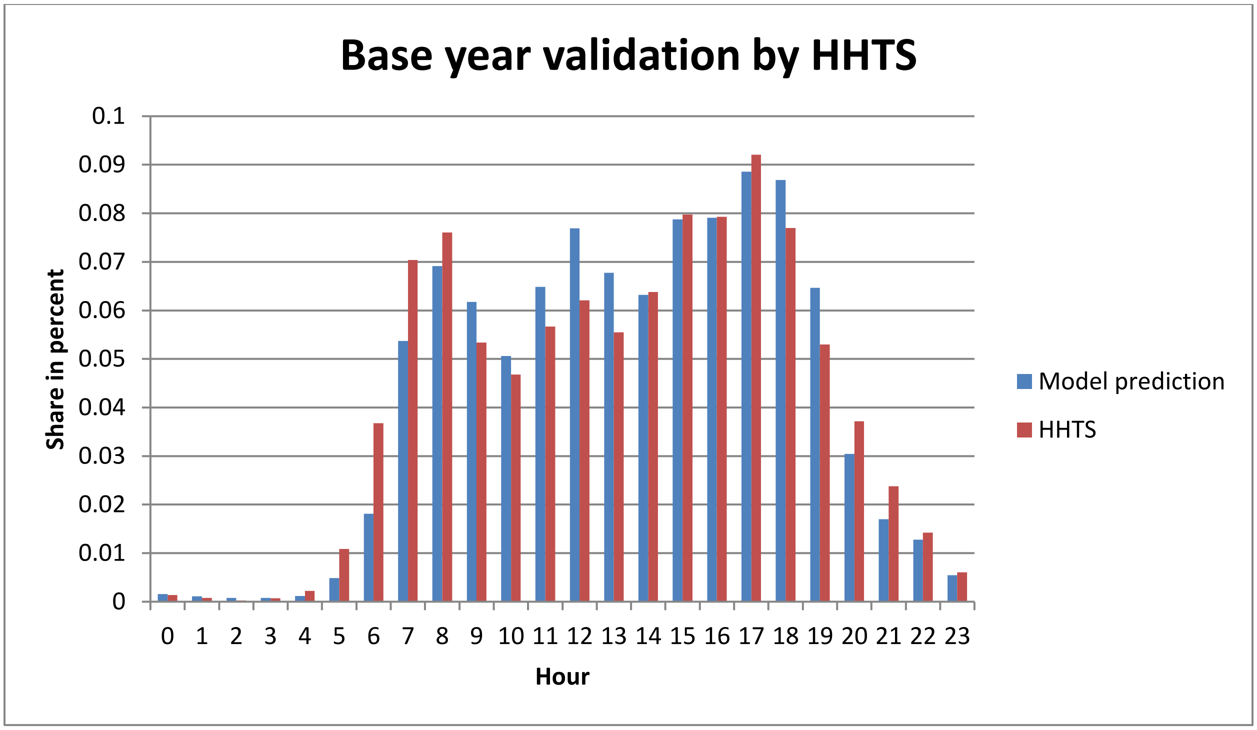

Figure 23 Model validation by comparing predicted distribution versus HHTS distribution

Normalized root mean square for this comparison is 0.09.

It should be noted here that all the presented result are outputs of one iteration of the loop, which shows the way methodology works, and gives initial results. Improved results can be obtained by continuing with more iterations until convergence, as described in the methodology part.

PEAK SPREADING CHAPTER 6: PEAK SPREADING PREDICTION

In the methodology part, the way demand distribution can be obtained was described in detail. In this part demand profile for the base year 2007 and future year 2030 are compared to assess how demand shifts to the shoulders of the peak. One way of doing this comparison is to compare observed base year distribution from household travel survey with the predicted distribution for the future year. Another way is to compare model predictions for both base and future years. The second method is used here, since the results are the outputs of only one iteration and may not perfectly match the reality; thus comparing model outputs is a more reasonable comparison. Prediction outputs for each of the trip purposes are presented separately, and then they are combined to show the overall peak spreading results.

6-1 HOME BASED WORK TRIP RESULTS

Initial run of the MSTM shows changes in the network-wide average skim values as described in Figure 23:

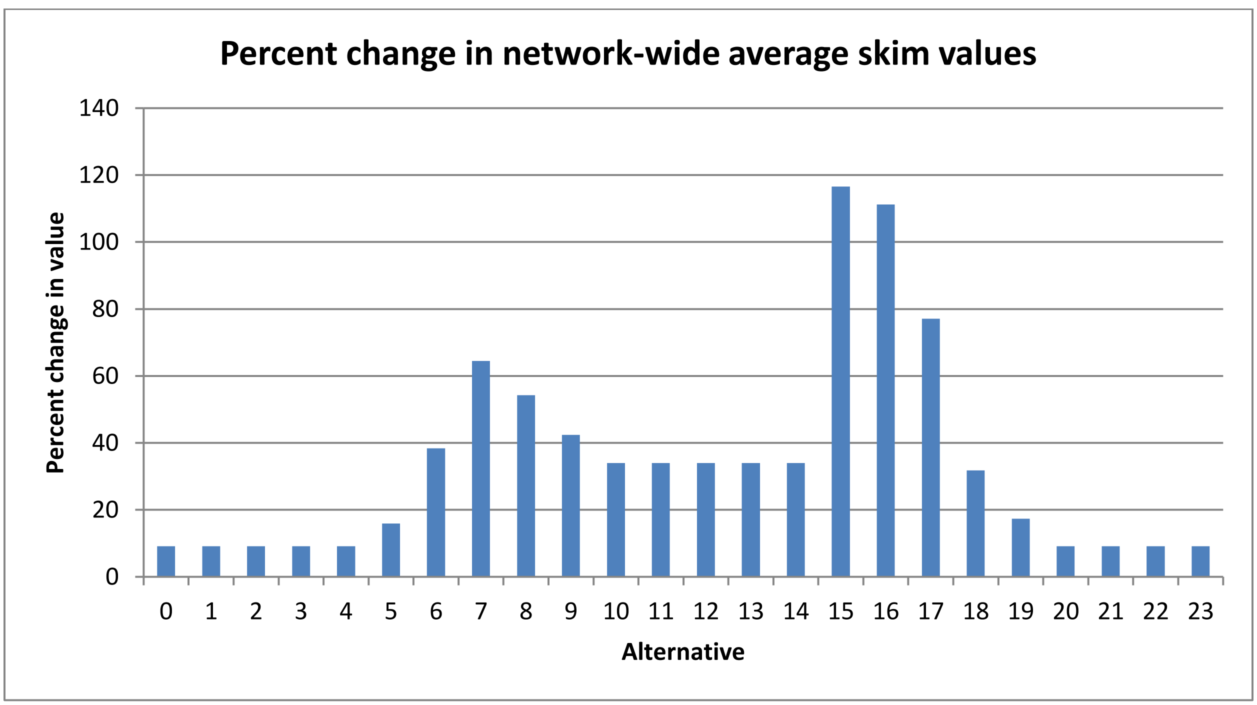

Figure 24 Percent change in network-wide average skim values for HBW trips

This network-wide average is calculated by multiplying trip tables and skim matrices, and dividing the results by total number of trips. The average skims show increased congestion for all intervals, and the increase is more severe in the afternoon peak. Total number of trips for the base year is 291425, and for the future year is 378032. Using this input data in the prediction process, the distribution of trips is obtained and depicted in Figure 24:

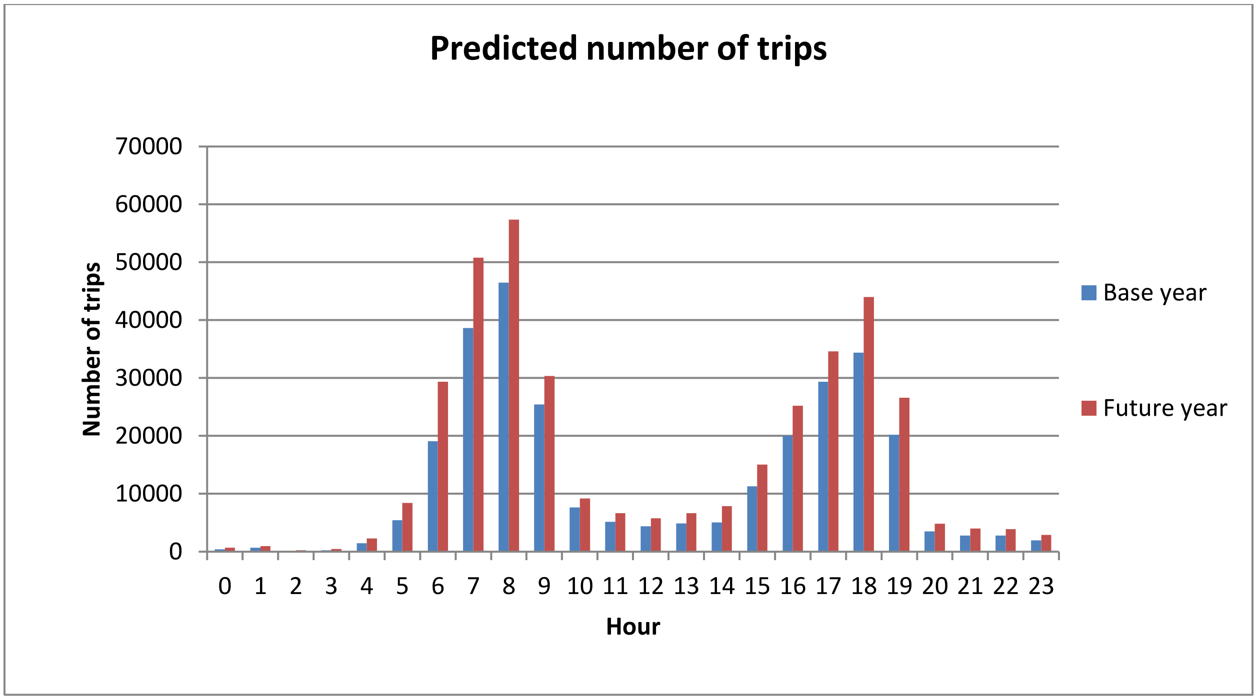

Figure 25 Predicted distribution of HBW trips

Figure 25 better shows the change in the distribution. It represents the percent change in share from total number of trips:

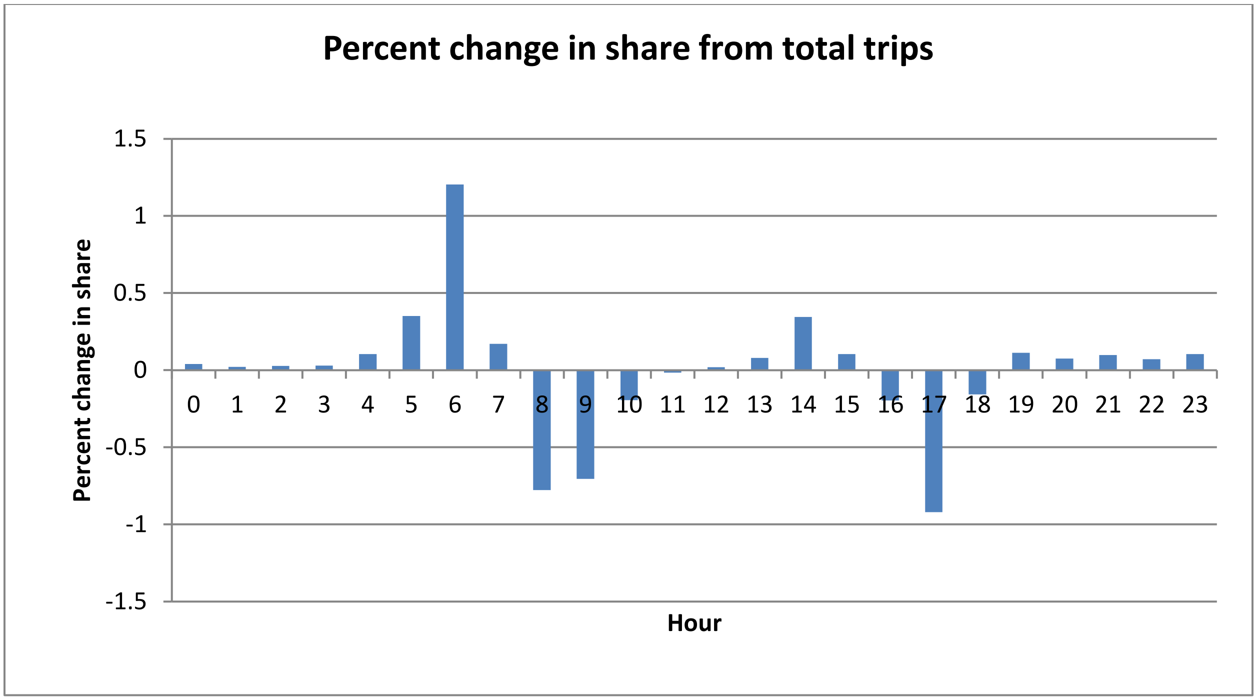

Figure 26 Percent change in share from total HBW trips

The figure shows that trips are shifting from the beginning of the peak hours to earlier time periods. In general, the figure shows that the share of the peak hours is decreasing.

6.2 HOME BASE SHOPPING TRIP RESULTS

Percent change in network-wide average skim values can be seen in the Figure 26:

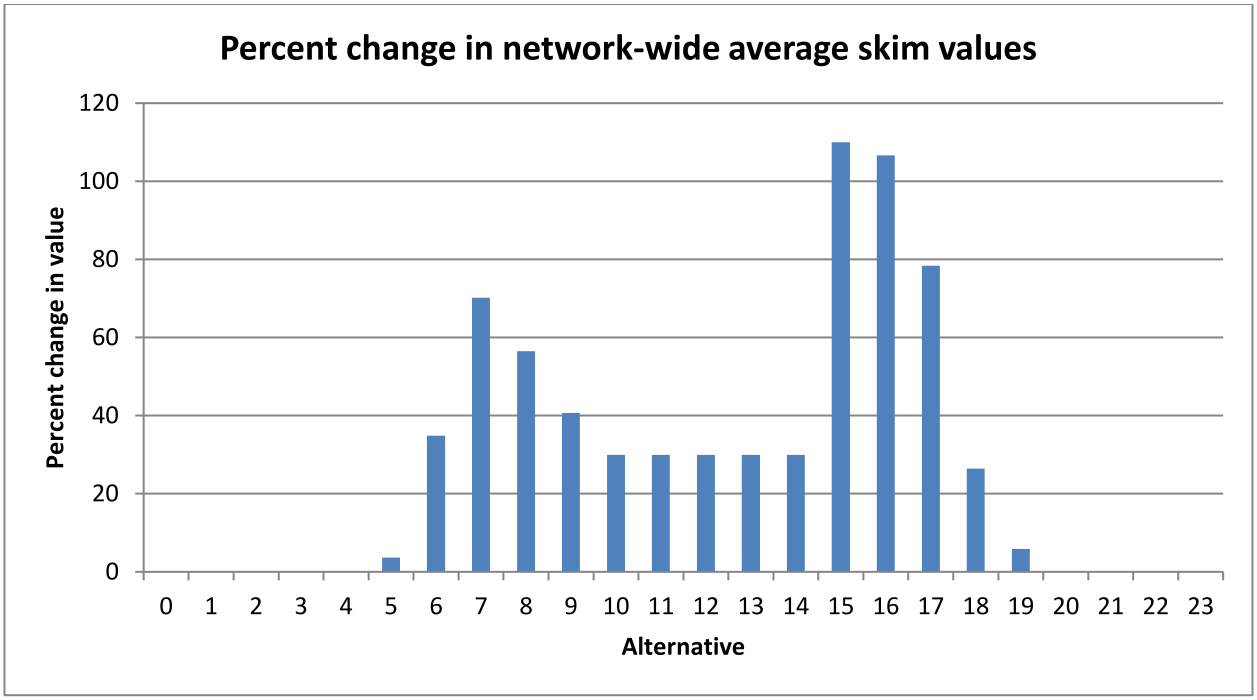

Figure 27 Percent change in network-wide average skim values for HBS trips

It can be seen that MSTM shows higher skims for future year, and the increase is more significant at the afternoon peak hours. Number of trips is 319991 for the base year, and 382367 for the future year. The outputs of the prediction can be seen in Figures 27 and 28:

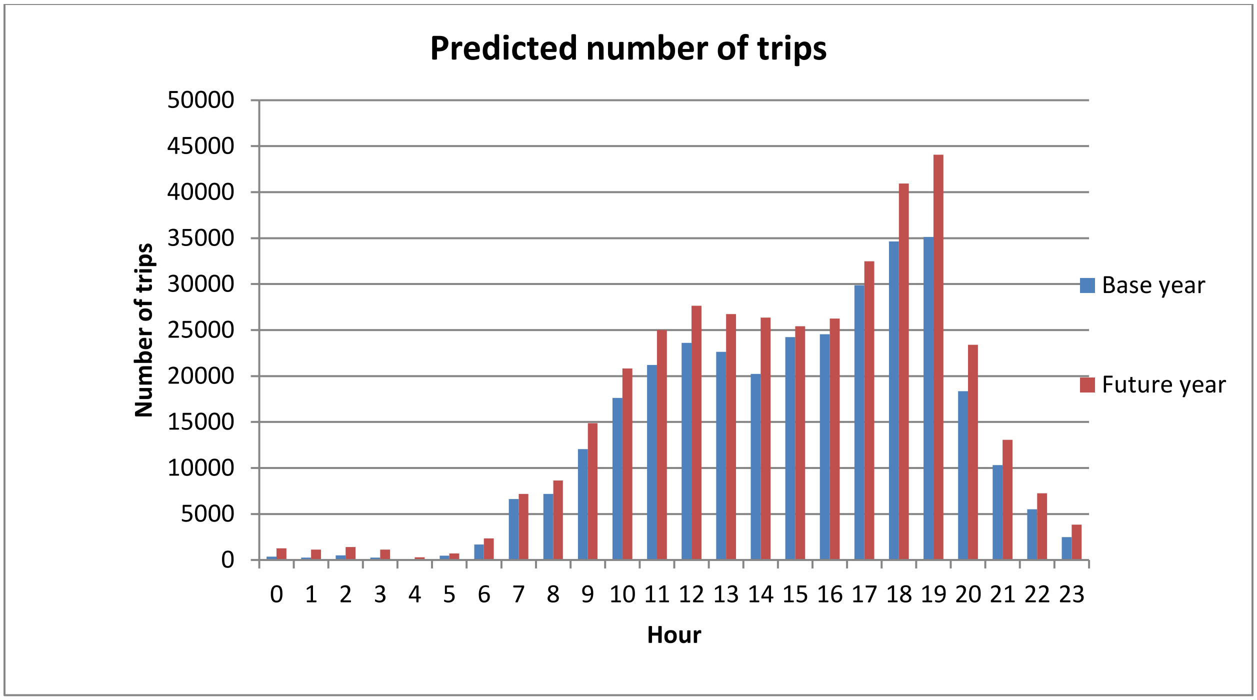

Figure 28 Predicted distribution of HBS trips

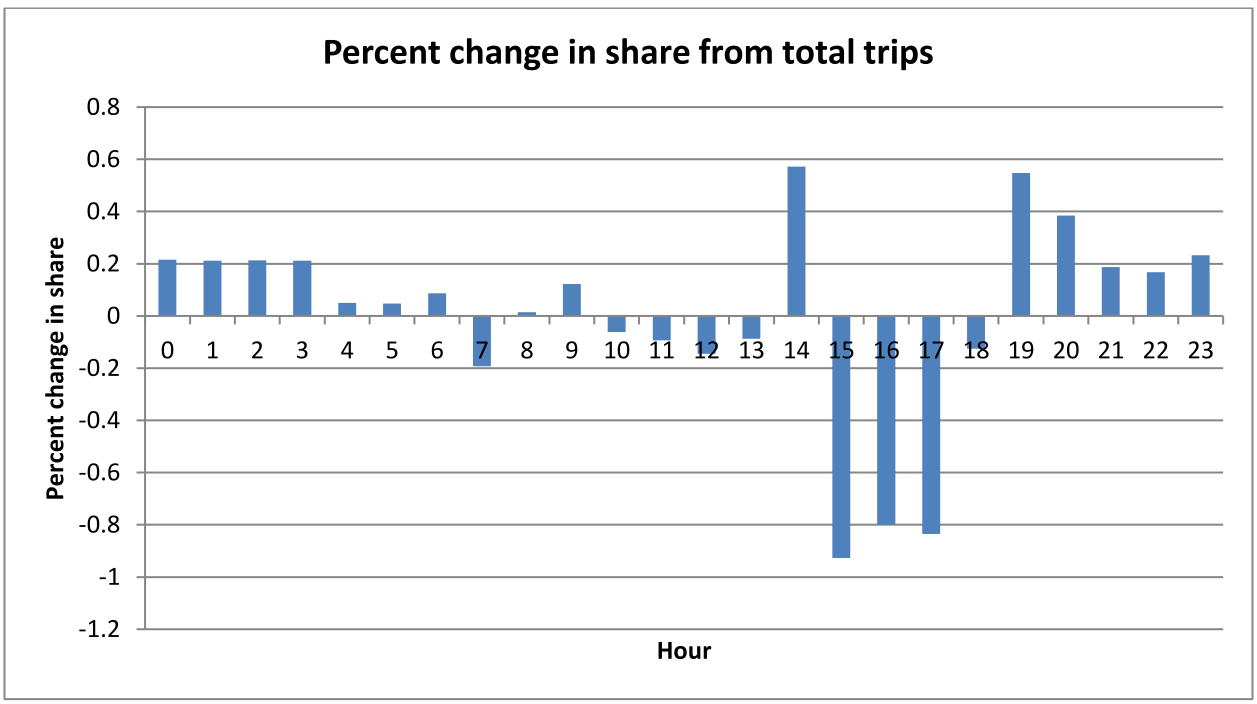

Figure 29 Percent change in share from total HBS trips

The results show that trips are being shifted from afternoon peak hour to earlier or later intervals. Slight shift is also observable around 7am in the morning peak.

6.3 HOME BASE OTHER TRIP RESULTS

Figure 29 shows the percent change in network-wide average skim values obtained from MSTM outputs:

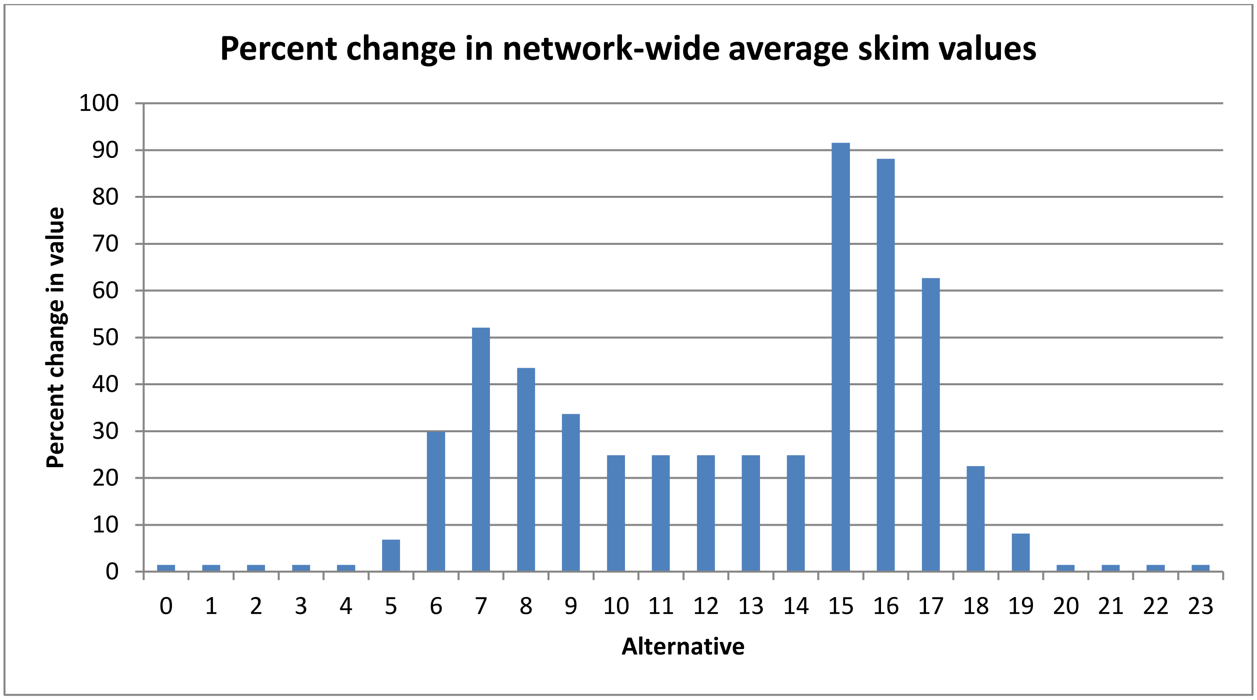

Figure 30 Percent change in network-wide average skim values for HBO trips

Congestion gets more severe all along the day, specifically in the afternoon peak. Number of trips in the base year is 486430, and in the future year is 644947. The results of prediction are presented in Figures 30 and 31:

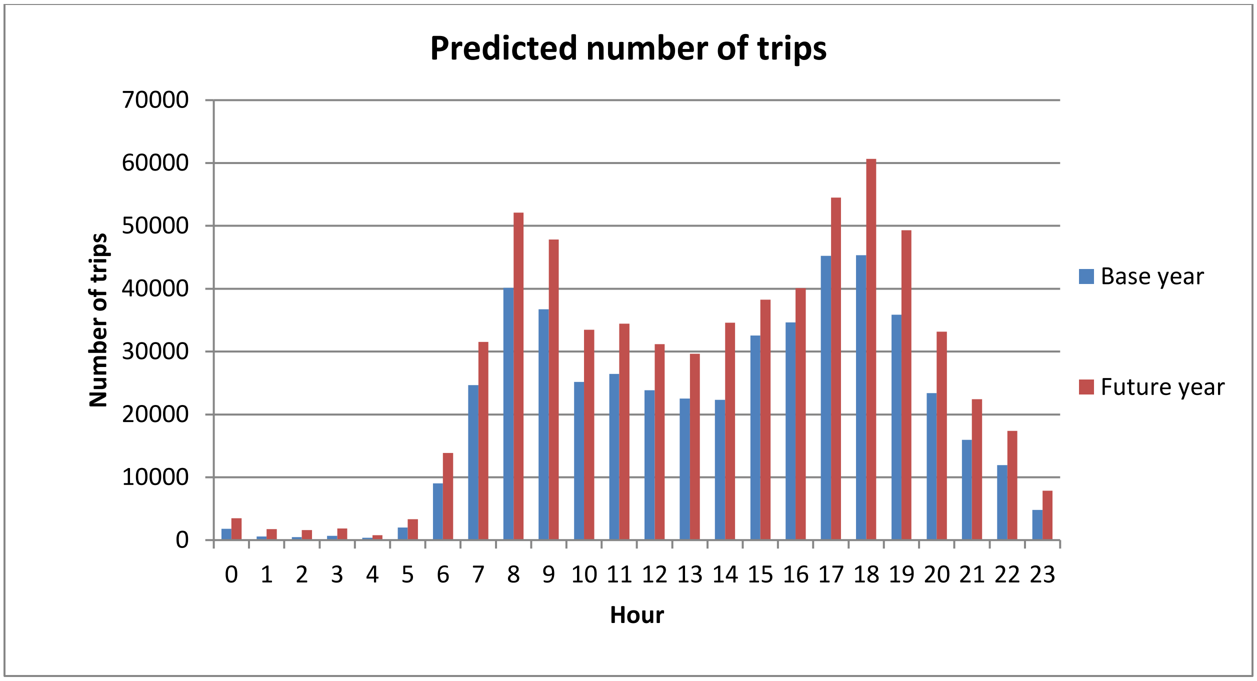

Figure 31 Predicted distribution of HBO trips

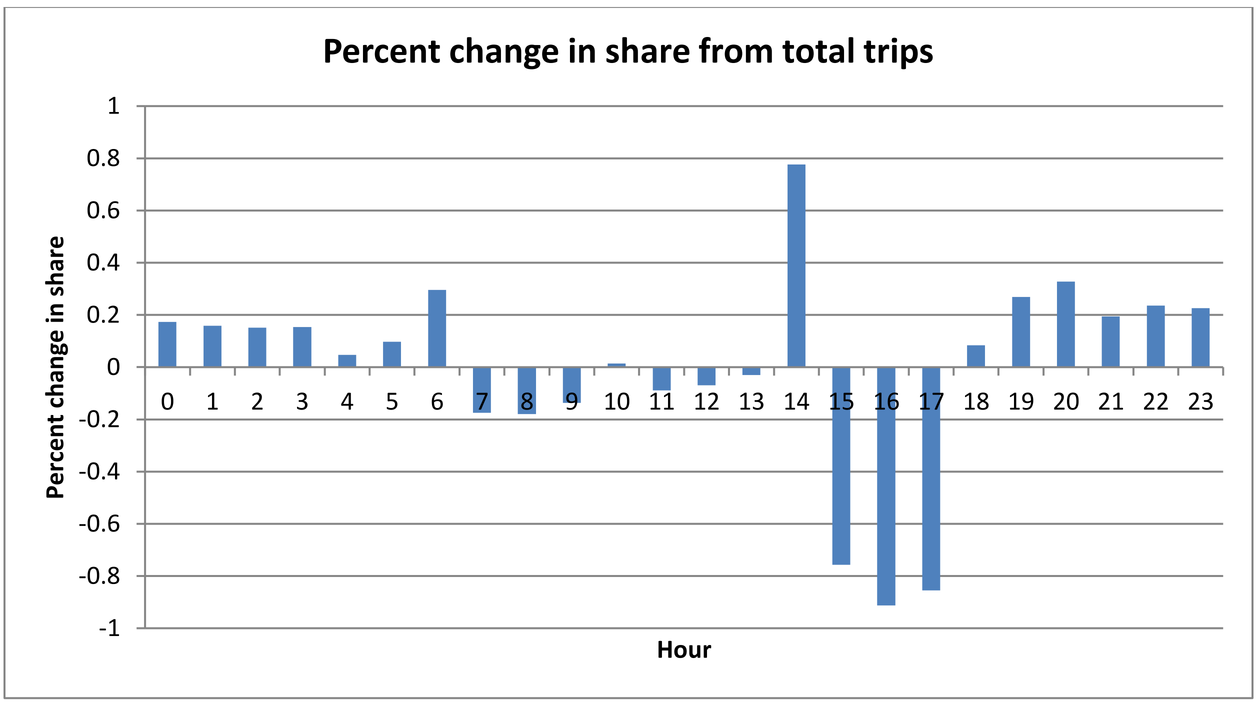

Figure 32 Percent change in share from total HBO trips

Similar to previous models, afternoon peak experiences shifts to the shoulder of the peak. Slight shift is also observable during the morning peak toward the peak shoulders.

6.4 HOME BASE SCHOOL TRIP RESULTS

Figure 32 shows the percent change network-wide average skim values:

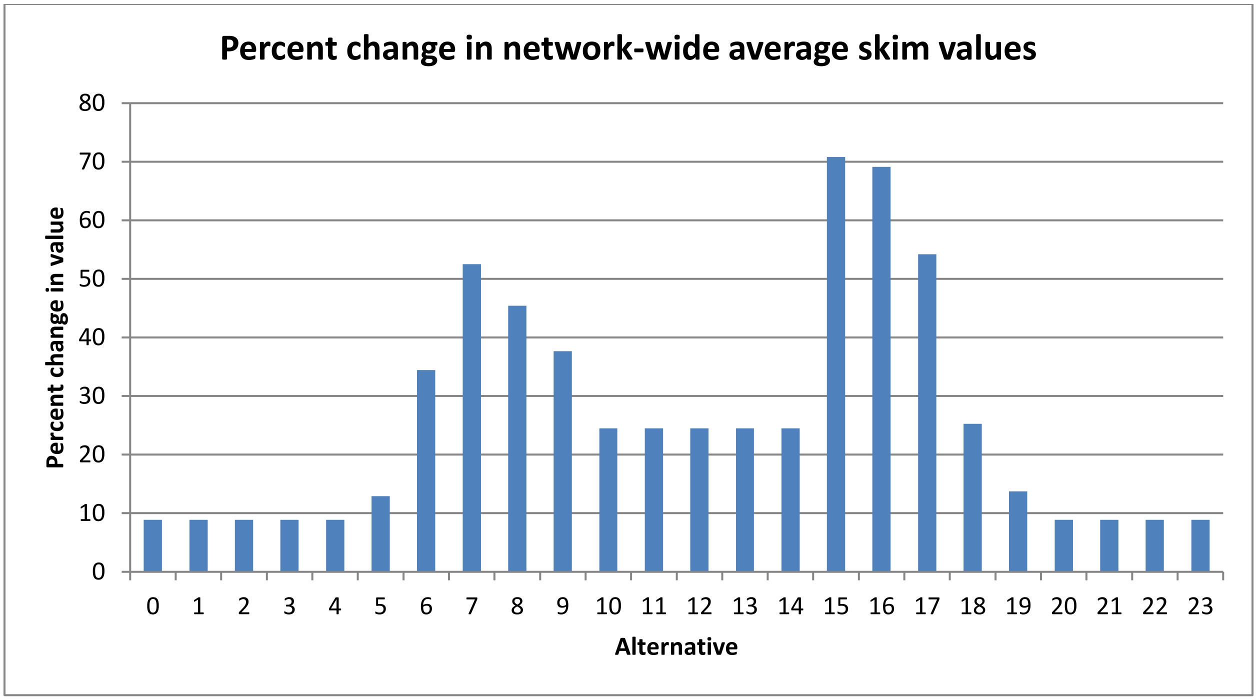

Figure 33 Percent change in network-wide average skim values for HBSch trips

More severe congestion is observable similar to previous purposes. Base year number of trips is 94359, and future year number of trips is 113022. The outputs of prediction are presented in the Figures 33 and 34:

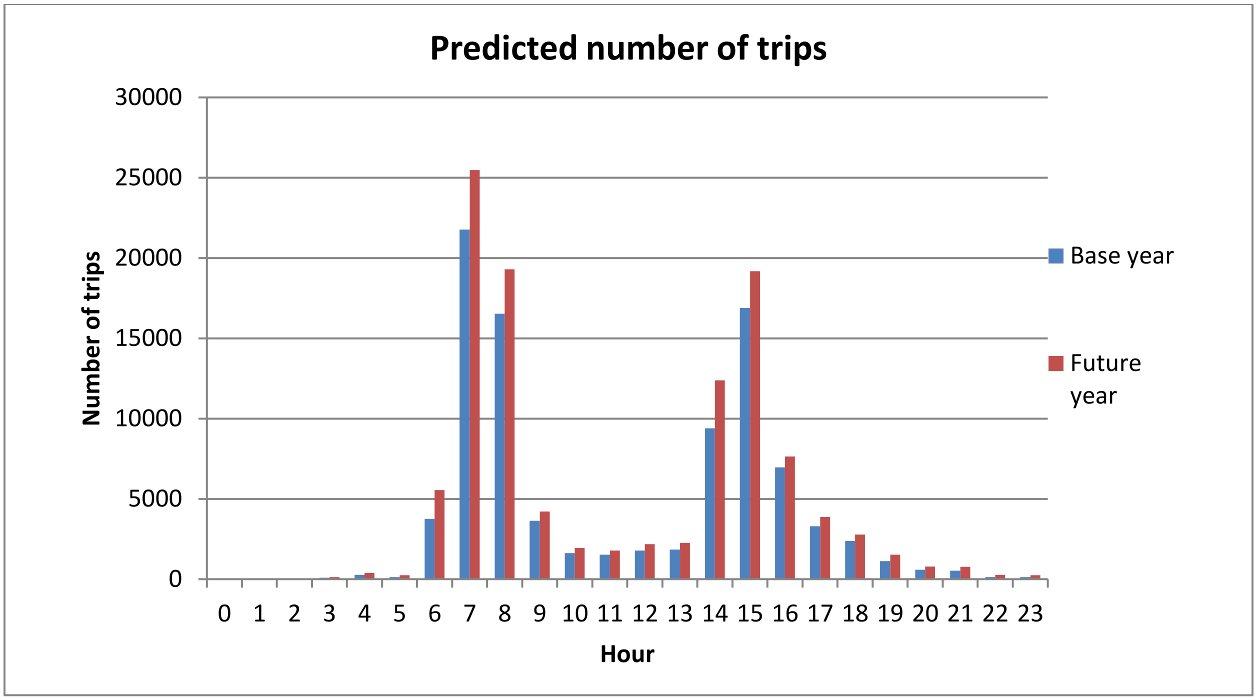

Figure 34 Predicted distribution of HBSch trips

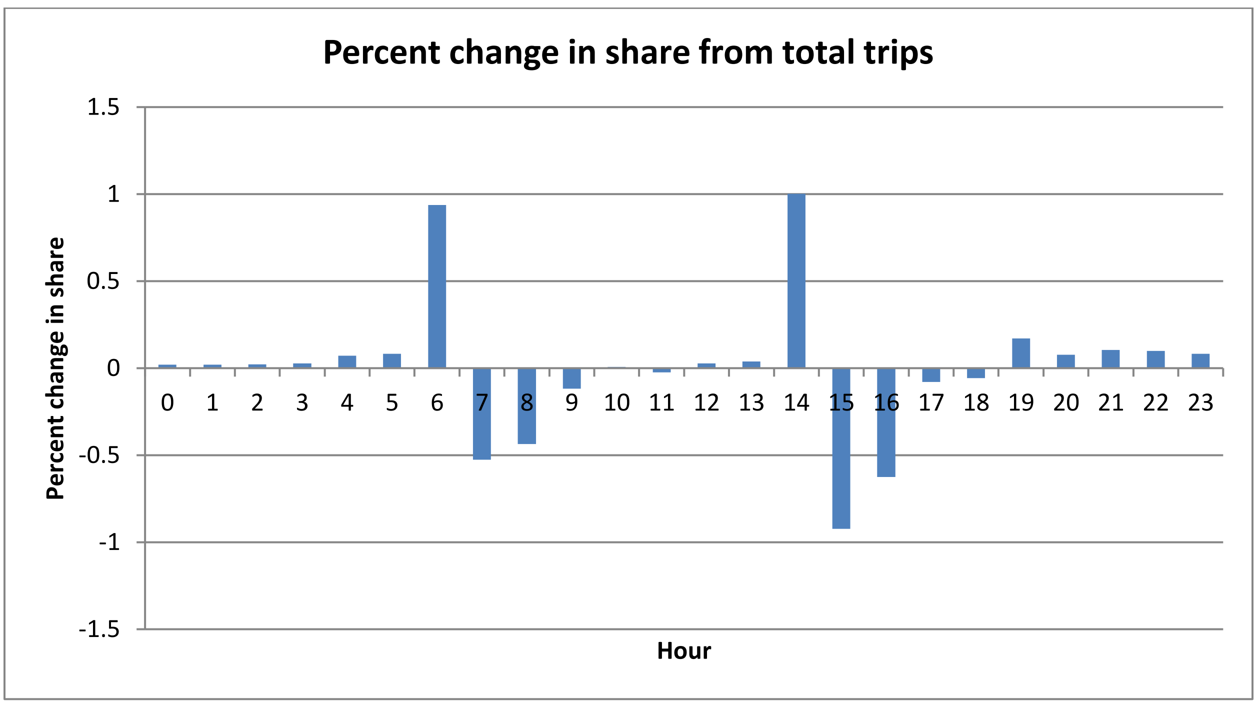

Figure 35 Percent change in share from total HBSch trips

School trips are being shifted to the earlier time periods that the road is less congested.

6.5 NON-HOME BASE WORK TRIP RESULTS

Similar to previous models, skim values get higher for the future year as can be seen in Figure 35.

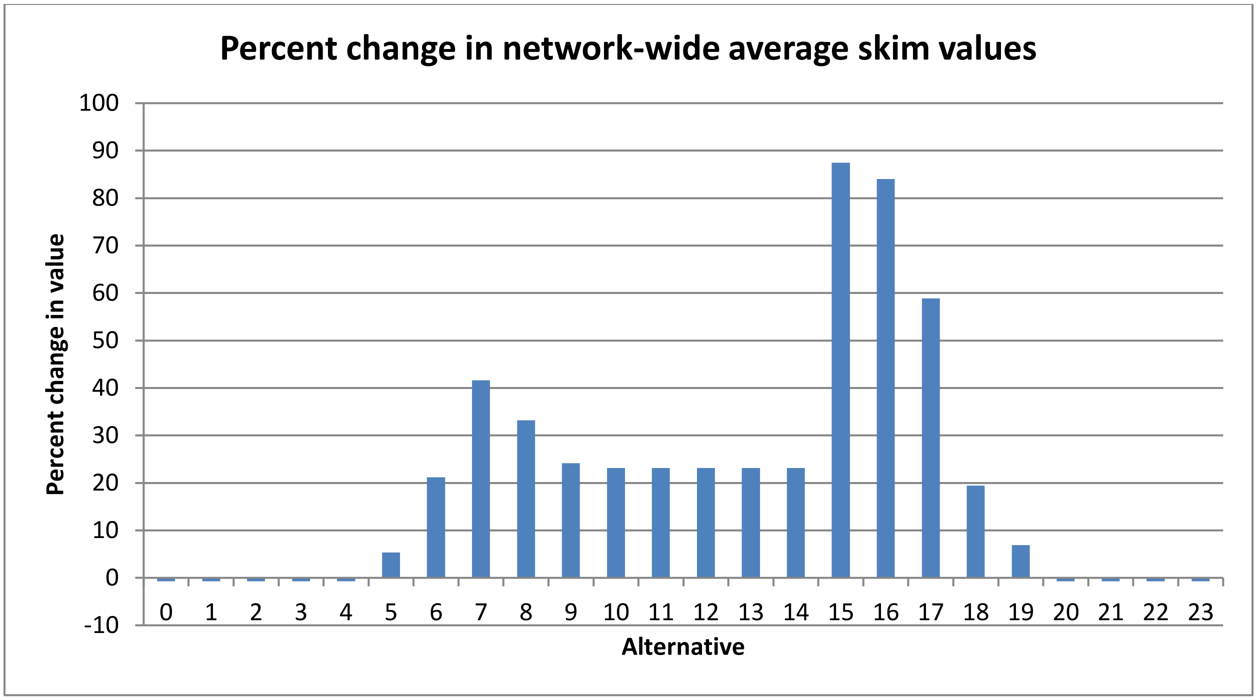

Figure 36 Percent change in network-wide average skim values for NHBW trips

Number of trips for the base year is 378896, and for the future year is 497827. The prediction outputs can be seen in Figures 36 and 37:

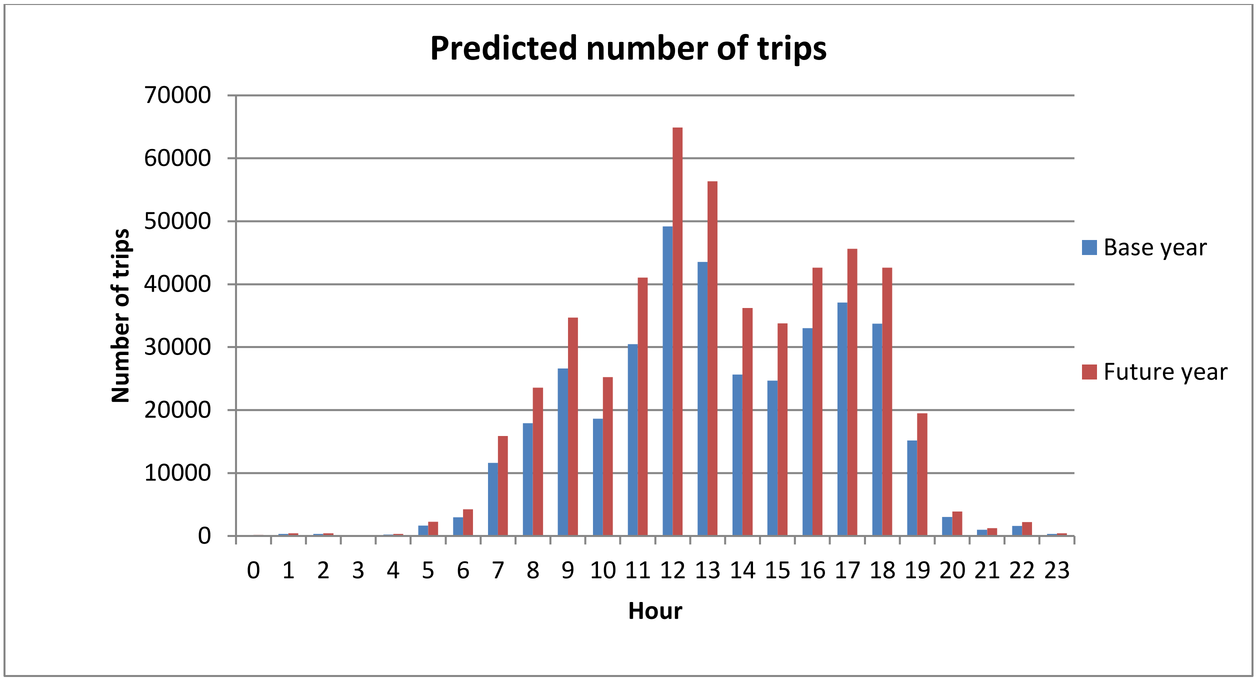

Figure 37 Predicted distribution of NHBW trips

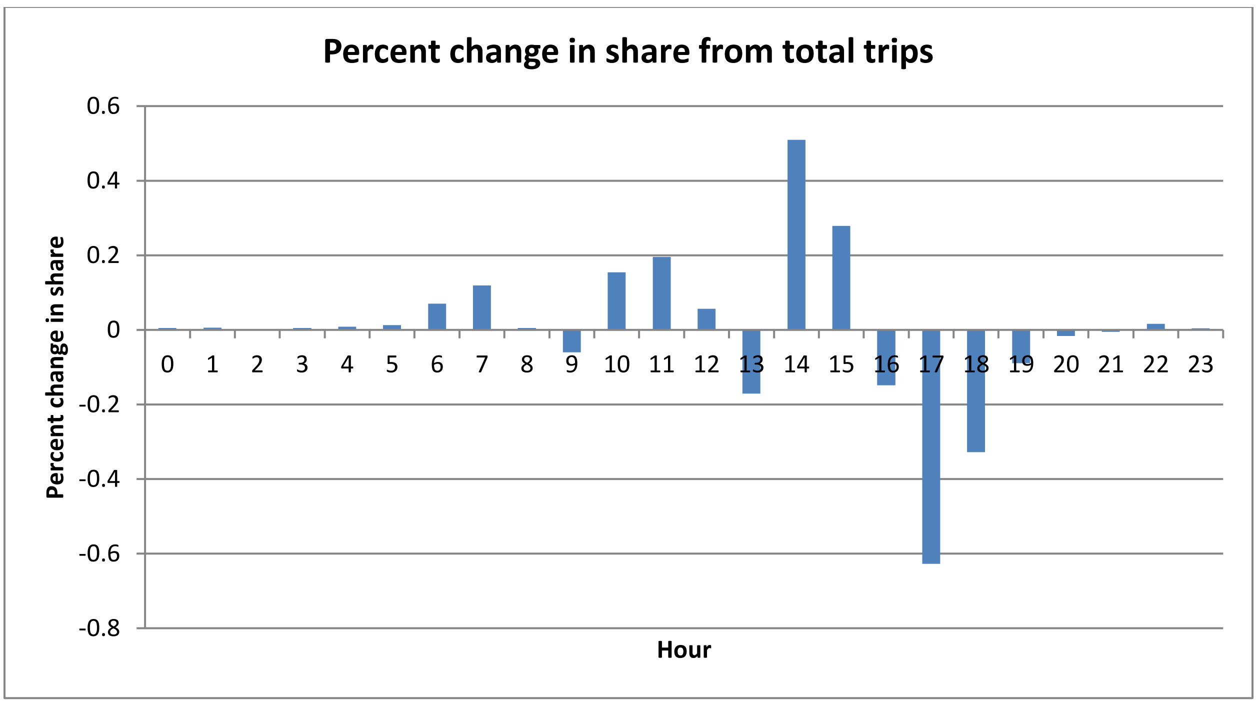

Figure 38 Predicted change in share from total NHBW trips

This trip purpose has afternoon peak shifts to earlier less congested intervals.

6.6 NON-HOME BASE OTHER TRIP RESULTS

Figure 38 shows the similar trend as previous figures. The only difference is the lower skim value for future year during night time, which should be a bug of MSTM results.

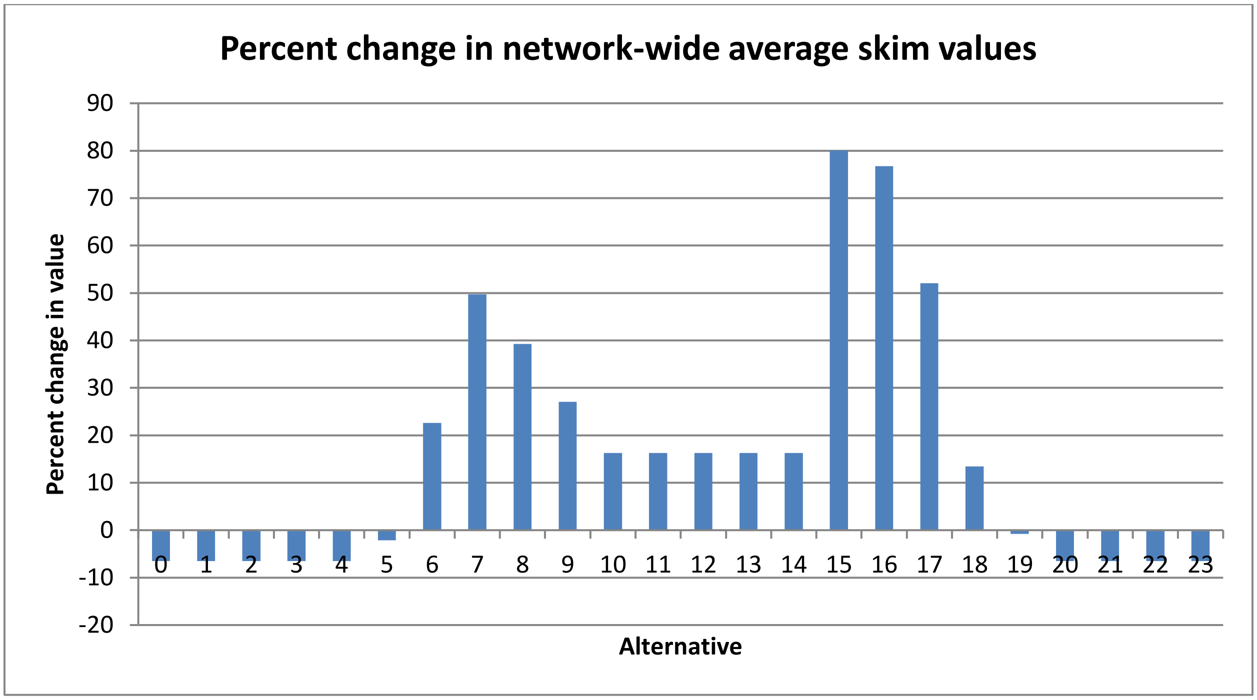

Figure 39 Percent change in network-wide average skim values for NHBO trips

Number of trips for base and future year are 478335 and 620676 respectively. Prediction outputs show some shifts in the afternoon period toward peak shoulders as it is showed in figures 39 and 40.

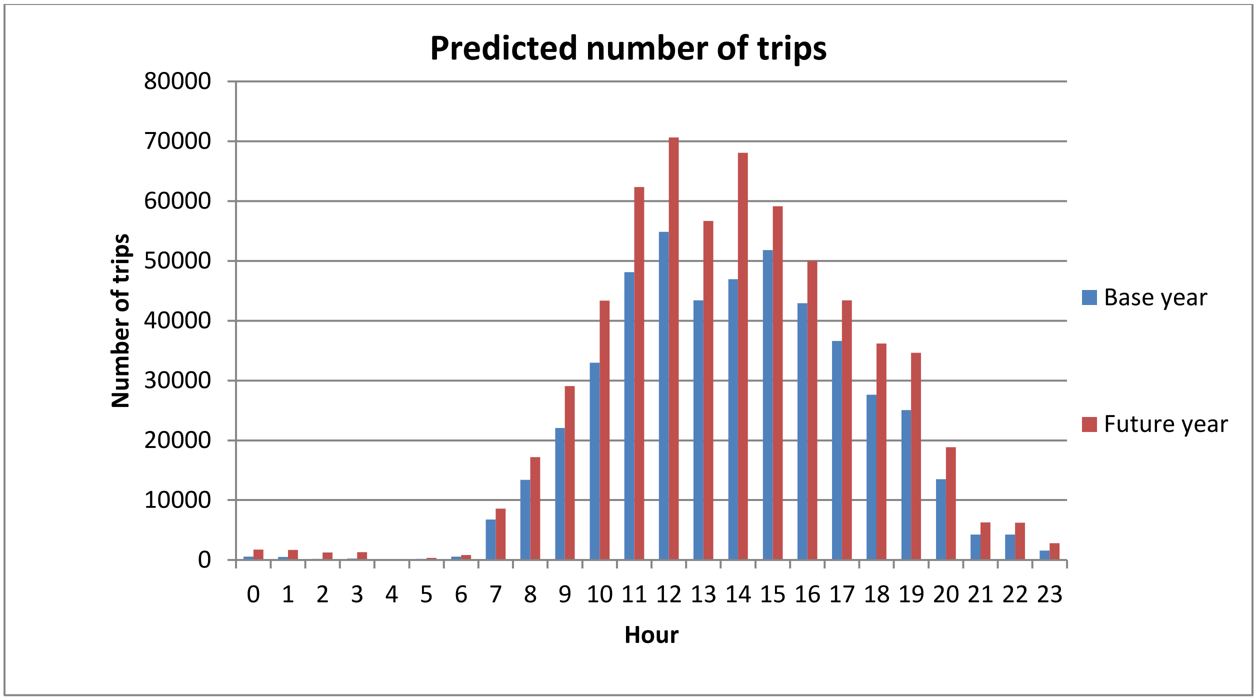

Figure 40 Predicted distribution of NHBO trips

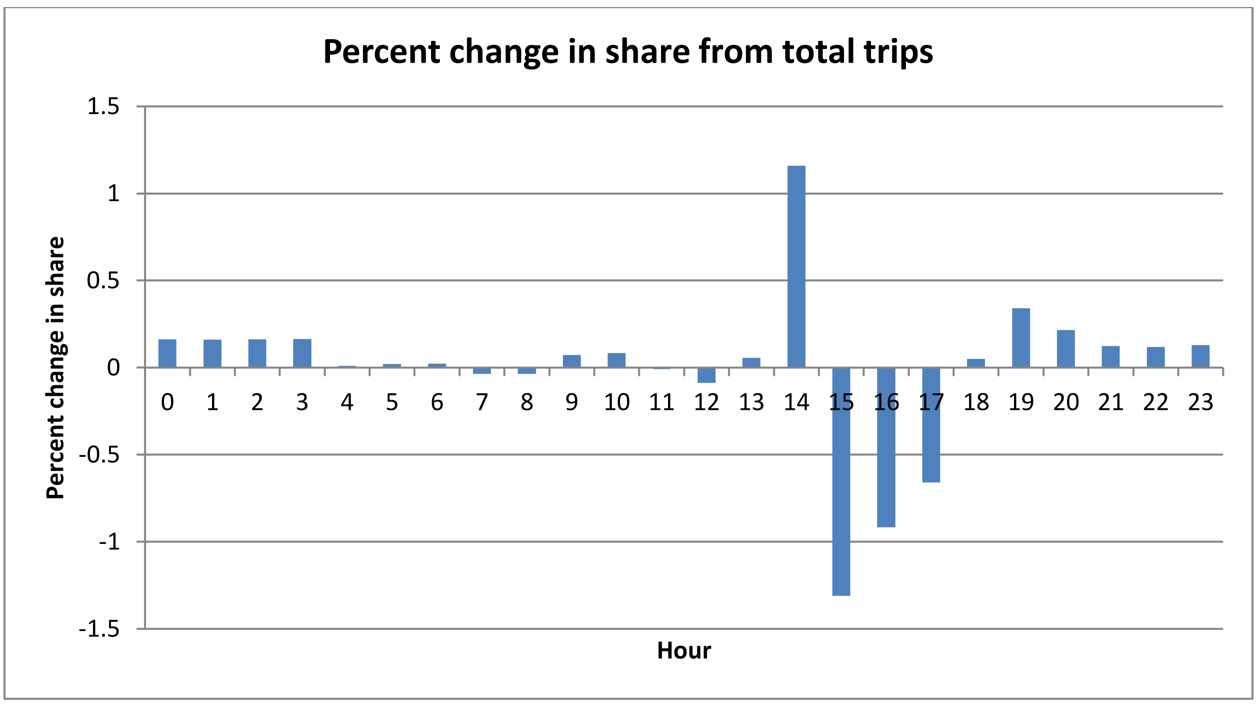

Figure 41 Percent change in share from total NHBO trips

6.7 OVERAL PEAK SPREADING RESULTS

Results of comparison between base year and future year demand profiles of different trip purposes were presented separately in previous sections. Now they are combined together to show the overall demand profile. The change in skim values is presented first in the Figures 41 and 42:

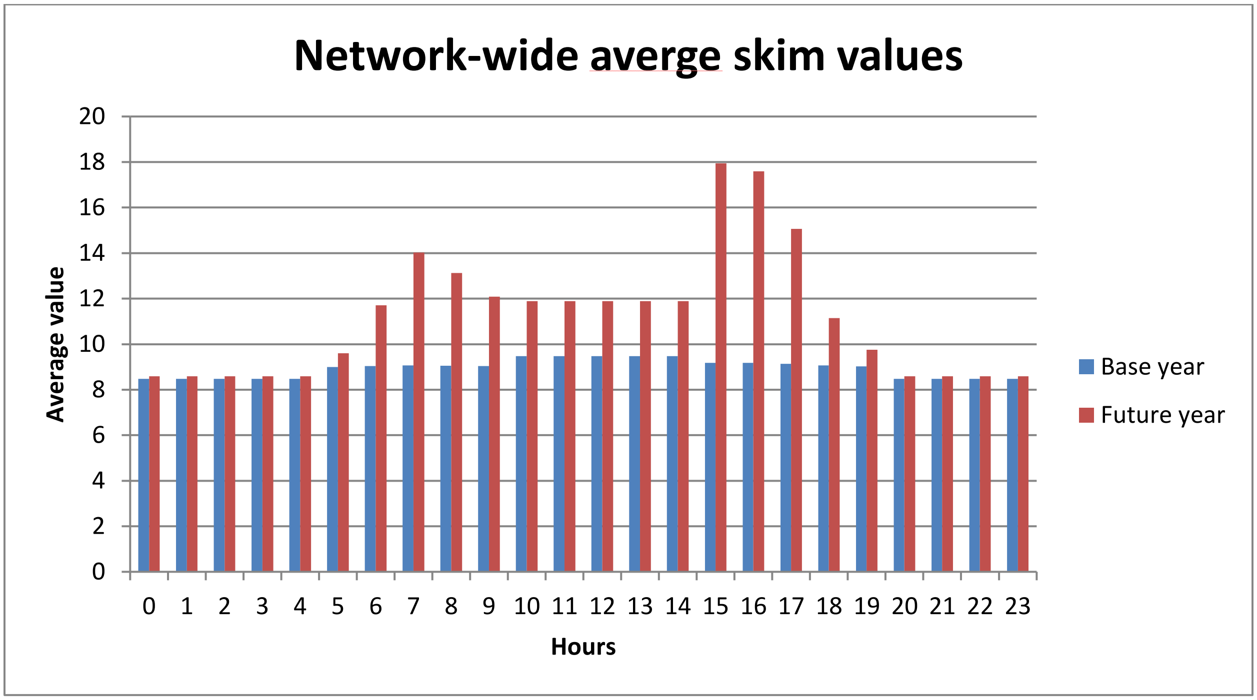

Figure 42 Overall network-wide average skim values

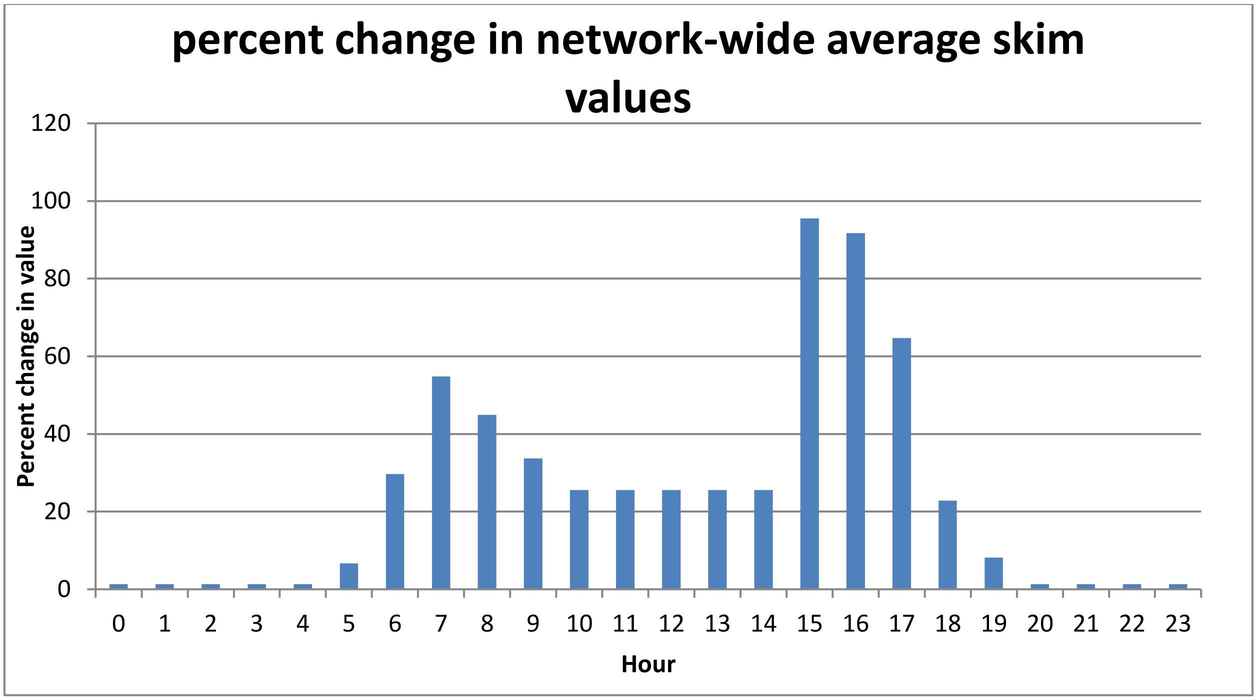

Figure 43 Percent change in overall network-wide average skim values

Based on these inputs, the overall prediction results are obtained and presented in Figures 43 and 44:

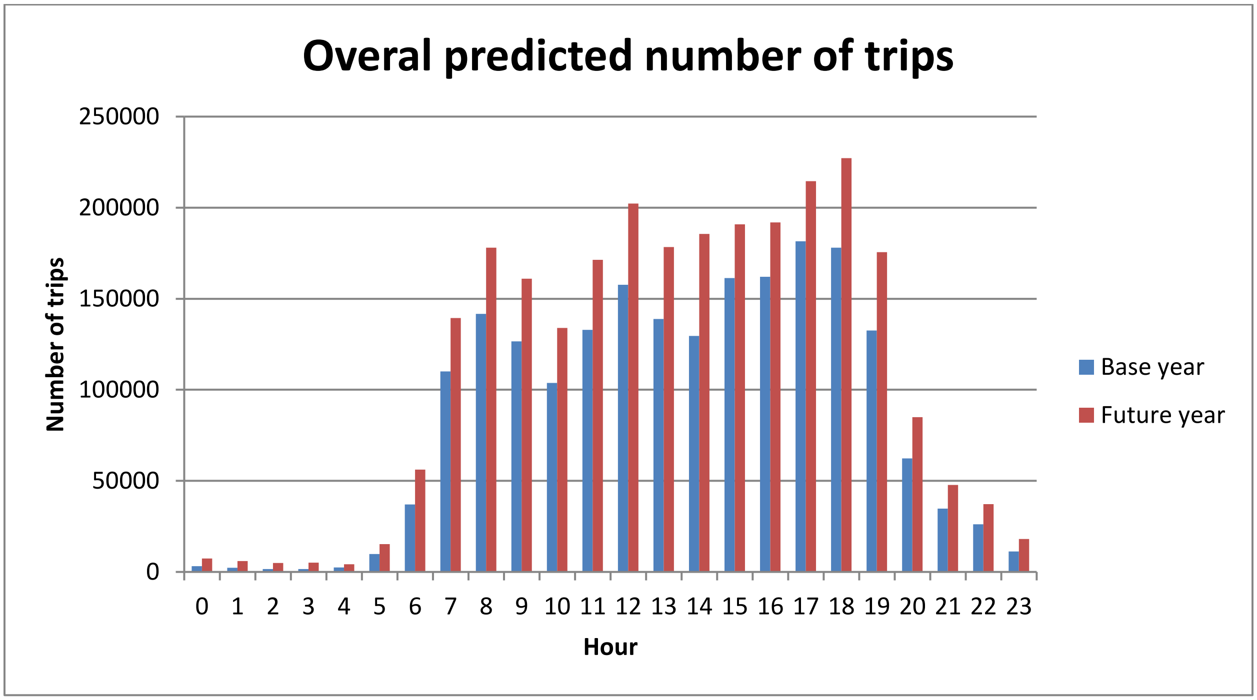

Figure 44 Overall predicted distribution of trips

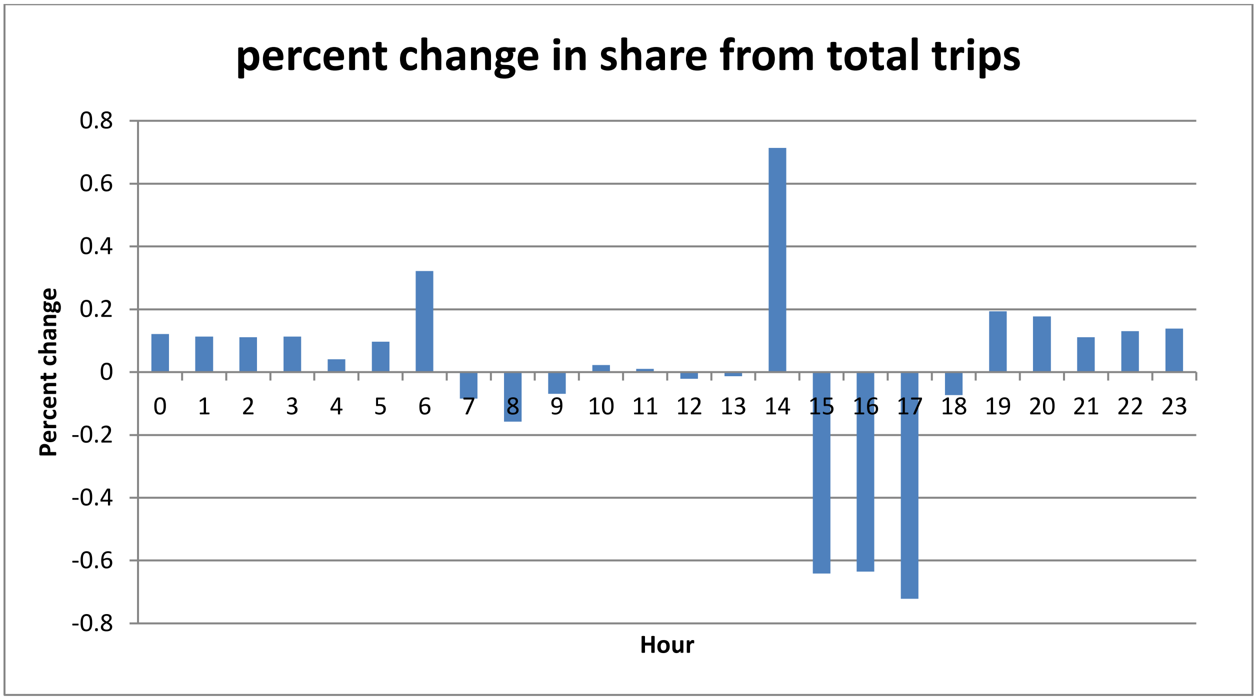

Figure 45 Percent change in share from total trips

The overall result shows that afternoon peak hour share will be decreased in the future year. Considerable amount of this shifted demand goes to the left peak shoulder. Slight shift can also be seen in the morning peak to the left shoulder of the peak.

It should be noted again, that this in the result of only one iteration to show how the framework works. More iterations are needed to reach improved results.

PEAK SPREADING CHAPTER 7: SUMMARY AND CONCLUSION

In this study discrete choice models were combined with MSTM to model departure time choice of the travelers in Montgomery County, Maryland. 12 time intervals were assumed as alternatives. Skim value, travel time reliability and scheduling delay penalties were considered as attributes. Separate models were estimated for each trip purposes. An iterative framework was proposed for model estimation, and results of one iteration were presented. The first step for the modeling was to edit cube codes of MSTM to produce skim matrices for 12 intervals. This was done by using static hourly factors for the first iteration. The hourly skims were combined with TPB-BMC Household Travel survey data to estimate a departure time choice model. No data was available on preferred arrival time of travelers and it was estimated using skim matrices. The estimated models showed negative effect of longer travel time, unreliability, and scheduling delay as expected. Scheduling delays showed to be less important for travelers in HBS, and HBO trips in comparison with HBW trips. Estimated models were used to predict demand distribution for two scenarios, base year (2007) and future year (2030). Another iterative method was proposed for forecasting and results of one iteration were presented. Prediction results were compared and slight changes in demand distribution were observed. It was shown that trips shift from peak hour to shoulders of the peak, specifically 6am and 14pm. While HBW showed more significant shift in the morning peak, other trip purposes had their major shift in the afternoon.

There are many ways to improve the results of this study for the future. First of all, the first iteration results should become the input for another round of iteration, and the process should be repeated until convergence. The model should also be expended to cover the entire state of Maryland. Another idea for improvement is about assumptions on the PAT. A travel survey that includes PAT information can be conducted, and it can be used in model estimation instead of HHTS. If the proposed model of PAT based on skims is being used, its parameter should be estimated using the dataset in the future. The reliability model is another part that can be improved. Incident and weather data can be added in the regression to better predict travel time reliability. In addition discrete choice models can be substituted by continuous choice models that can better represent temporal resolutions.

PEAK SPREADING CHAPTER 7: REFRENCES

Abrantes, P. A.; Wardman, M. R. Meta-analysis of UK values of travel time: An update. **Transportation Research Part A: Policy and Practice,** v. 45, n. 1, p. 1-17, 2011. ISSN 0965-8564.

Barnes, J. **Peak Spreading Analysis: Review of Relevant Issues and Synthesis of Current Practice, Phase I**. 1998

Bates, J. et al. The valuation of reliability for personal travel. **Transportation Research Part E: Logistics and Transportation Review,** v. 37, n. 2, p. 191-229, 2001. ISSN 1366-5545.

Ben-Akiva, M.; Morikawa, T.; Shiroishi, F. Analysis of the reliability of stated preference data in estimating mode choice models. TRANSPORT POLICY, MANAGEMENT & TECHNOLOGY TOWARDS 2001: SELECTED PROCEEDINGS OF THE FIFTH WORLD CONFERENCE ON TRANSPORT RESEARCH, 1989.

Bhat, C. R. Accommodating flexible substitution patterns in multi-dimensional choice modeling: formulation and application to travel mode and departure time choice. **Transportation Research Part B: Methodological,** v. 32, n. 7, p. 455-466, 1998a. ISSN 0191-2615.

______. Analysis of travel mode and departure time choice for urban shopping trips. **Transportation Research Part B: Methodological,** v. 32, n. 6, p. 361-371, 1998b. ISSN 0191-2615.

Bhat, C. R.; Sardesai, R. The impact of stop-making and travel time reliability on commute mode choice. **Transportation Research Part B: Methodological,** v. 40, n. 9, p. 709-730, 2006. ISSN 0191-2615.

Bhat, C. R.; Steed, J. L. A continuous-time model of departure time choice for urban shopping trips. **Transportation Research Part B: Methodological,** v. 36, n. 3, p. 207-224, 2002. ISSN 0191-2615.

Bierlaire, M. BIOGEME: a free package for the estimation of discrete choice models. Swiss Transport Research Conference, 2003.

Bolduc, D.; Ben-Akiva, M. A multinomial probit formulation for large choice sets. LES METHODES D'ANALYSE DES COMPORTEMENTS DE DEPLACEMENTS POUR LES ANNEES 1990-6E CONFERENCE INTERNATIONALE SUR LES COMPORTEMENTS DE DEPLACEMENTS, CHATEAU BONNE ENTENTE, QUEBEC, 22, 23, 24 MAI 1991, VOLUME 2, 1991.

Börjesson, M. Joint RP–SP data in a mixed logit analysis of trip timing decisions. **Transportation Research Part E: Logistics and Transportation Review,** v. 44, n. 6, p. 1025-1038, 2008. ISSN 1366-5545.

Cambridge Systematics, I. a. B.-A. A., Inc. **Advanced Urban Travel Demand Forecasting, prepared for the Travel Model Improvement Program, US Department of Transportation and the Federal Highway Administration, Washington DC , 1996**. report no. DOT

Cardell, N. S.; Dunbar, F. C. Measuring the societal impacts of automobile downsizing. **Transportation Research Part A: General,** v. 14, n. 5, p. 423-434, 1980. ISSN 0191-2607.

Carrion, C.; Levinson, D. Value of travel time reliability: A review of current evidence. **Transportation research part A: policy and practice,** v. 46, n. 4, p. 720-741, 2012. ISSN 0965-8564.

Chen, A. et al. Effect of route choice models on estimating network capacity reliability. **Transportation Research Record: Journal of the Transportation Research Board**, n. 1733, p. 63-70, 2000. ISSN 0361-1981.

Chen, C.; Skabardonis, A.; Varaiya, P. Travel time reliability as a measure of service, in '82nd Transportation Research Board'. **Washing DC, USA**, 2003.

Costinett, P. et al. **Maryland statewide transportation model user's guide: draft report**. Tech rep, Maryland DOT State Highway Administration. 2009

De Jong, G. et al. A model for time of day and mode choice using error components logit. **Transportation Research Part E: Logistics and Transportation Review,** v. 39, n. 3, p. 245-268, 2003. ISSN 1366-5545.

Dong, J.; Mahmassani, H. Flow breakdown and travel time reliability. **Transportation Research Record: Journal of the Transportation Research Board**, n. 2124, p. 203-212, 2009. ISSN 0361-1981.

Dowling, R. G. et al. Reliability Breakpoints on Freeways. Transportation Research Board 88th Annual Meeting, 2009.

FHA, D. **Travel time reliability: Making it there on time, all the time. US Department of Transportation, Federal Highway Administration** 2010.

Hyman, G. The development of operational models for time period choice. **Department of the Environment, Transport and the Regions, HETA Division, London**, 1997.

Jara-Díaz, S. **Transport economic theory**. 2007. ISBN 0080450288.

Koppelman, F. **Improving our Understanding of How Highway Congestion and Price Affect Travel Demand**. 2013. ISBN 0309129699.

Lam, T. C.; Small, K. A. The value of time and reliability: measurement from a value pricing experiment. **Transportation Research Part E: Logistics and Transportation Review,** v. 37, n. 2, p. 231-251, 2001. ISSN 1366-5545.

Lemp, J.; Kockelman, K. Empirical investigation of continuous logit for departure time choice with Bayesian methods. **Transportation Research Record: Journal of the Transportation Research Board**, n. 2165, p. 59-68, 2010. ISSN 0361-1981.

Levinson, D. The value of advanced traveler information systems for route choice. **Transportation Research Part C: Emerging Technologies,** v. 11, n. 1, p. 75-87, 2003. ISSN 0968-090X.

Levinson, D. et al. Weighting waiting: evaluating perception of in-vehicle travel time under moving and stopped conditions. **Transportation Research Record: Journal of the Transportation Research Board**, n. 1898, p. 61-68, 2004. ISSN 0361-1981.

Liu, H. X.; Recker, W.; Chen, A. Uncovering the contribution of travel time reliability to dynamic route choice using real-time loop data. **Transportation Research Part A: Policy and Practice,** v. 38, n. 6, p. 435-453, 2004. ISSN 0965-8564.

Liu, Y.-H.; Mahmassani, H. Dynamic aspects of commuter decisions under advanced traveler information systems: modeling framework and experimental results. **Transportation Research Record: Journal of the Transportation Research Board**, n. 1645, p. 111-119, 1998. ISSN 0361-1981.

Lomax, T. et al. Selecting travel reliability measures. **Texas Transportation Institute monograph (May 2003)**, 2003.

Loudon, W. R.; Ruiter, E. R.; Schlappi, M. L. **Predicting Peak-Spreading Under Congested Conditions**. 1988. ISBN 0309047692.

Lyman, K.; Bertini, R. Using travel time reliability measures to improve regional transportation planning and operations. **Transportation Research Record: Journal of the Transportation Research Board**, n. 2046, p. 1-10, 2008. ISSN 0361-1981.

Mahmassani, H. et al. SHRP 2 Report 52-L04-RR-1: Incorporating Reliability Performance Measures in Operations and Planning Modeling Tools. **Transportation Research Board of the National Academies, Washington, DC**, 2013.

McFadden, D. **Modelling the choice of residential location**. Institute of Transportation Studies, University of California, 1978.

McFadden, D.; Train, K. Mixed MNL models for discrete response. **Journal of applied Econometrics,** v. 15, n. 5, p. 447-470, 2000. ISSN 0883-7252.

Mishra, S. et al. Development of Maryland statewide transportation model and its application in scenario planning. Transportation Research Board 92nd Annual Meeting, 2013.

______. A functional integrated land use-transportation model for analyzing transportation impacts in the Maryland-Washington, DC Region. **Sustainability: Science, Practice, & Policy,** v. 7, n. 2, p. 60-69, 2011. ISSN 1548-7733.

Noland, R. B.; Polak, J. W. Travel time variability: a review of theoretical and empirical issues. **Transport Reviews,** v. 22, n. 1, p. 39-54, 2002. ISSN 0144-1647.

Pu, W. Analytic relationships between travel time reliability measures. **Transportation Research Record: Journal of the Transportation Research Board**, n. 2254, p. 122-130, 2011. ISSN 0361-1981.

Rakha, H. et al. Estimating path travel-time reliability. Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE, 2006, IEEE. p.236-241.

Shires, J. D.; De Jong, G. C. An international meta-analysis of values of travel time savings. **Evaluation and program planning,** v. 32, n. 4, p. 315-325, 2009. ISSN 0149-7189.

Small, K. A. The scheduling of consumer activities: work trips. **The American Economic Review**, p. 467-479, 1982. ISSN 0002-8282.

______. A discrete choice model for ordered alternatives. **Econometrica: Journal of the Econometric Society**, p. 409-424, 1987. ISSN 0012-9682.

Small, K. A.; Verhoef, E. T. **The economics of urban transportation**. Routledge, 2007. ISBN 1134495706.

Sumalee, A.; Watling, D. P. Partition‐based algorithm for estimating transportation network reliability with dependent link failures. **Journal of Advanced Transportation,** v. 42, n. 3, p. 213-238, 2008. ISSN 2042-3195.

Systematics, C. Inc., Dowling Associates, Inc., System Metrics Group, Inc., Texas Transportation Institute (2008) NCHRP Report 618: Cost-effective performance measures for travel time delay, variation, and reliability. **Transportation Research Board, Washington, DC,** v. 9,

______. **Analytical procedures for determining the impacts of reliability mitigation strategies**. Transportation Research Board, 2013. ISBN 0309129265.

Tilahun, N. Y.; Levinson, D. M. A moment of time: reliability in route choice using stated preference. **Journal of Intelligent Transportation Systems,** v. 14, n. 3, p. 179-187, 2010. ISSN 1547-2450.

Van Lint, J.; Van Zuylen, H. Monitoring and predicting freeway travel time reliability: using width and skew of day-to-day travel time distribution. **Transportation Research Record: Journal of the Transportation Research Board**, n. 1917, p. 54-62, 2005. ISSN 0361-1981.

van Vuren, T. et al. Modelling peak spreading in continuous time. TRANSPORTATION PLANNING METHODS. PROCEEDINGS OF SEMINAR F, EUROPEAN TRANSPORT CONFERENCE, 27-29 SEPTEMBER 1999, CAMBRIDGE, UK., 1999.

Vickrey, W. S. Congestion theory and transport investment. **The American Economic Review**, p. 251-260, 1969. ISSN 0002-8282.

Wang, J. J. Timing utility of daily activities and its impact on travel. **Transportation Research Part A: Policy and Practice,** v. 30, n. 3, p. 189-206, 1996. ISSN 0965-8564.

Xiong, C.; Zhang, L. Positive model of departure time choice under road pricing and uncertainty. **Transportation Research Record: Journal of the Transportation Research Board**, n. 2345, p. 117-125, 2013. ISSN 0361-1981.

Zamparini, L.; Reggiani, A. Meta-analysis and the value of travel time savings: a transatlantic perspective in passenger transport. **Networks and Spatial Economics,** v. 7, n. 4, p. 377-396, 2007. ISSN 1566-113X.

Zeid, M.; Rossi, T.; Gardner, B. Modeling time-of-day choice in context of tour-and activity-based models. **Transportation Research Record: Journal of the Transportation Research Board**, n. 1981, p. 42-49, 2006. ISSN 0361-1981.

Zhang, L. Developing a positive approach to travel demand forecasting: Theory and model. **Traffic and Transportation Theory,** v. 17, p. 136-150, 2007.

______. Travel Time Reliability as an Emergent Property of Transportation Networks. Transportation Research Board 91st Annual Meeting, 2012.

APPENDIX

Peak Spreading Data Preparation Methodology

I Introduction

This appendix summarizes how the trip tables and skim matrices data were obtained for each origin destination pair for both the base year (2007) and the future year (2030). The steps to obtain these data include running the MSTM and obtaining trips and skims for the required time period. The appendix also provides the CUBE scripts for extracting the trip and skim data.

II MSTM trip tables:

The first step in this procedure included extracting the Montgomery sub-area within MSTM. This was performed in CUBE and is based on version 1.0.60 of the MSTM. The script that was executed for this process was written in CUBE. It is a modified version of the highway assignment script. Upon completion of the script, a set of 6 O-D trip matrices will be created for 4 time periods. The four time period matrices are converted into 12 time period OD trip matrices using the 12 time period factors. The trip matrices are then added for all 12 time periods for each of the six trip purposes to create six O-D trip matrices. The following is the CUBE script for the highway sub area analysis for extracting the trip matrices:

<u>Script I</u>

```
; Maryland Statewide Travel Demand Model (MSTM)
;
;===========================================================================
READ File = '..\..\stamp.log'
LOOP ToD=1,4
  IF (ToD=1) prd = 'AM'  , Ispk = 'PK', prd2='AM' , spd='CONGSPD', ConFac = 0.39
  IF (ToD=2) prd = 'MD'  , Ispk = 'OP', prd2='OP' , spd='CONGSPD', ConFac = 0.21
  IF (ToD=3) prd = 'PM'  , Ispk = 'PK', prd2='PM' , spd='CONGSPD', ConFac = 0.34
  IF (ToD=4) prd = 'NT'  , Ispk = 'OP', prd2='OP' , spd='FFSPD',   ConFac = 0.22

; Highway Assignment for all vehicles
RUN PGM=HIGHWAY   PRNFILE='..\@scenario@\Outputs\@prd@ Highway Assignment SA.PRN'  MSG='@prd@ Sub
Area Highway Assignment'
  NETI     =  ..\..\@scenario@\Inputs\MSTM.net              ;Input Network
  MATI[1 ] = ..\..\@scenario@\Outputs\Veh_HBW1_@prd@.trp     ; <--+
  MATI[2 ] = ..\..\@scenario@\Outputs\Veh_HBW2_@prd@.trp     ;    |
  MATI[3 ] = ..\..\@scenario@\Outputs\Veh_HBW3_@prd@.trp     ;    |
  MATI[4 ] = ..\..\@scenario@\Outputs\Veh_HBW4_@prd@.trp     ;    |
  MATI[5 ] = ..\..\@scenario@\Outputs\Veh_HBW5_@prd@.trp     ;    |
  MATI[6 ] = ..\..\@scenario@\Outputs\Veh_HBS1_@prd@.trp     ;    |
  MATI[7 ] = ..\..\@scenario@\Outputs\Veh_HBS2_@prd@.trp     ;    |
  MATI[8 ] = ..\..\@scenario@\Outputs\Veh_HBS3_@prd@.trp     ;    |
  MATI[9 ] = ..\..\@scenario@\Outputs\Veh_HBS4_@prd@.trp     ;    |      T1: SOV
  MATI[10] = ..\..\@scenario@\Outputs\Veh_HBS5_@prd@.trp     ;    |      T2: HOV2
  MATI[11] = ..\..\@scenario@\Outputs\Veh_HBO1_@prd@.trp     ;    |      T2: HOV3
  MATI[12] = ..\..\@scenario@\Outputs\Veh_HBO2_@prd@.trp     ;    |
```

```
  MATI[13] = ..\..\@scenario@\Outputs\Veh_HBO3_@prd@.trp     ;    |
  MATI[14] = ..\..\@scenario@\Outputs\Veh_HBO4_@prd@.trp     ;    |
  MATI[15] = ..\..\@scenario@\Outputs\Veh_HBO5_@prd@.trp     ;    |
  MATI[16] = ..\..\@scenario@\Outputs\Veh_HBSc_@prd@.trp     ;    |
  MATI[17] = ..\..\@scenario@\Outputs\Veh_NHBW_@prd@.trp     ;    |
  MATI[18] = ..\..\@scenario@\Outputs\Veh_OBO_@prd@.trp
;=========== Added for Subarea Analysis ==============
     FILEI SUBAREANETI = ..\..\@scenario@\Inputs\Mont_subarea.net     ;<--- Revise SubArea
Network as needed
;====================================================

  FILEO NETO = ..\..\@scenario@\Outputs\MSTMHwySAAsgn_@prd@.tmp ;<--- Revise SubArea Trip Table
Outputs as needed
  MATO[1]=..\..\@scenario@\Outputs\RT_Dist_@prd@.skm, MO=21-22

;=========== Added for Subarea Analysis ==============
   FILEO SUBAREAMATO = ..\..\@scenario@\outputs\MontCo_@prd@.trp
;====================================================

 ; DistributeINTRASTEP ProcessID='HwyAssignIDP',ProcessList=1-@maxcores@,MinGroupSize=77,
SavePrn=T

  ;Set run PARAMETERS and Controls
  PARAMETERS ZONEMSG=100,  MAXITERS=@maxIterns@, COMBINE=EQUI, GAP= 0.0, RELATIVEGAP =
@RelativeGap@

PHASE=LINKREAD

  T0 = 60* (LI.DISTANCE/LI.@spd@)
  C  = LI.@Ispk@CAP*LI.@prd2@LANE/@ConFac@

  LW.COSTa = T0 + (LI.TOLL@ispk@/@VoTa@) + 0.25*LI.DISTANCE
  LW.COSTb = T0 + (LI.TOLL@ispk@/@VoTb@) + 0.25*LI.DISTANCE
  LW.COSTc = T0 + (LI.TOLL@ispk@/@VoTc@) + 0.25*LI.DISTANCE
  LW.COSTd = T0 + (LI.TOLL@ispk@/@VoTd@) + 0.25*LI.DISTANCE
  LW.COSTe = T0 + (LI.TOLL@ispk@/@VoTe@) + 0.25*LI.DISTANCE
  ; update COSTf: average of free-flow time and congested speed is used for regional autos and
trucks
  LW.COSTf = ((LI.DISTANCE*60)/LI.FFSPD * 0.5 + T0 * 0.5) + (LI.TOLL@ispk@/@VoTe@) +
0.25*LI.DISTANCE

 ; Recode facility type (SWFT) into VDF groups.
  IF (LI.SWFT = 1,2,3,7,8,9)      LINKCLASS = 1     ; Freeway/Expwy & Ramps
  IF (LI.SWFT = 4,5,6)            LINKCLASS = 2     ; Arterial
  IF (LI.SWFT = 10)               LINKCLASS = 3     ; Collectors/Local
  IF (LI.SWFT = 11)               LINKCLASS = 4     ; Centroid Connectors

       ; Set link usage restrictions for this period.  Definitions:
       ; 0,1 = no restriction            3 = HOV3
       ; 2   = HOV2                      4 = no trucks
       ; 6   = Transit Only              9 = No vehicles at all

;Rail tracks, Drive to PNR, and other PNR/Transit Links OR  No vehicles and Transit vehicles Only
Links)

  IF (LI.SWFT= 13,15,21,22,23,24 || LI.@prd2@LIMIT = 6,9) ADDTOGROUP = 1
  IF (LI.@prd2@LIMIT = 4)                                 ADDTOGROUP = 2      ; no Trucks (MT or
HT)
  IF (LI.@prd2@LIMIT = 2)                                 ADDTOGROUP = 3      ; HOV2  only
  IF (LI.@prd2@LIMIT = 3)                                 ADDTOGROUP = 4      ; HOV3+ only

ENDPHASE

PHASE=ILOOP
; HBW
  MW[1] = MI.1.1 + MI.2.1 + MI.3.1 + MI.4.1 + MI.5.1  +   ; (SOV HBW trips (all Incomes)
          MI.1.2 + MI.2.2 + MI.3.2 + MI.4.2 + MI.5.2  +   ; (HV2 HBW trips (all Incomes)
          MI.1.3 + MI.2.3 + MI.3.3 + MI.4.3 + MI.5.3      ; (HV3 HBW trips (all Incomes)
 ; HBS
  MW[2] = MI.6.1 + MI.7.1 + MI.8.1 + MI.9.1 + MI.10.1  +   ; (SOV HBS trips (all Incomes)
          MI.6.2 + MI.7.2 + MI.8.2 + MI.9.2 + MI.10.2  +   ; (HV2 HBS trips (all Incomes)
```

```
        MI.6.3 + MI.7.3 + MI.8.3 + MI.9.3 + MI.10.3      ; (HV3 HBS trips (all Incomes)
  ;HBO
  MW[3] = MI.11.1 + MI.12.1 + MI.13.1 + MI.14.1 + MI.15.1  +   ; (SOV HBO trips (all Incomes)
          MI.11.2 + MI.12.2 + MI.13.2 + MI.14.2 + MI.15.2  +   ; (HV2 HBO trips (all Incomes)
          MI.11.3 + MI.12.3 + MI.13.3 + MI.14.3 + MI.15.3      ; (HV3 HBO trips (all Incomes)
 ; HBSC
  MW[4] = MI.16.1 + MI.16.2 + MI.16.3

  ;NHBW

  MW[5] = MI.17.1 + MI.17.2 + MI.17.3

   ;OBO

  MW[6] = MI.18.1 + MI.18.2 + MI.18.3

/*
  ; SOV
  PATHLOAD VOL[1 ] = MI.1.1+MI.6.1 +MI.11.1,                           EXCLUDEGROUP=1,3,4,
PATH=LW.COSTa      ; Inc Gp 1
  PATHLOAD VOL[2 ] = MI.2.1+MI.7.1 +MI.12.1,                           EXCLUDEGROUP=1,3,4,
PATH=LW.COSTb      ; Inc Gp 2
  PATHLOAD VOL[3 ] = MI.3.1+MI.8.1 +MI.13.1 +MI.16.1+MI.17.1+MI.18.1,  EXCLUDEGROUP=1,3,4,
PATH=LW.COSTc      ; Inc Gp 3
  PATHLOAD VOL[4 ] = MI.4.1+MI.9.1 +MI.14.1,                           EXCLUDEGROUP=1,3,4,
PATH=LW.COSTd      ; Inc Gp 4
  PATHLOAD VOL[5 ] = MI.5.1+MI.10.1+MI.15.1,                           EXCLUDEGROUP=1,3,4,
PATH=LW.COSTe      ; Inc Gp 5
  ; HOV2
  PATHLOAD VOL[6 ] = MI.1.2+MI.6.2 +MI.11.2,                           EXCLUDEGROUP=1,4,
PATH=LW.COSTa      ; Inc Gp 1
  PATHLOAD VOL[7 ] = MI.2.2+MI.7.2 +MI.12.2,                           EXCLUDEGROUP=1,4,
PATH=LW.COSTb      ; Inc Gp 2
  PATHLOAD VOL[8 ] = MI.3.2+MI.8.2 +MI.13.2 +MI.16.2+MI.17.2+MI.18.2,  EXCLUDEGROUP=1,4,
PATH=LW.COSTc      ; Inc Gp 3
  PATHLOAD VOL[9 ] = MI.4.2+MI.9.2 +MI.14.2,                           EXCLUDEGROUP=1,4,
PATH=LW.COSTd      ; Inc Gp 4
  PATHLOAD VOL[10] = MI.5.2+MI.10.2+MI.15.2,                           EXCLUDEGROUP=1,4,
PATH=LW.COSTe      ; Inc Gp 5
  ; HOV3+
  PATHLOAD VOL[11] = MI.1.3+MI.6.3 +MI.11.3,                           EXCLUDEGROUP=1,
PATH=LW.COSTa      ; Inc Gp 1
  PATHLOAD VOL[12] = MI.2.3+MI.7.3 +MI.12.3,                           EXCLUDEGROUP=1,
PATH=LW.COSTb      ; Inc Gp 2
  PATHLOAD VOL[13] = MI.3.3+MI.8.3 +MI.13.3 +MI.16.3+MI.17.3+MI.18.3,  EXCLUDEGROUP=1,
PATH=LW.COSTc      ; Inc Gp 3
  PATHLOAD VOL[14] = MI.4.3+MI.9.3 +MI.14.3,                           EXCLUDEGROUP=1,
PATH=LW.COSTd      ; Inc Gp 4
  PATHLOAD VOL[15] = MI.5.3+MI.10.3+MI.15.3,                           EXCLUDEGROUP=1,
PATH=LW.COSTe      ; Inc Gp 5

  PATHLOAD VOL[16] = MI.19.1,                                          EXCLUDEGROUP=1,3,4,
PATH=LW.COSTe      ; CV
  PATHLOAD VOL[17] = MI.19.2,                                          EXCLUDEGROUP=1,2,3,4,
PATH=LW.COSTe, MW[21]=pathtrace(LI.distance), NOACCESS=0 ; sdSUT
  PATHLOAD VOL[18] = MI.19.3,                                          EXCLUDEGROUP=1,2,3,4,
PATH=LW.COSTe      ; sdMUT
  PATHLOAD VOL[19] = MI.19.4,                                          EXCLUDEGROUP=1,2,3,4,
PATH=LW.COSTf, MW[22]=pathtrace(LI.distance), NOACCESS=0  ; ldTRK
  PATHLOAD VOL[20] = MI.19.5,                                          EXCLUDEGROUP=1,
PATH=LW.COSTf      ; RA+ EE Autos
*/

  ; Coarse assignment (to reduce model run times)
  ; All incomes are combined and assumed to be "COSTc"
  ; SOV, HOV2 and HOV3 are all combined and assumed to be SOV
  ; Trucks, Commercial Vehicles and Regional Autos are not assigned.


  PATHLOAD        VOL[1] = MW[1],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD        VOL[2] = MW[2],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
```

```
  PATHLOAD        VOL[3] = MW[3],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD        VOL[4] = MW[4],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD        VOL[5] = MW[5],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD        VOL[6] = MW[6],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc

  ;SUB AREA ANALYSIS
  PATHLOAD SUBAREAMAT[1] = MW[1],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD SUBAREAMAT[2] = MW[2],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD SUBAREAMAT[3] = MW[3],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD SUBAREAMAT[4] = MW[4],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD SUBAREAMAT[5] = MW[5],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc
  PATHLOAD SUBAREAMAT[6] = MW[6],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc

ENDPHASE

PHASE=ADJUST

function {
;    V=VOL[1]+VOL[2]+VOL[3]+VOL[4]+VOL[5]+ VOL[6]+VOL[7]+VOL[8]+VOL[9]+ VOL[10]+ VOL[11]+
;      VOL[12]+ VOL[13]+ VOL[14]+ VOL[15]+ VOL[16]+ VOL[17]*@PCE_SUT@+ VOL[18]*@PCE_MUT@+
VOL[19]*@PCE_ldTRK@+ VOL[20]

    V = VOL[1] + VOL[2]
    TC[1] = Min(T0 * (1 + 0.70*(V/C)^8), T0*100)
    TC[2] = Min(T0 * (1 + 0.55*(V/C)^6), T0*100)
    TC[3] = Min(T0 * (1 + 0.17*(V/C)^4), T0*100)
    TC[4] = T0
    }

  LW.COSTa=TIME + (LI.TOLL@Ispk@/@VoTa@) + 0.25*LI.DISTANCE
  LW.COSTb=TIME + (LI.TOLL@Ispk@/@VoTb@) + 0.25*LI.DISTANCE
  LW.COSTc=TIME + (LI.TOLL@Ispk@/@VoTc@) + 0.25*LI.DISTANCE
  LW.COSTd=TIME + (LI.TOLL@Ispk@/@VoTd@) + 0.25*LI.DISTANCE
  LW.COSTe=TIME + (LI.TOLL@Ispk@/@VoTe@) + 0.25*LI.DISTANCE
  ; update COSTf: average of free-flow time and congested speed is used for regional autos and
trucks
  LW.COSTf = ((LI.DISTANCE*60)/LI.FFSPD * 0.5 + TIME * 0.5) + (LI.TOLL@ispk@/@VoTe@) +
0.25*LI.DISTANCE

ENDPHASE
ENDRUN
ENDLOOP

*del *.prn
*del *.bak
*del *.prj
*del *.var
*del *.000
*del *.001
*del *.002
*del *.003
*del *.004
*del *.005
```

Stamp.log file:

```
;USER-DEFINED PARAMETERS ENTERED AT MODEL EXECUTION
;
START_TIME = '04:24 PM'
START_DATE = '08/13/2014'
SCENARIO   = 'CLRP30_2040'
PREFIX     = 'CLRP30'
YEAR       = '2040'
ITERS      = 6
MAXCORES   = 24
MaxIterns  = 50
;
;----- END OF USER-DEFINED PARAMETERS -----
; MSTM
; parameter.dat
; various zone ranges and other parameters needed to run all steps of the model
;
; General parameters
;
YEAR = '2040'
VERS = '1.0.60'
zones =1873                             ;Highest zone number
zoneblank='600-608,1010-1018,1084-1092,1179-1187,1272-1280,1429-1437,1461-1469,1500-1508,1606-
1614,1646-1650,1675-1683,1698-1832'
zoneblank2='600-608,1010-1018,1084-1092,1179-1187,1272-1280,1429-1437,1461-1469,1500-1508,1606-
1614,1675-1683,1698-1832'
lastSMZ=1674
washzones = '1188-1307'
baltzones = '1-110'
cbdzones  = '1-110,1188-1271,1281-1304'
riverReg1 = '1-599,609-1009,1054-1083,1188-1271,1625-1633,1667-1674'
riverReg2 = '1093-1178,1450-1460,1509-1605,1658-1666'
riverReg3 = '1019-1053,1281-1428,1438-1449,1470-1499,1615-1624'
baltReg3  = '111-405,525-599'
baltReg5  = '406-524,944-966'
washReg4  = '609-943,1308-1355'
washReg6  = '992-1009,1356-1397'
rurReg7   = '967-991'
rurReg8   = '1398-1442,1470-1499'
SurveyZones = '1-174,176-210,212-368,370-599,609-744,747,749-765,767-928,930-934,937-939,943-
1009,1188-1197,1199-1208,1210-1271,1281-1428,1470-1473'
Extreg1  = '1509-1543,1634-1645'
Extreg2  = '1615-1633'
Extreg3  = '1093-1178,1443-1460,1544-1605'
Extreg4  = '1019-1083'
```

```
MontgomeryCounty = '609-766,773'
PrinceGeorgesCounty = '767-772,774-943'
BaltimoreCityCounty = '1-110'
BaltimoreCounty = '218-405'
HowardCounty = '525-599'
WashingtonDCCounty = '1188-1271'
AnneArundelCounty = '111-217'

; Highway skim parameters
odtrace = '(i=777 && j=797)'          ; Trace zones for hwy skim

; Trip generation parameters
doGQ     = 1                            ; 1 to include GQ trips, 0 to exclude

cbd      = '62-69,1188-1194'            ; CBD zones (Balt., Wash.)
tgtrace  = '0'                          ; Trace zone for generation (pick one zone only)

; Trip distribution parameters
tdtrace  = '0'                          ; Trace zones for distribution

; Mode choice parameters
row      = 0                            ; production zone to trace (0= no trace)
col      = 0                            ; attraction zone to trace (0= no trace)
hovdef   = 2                            ; minimum occupancy for HOV lanes
opcostmi =  9.9                         ; Auto Operating Cost, Cents/mi (in 2000 $)
skimwarn = 1                            ; 1 = Warn If Transit Access but No Paths
avgDurWk = 6                            ; average parking duration; work trips; hours
avgDurNw = 2                            ; average parking duration; non-work trips; hours
LowRailNode = 4105                      ; lowest rail node number ; It was earlier rail1
HiRailNode = 4499                       ; highest rail node number ; It was earlier rail2
LowMarcNode   = 4000                    ; lowest MARC node number
HiMarcNode   = 4100                     ; highest MARC node number
LowBusNode = 5000                       ; lowest bus node number (called bus1 earlier)
crivtfac = 0.75                         ; commuter rail IVT adjustment factor

; Assignment parameters
RelativeGap = .005
;
VoTa = 8.4
VoTb = 25
VoTc = 41.7
VoTd = 50.4
VoTe = 106.4      ; Value of time, in cents/minute (equiv. to $14/hour) (for income class e ,
most expensive)
VoT  =  23.33     ; Average value of time in cents/minute (equiv. to $14/hour)
```

```
PCE_SUT = 1.5
PCE_MUT = 2.5
PCE_ldTRK = 2.0

END_TIME   = '06:30 AM'
END_DATE   = '08/14/2014'
SCENARIO   = 'CLRP30_2040'
```

III MSTM skim matrices:

Once the trip matrices are created, the 12 time period travel time matrices or skims are created using the congested speed of the links of the Montgomery sub-area network. The CUBE Script II is used to create the sub-area network files which consists the congested speed of the links. Finally, CUBE Script III is used for creating the travel time matrices or skims for the links for which the output of Script II is used as the input.

<u>Script II</u>

```
; Maryland Statewide Travel Demand Model (MSTM)
; Script: Highway Assignment for Sub Area Analysis
;         12 periods
;===========================================================================

READ File = '..\..\stamp.log'

LOOP ToD=1,12
  IF (ToD=1)  prd = 'AM_period_1'  , Ispk = 'PK', prd2='AM' , spd='CONGSPD', ConFac = 1
  IF (ToD=2)  prd = 'AM_period_2'  , Ispk = 'PK', prd2='AM' , spd='CONGSPD', ConFac = 1
  IF (ToD=3)  prd = 'AM_period_3'  , Ispk = 'PK', prd2='AM' , spd='CONGSPD', ConFac = 1
  IF (ToD=4)  prd = 'AM_period_4'  , Ispk = 'PK', prd2='AM' , spd='CONGSPD', ConFac = 1
  IF (ToD=5)  prd = 'AM_period_5'  , Ispk = 'PK', prd2='AM' , spd='CONGSPD', ConFac = 1
  IF (ToD=6)  prd = 'MD_period_6'  , Ispk = 'OP', prd2='OP' , spd='CONGSPD', ConFac = 0.210
  IF (ToD=7)  prd = 'PM_period_7'  , Ispk = 'PK', prd2='PM' , spd='CONGSPD', ConFac = 1
  IF (ToD=8)  prd = 'PM_period_8'  , Ispk = 'PK', prd2='PM' , spd='CONGSPD', ConFac = 1
  IF (ToD=9)  prd = 'PM_period_9'  , Ispk = 'PK', prd2='PM' , spd='CONGSPD', ConFac = 1
  IF (ToD=10) prd = 'PM_period_10' , Ispk = 'PK', prd2='PM' , spd='CONGSPD', ConFac = 1
  IF (ToD=11) prd = 'PM_period_11' , Ispk = 'PK', prd2='PM' , spd='CONGSPD', ConFac = 1
  IF (ToD=12) prd = 'NT_period_12' , Ispk = 'OP', prd2='OP' , spd='FFSPD',   ConFac = 0.220


; Highway Assignment for all vehicles
RUN PGM=HIGHWAY   PRNFILE='Assign\@prd@ Highway Assignment SA.PRN'  MSG='@prd@ Sub Area Highway
Assignment'

  NETI       =  Assign\MontCo.net               ;Input Network
  MATI[1]    =  Assign\@prd@.trp

  FILEO NETO = Assign\@prd@.net

  DistributeINTRASTEP ProcessID='HwyAssignIDP',ProcessList=1-@maxcores@,MinGroupSize=77,
SavePrn=T

  ;Set run PARAMETERS and Controls
  PARAMETERS ZONEMSG=100,  MAXITERS=@maxIterns@, COMBINE=EQUI, GAP= 0.0, RELATIVEGAP =
@RelativeGap@

PHASE=LINKREAD
```

```
  T0 = 60* (LI.DISTANCE/LI.@spd@)
  C  = LI.@Ispk@CAP*LI.@prd2@LANE/@ConFac@

  LW.COSTa = T0 + (LI.TOLL@ispk@/@VoTa@) + 0.25*LI.DISTANCE
  LW.COSTb = T0 + (LI.TOLL@ispk@/@VoTb@) + 0.25*LI.DISTANCE
  LW.COSTc = T0 + (LI.TOLL@ispk@/@VoTc@) + 0.25*LI.DISTANCE
  LW.COSTd = T0 + (LI.TOLL@ispk@/@VoTd@) + 0.25*LI.DISTANCE
  LW.COSTe = T0 + (LI.TOLL@ispk@/@VoTe@) + 0.25*LI.DISTANCE
  ; update COSTf: average of free-flow time and congested speed is used for regional autos and
trucks
  LW.COSTf = ((LI.DISTANCE*60)/LI.FFSPD * 0.5 + T0 * 0.5) + (LI.TOLL@ispk@/@VoTe@) +
0.25*LI.DISTANCE

 ; Recode facility type (SWFT) into VDF groups.
  IF (LI.SWFT = 1,2,3,7,8,9)      LINKCLASS = 1     ; Freeway/Expwy & Ramps
  IF (LI.SWFT = 4,5,6)            LINKCLASS = 2     ; Arterial
  IF (LI.SWFT = 10)               LINKCLASS = 3     ; Collectors/Local
  IF (LI.SWFT = 11)               LINKCLASS = 4     ; Centroid Connectors

       ; Set link usage restrictions for this period.  Definitions:
       ; 0,1 = no restriction            3 = HOV3
       ; 2   = HOV2                      4 = no trucks
       ; 6   = Transit Only              9 = No vehicles at all

;Rail tracks, Drive to PNR, and other PNR/Transit Links OR  No vehicles and Transit vehicles Only
Links)

  IF (LI.SWFT= 13,15,21,22,23,24 || LI.@prd2@LIMIT = 6,9) ADDTOGROUP = 1
  IF (LI.@prd2@LIMIT = 4)                                 ADDTOGROUP = 2      ; no Trucks (MT or
HT)
  IF (LI.@prd2@LIMIT = 2)                                 ADDTOGROUP = 3      ; HOV2  only
  IF (LI.@prd2@LIMIT = 3)                                 ADDTOGROUP = 4      ; HOV3+ only

ENDPHASE

PHASE=ILOOP

  MW[1] = MI.1.1     ; M1 Trips
  MW[2] = MI.1.2     ; M2 Trips
  MW[3] = MI.1.3     ; M3 Trips
  MW[4] = MI.1.4     ; M4 Trips
  MW[5] = MI.1.5     ; M5 Trips
  MW[6] = MI.1.6     ; M6 Trips

  PATHLOAD        VOL[1] = MW[1],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc      ; M1 Trips
  PATHLOAD        VOL[2] = MW[2],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc      ; M2 Trips
  PATHLOAD        VOL[3] = MW[3],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc      ; M3 Trips
  PATHLOAD        VOL[4] = MW[4],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc      ; M4 Trips
  PATHLOAD        VOL[5] = MW[5],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc      ; M5 Trips
  PATHLOAD        VOL[6] = MW[6],  EXCLUDEGROUP=1,3,4, PATH=LW.COSTc      ; M6 Trips

ENDPHASE

PHASE=ADJUST

function {

    V = VOL[1] + VOL[2] + VOL[3] + VOL[4] + VOL[5] + VOL[6]

    TC[1] = Min(T0 * (1 + 0.70*(V/C)^8), T0*100)
    TC[2] = Min(T0 * (1 + 0.55*(V/C)^6), T0*100)
    TC[3] = Min(T0 * (1 + 0.17*(V/C)^4), T0*100)
    TC[4] = T0
    }

  LW.COSTa=TIME + (LI.TOLL@Ispk@/@VoTa@) + 0.25*LI.DISTANCE
  LW.COSTb=TIME + (LI.TOLL@Ispk@/@VoTb@) + 0.25*LI.DISTANCE
  LW.COSTc=TIME + (LI.TOLL@Ispk@/@VoTc@) + 0.25*LI.DISTANCE
  LW.COSTd=TIME + (LI.TOLL@Ispk@/@VoTd@) + 0.25*LI.DISTANCE
  LW.COSTe=TIME + (LI.TOLL@Ispk@/@VoTe@) + 0.25*LI.DISTANCE
```

```
  ; update COSTf: average of free-flow time and congested speed is used for regional autos and
trucks
  LW.COSTf = ((LI.DISTANCE*60)/LI.FFSPD * 0.5 + TIME * 0.5) + (LI.TOLL@ispk@/@VoTe@) +
0.25*LI.DISTANCE

ENDPHASE
ENDRUN
ENDLOOP  ;end time of day loop

*del *.prn
*del *.bak
*del *.prj
*del *.var
*del *.000
*del *.001
*del *.002
*del *.003
*del *.004
*del *.005
```

Script III

```
RUN PGM=HIGHWAY
FILEO MATO[1] = AM_period_1.SKM,
 MO = 1, NAME = TIMEP
;FILEI ZDATI[1] = zone.dbf
FILEI NETI = AM_period_1.NET

PROCESS PHASE=LINKREAD

ENDPROCESS

PROCESS PHASE=ILOOP

LW.TIMEP = 60*LI.DISTANCE/(0.1+LI.CSPD_1)

PATHLOAD PATH = LW.TIMEP,

MW[1] = PATHTRACE(LW.TIMEP)
;MW[2] = PATHTRACE(LI.DISTANCE)

COMP MW[1][I] = rowmin(1) * 0.5
;COMP MW[2][I] = rowmin(2) * 0.5

ENDPROCESS
PROCESS PHASE=ADJUST
ENDPROCESS
ENDRUN
```