ABSTRACT

Title of Document:	INCORPORATING RELIABILITY AND PEAK SPREADING INTO MARYLAND STATEWIDE TRANSPORTATION MODEL
	Sepehr Ghader, Masters of Science, 2015
Directed By:	Professor Lei Zhang, Department of Civil and Environmental Engineering

This thesis proposes two sub-components in MSTM to incorporate more advanced methods in four-step models. The first addresses travel time reliability by proposing a method to measure the value, to forecast, and to incorporate reliability in the transportation planning process. Empirically observed travel time data from INRIX are used in an introduced method to measure OD-based reliability. The measured reliability is utilized to find the value of reliability for a specific mode choice problem and to establish the relationship between travel time and reliability. Findings are combined with MSTM to find the economic benefits of improving the network in a case study. The second addresses the peak spreading. Discrete choice models are combined with MSTM to model departure time choice. A method is introduced to estimate preferred arrival time of travelers based on skim values. Two iterative frameworks are proposed to estimate the model and predict the demand distribution.

INCORPORATING RELIABILITY AND PEAK SPREADING INTO MARYLAND STATEWIDE TRANSPORTATION MODEL

By

Sepehr Ghader

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Advisory Committee:
Professor Lei Zhang, Chair/ Advisor
Professor Paul Schonfeld
Professor Cinzia Cirillo

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Introduction

The Maryland Statewide Transportation Model (MSTM) is a transportation model developed by the 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 four steps including trip generation, destination choice, mode choice, 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 for designing, analyzing, and assisting the implementation of various land use, transportation planning, demand management, and other transportation-related policies in Maryland. This thesis proposes two sub-components in MSTM to incorporate state-of-the art practices and recent developments in travel demand modeling. Each subcomponent is described in a separate chapter.

The first sub-component described in chapter one addresses travel time reliability in MSTM. Reliability can affect various steps of a traditional travel model, such as mode choice and trip assignment. Reliability plays a crucial role in economic evaluation of projects, and describes the performance of a transportation network. When the 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 the value of reliability savings can affect the results.

The reliability chapter proposes a method to measure the value, to forecast, and to incorporate reliability in the transportation planning process. This study uses empirically observed reliability that is obtained from INRIX (Global company which provides a variety of internet services and mobile applications pertaining to road traffic and driver services) to find the origin-destination-based reliability. OD-based reliability can be easily incorporated in travel models, because most of travel models are based on zone systems. Previous studies are mainly focused on reliability of a specific link or corridor, and introducing OD-based reliability is novel in the field. The OD-based reliability is combined with a household travel survey to find the value of reliability by estimating a random utility model. This value is based on empirically observed travel time data and revealed preference choices; which makes it unique and important, because most previous studies are based on stated preference surveys. Thereafter the reliability data are combined with travel time data to establish the relationship between travel time and travel time reliability based on observed data. This relationship is based on OD travel time and reliability, which makes it easily compatible with MSTM or any other travel model. It is used to forecast reliability when travel time is available. These findings are combined with MSTM in four different scenarios of a case study to find the value of reliability savings in state, county, zone and corridor levels. The results of this chapter can be considered as a guideline on how reliability can be considered in planning and decision making by using readily available data sources such as household travel survey and historical travel time data.

The second sub-component addresses the spread of peak travels because of changes in supply and demand. Currently, four pre-defined hourly factors are being used in MSTM to account for time of day. 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 shorter time periods. The appropriate method is expected to be sensitive to congestion, policies, and changes in behavior to more realistically demonstrate the distribution of demand in a typically modeled 24 hours. Such a model will predict demand shifts from peak hours to shoulders of the peak when roadways become more congested. The phenomenon is known as peak spreading, and it is addressed in the second chapter of the thesis.

Most of trip-based four step models use hourly factors similar to MSTM. This study proposes a framework that uses skim matrices and household travel survey to account for time of day with a discrete choice model. Such integration cannot be found in the previous literature. One major difficulty in departure time choice models is unavailability of data on preferred times. Here, a method to estimate preferred departure time is proposed and used, which was previously lacking in the literature. The results of chapter one are also used in the second chapter to make the models sensitive to reliability. Two iterative frameworks are proposed to estimate the departure time choice model and to predict demand distribution of any given scenario. The proposed framework does not require any new data collection, and it can be incorporated with most trip based four step models by using readily available data.

Chapter 1: Reliability

Section 1: Introduction

An appropriate travel demand model should be able to predict travelers' choices with adequate accuracy. These choices mainly consist of departure time choice, mode choice, route choice and en-route diversion choice. Unpredictable variation in travel times of a specific mode, route, or time is one of the most important attributes considered by travelers. The concept of travel time reliability (TTR) has been raised and employed in different studies to define and measure this unpredictable variation of travel time. According to Bhat and Sardesai (Bhat and Sardesai 2006), travelers consider reliability for two main reasons. Firstly, commuters may be faced with timing requirements and there are consequences associated with early or late arrival. Secondly, they inherently feel uncomfortable with unreliability because it brings worry and pressure. This behavioral consideration has been noted in many studies where they observed that some travelers accept longer travel times in order to make their trip more reliable (Jackson and Jucker 1982).

A reliability related term has become a significant part of travel models since early studies (Gaver Jr 1968) (Prashker 1979), and during the time many theoretical and experimental studies have considered reliability in their departure time choice, route choice or mode choice models, using stated preference (SP) or reveled preference (RP) surveys. While SP surveys describe a hypothetical situation for respondents, RP surveys ask about their actual choice, and do not contain usual perception errors found in SP surveys. While there are a large number of reliability studies using SP surveys, there are few studies that utilize RP surveys due to the lack of experimental settings that have significant difference among alternatives, and hardships in planning and deploying these surveys and gathering the data (Carrion and Levinson 2012a). Bates et al. (Bates et al. 2001) claimed it was virtually impossible to find RP situations with sufficient perceived variation in reliability and other appropriately compensating components of journey utility. Although there are some good examples of departure time choice and route choice research using RP surveys (Small 1982) (Lam and Small 2001) (Carrion and Levinson 2010) (Carrion and Levinson 2012b), they all analyze TTR in link-level or path-level. There is no previous study about OD-level TTR. Since trip based and activity based travel demand analysis and modeling are usually conducted at the zone level, OD-level TTR measure would be of great value in incorporating reliability into current planning process.

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. Similarly, 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); data source (e.g. revealed preference(RP) vs. (SP)); and others (Carrion and Levinson 2012a) (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 a critical indication of the operating conditions of any road. 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. Even though many studies have tried to measure behavioral response to reliability, their application to a transportation planning context is limited. 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) (Levinson et al. 2004) (Rakha et al. 2006) (Sumalee and Watling 2008) (Zhang 2012). 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; Hence, a framework to measure OD-based reliability to calculate network-wide reliability savings using available data will be very useful, and is currently lacking in the literature.

The main contribution of this study is introducing OD reliability based on empirically observed data to be used in planning process. OD reliability is important because it can easily be incorporated in planning processes or travel models. Besides, reliability and its value are measured and estimated using empirically observed travel times and household travel survey, which are easily available. This is very valuable since conducting new SP surveys for reliability is costly, and estimates based on SP surveys contain perception errors. The objective of this chapter is to develop a framework 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. 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, and its application is demonstrated in a real world case study.

The next section is literature review. The following section explains the methodology and the data used in detail. Section 4 discusses the details of estimating value of reliability through a mode choice model based on utility maximization theory. Section 5 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 for forecasting reliability situation in any given scenario. The case study section 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 section summarizes the proposed research and discusses future directions.

Section 2: Literature Review

Reliability was introduced to travel models in early studies. (Gaver Jr 1968) proposed a departure time choice model and mentioned that travelers predict variance of their travel time and depart with a safety margin, which he called “Head start time”. (Polak 1987) stated that reliability should be an explicit term in the models, and added a reliability variable to a mode choice model, which showed statistically significant improvement. The route choice model developed by Jackson and Juker (Jackson and Jucker 1982) can be considered as the first study that utilized expected utility theory and concept of reliability together. Jackson and Juker stated that travel time unreliability is a source of disutility in addition to travel time, and used a SP survey to assess the respondents' tradeoffs between travel time and reliability, and also calculated user's degree of risk aversion. Same method is used in other studies but with a different form of utility function (Polak 1987) (Senna 1994). Reliability has also gone through network traffic equilibrium models where (Mirchandani and Soroush 1987) incorporated travel time variance in the utility function, and showed how users shifted their route to more reliable ones.

Data for reliability studies are usually obtained from surveys. Qualitative questionnaires were the first surveys that were used in reliability studies where respondents were asked to rank the foremost reasons of their route choice, including some reasons that were related to reliability (Prashker 1979) (Chang and Stopher 1981) (Vaziri and Lam 1983). Then gradually quantitative SP surveys became dominant in the field and were utilized in numerous studies (Jackson and Jucker 1982). (Abdel-Aty et al. 1997) is one example. In a route choice study, Abdel-Aty et al. offered two routes to the respondents; one with fixed travel time every day, and the other with a possibility that the travel time increases on some day(s). The results showed that males are more willing to choose uncertain routes. In the scheduling study of (Small 1999), respondents were given two options with different travel time distributions and travel costs based on their preferred arrival time. Small found that unreliability had higher disutility for respondents with children and respondents with higher income. Some other studies such as (Small et al. 1995) (Koskenoja 1996) added nonlinearities in the scheduling models. SP surveys evolved later when (Cook et al. 1999) and (Bates et al. 2001) showed how presentation of travel time variability can have significant impact on the estimation, and their work was followed in different reliability studies (Hensher 2001) (Copley and Murphy 2002) (Hollander 2006) (Asensio and Matas 2008) (Tilahun and Levinson 2010).

While there are many examples of reliability studies using SP data in the literature, RP studies are limited. (Carrion and Levinson 2012a) related this scarcity to lack of experimental setting showing significant difference among alternatives and costs associated with planning, deploying and gathering data from these surveys. (Bates et al. 2001) claimed the scarcity of real examples with sufficient level of details for reliability studies as a reason. In addition to the scarcity of RP studies, the main focus of the few available literatures is on departure time and route choice, and they mainly consider link or path level data. Small used RP data on trip timing with travel time data gathered from the road network to develop a scheduling model (Small 1982). He showed that late arrival has more disutility than additional travel time, and early arrival is preferred to both of them. (Lam and Small 2001) collected RP data from users of State Route 91 in Los Angeles with both tolled and un-tolled lanes for their lane choice model (type of route choice models). Lam and Small gathered traffic data from the loop detectors for travel time and reliability measures, and considered both the standard deviation and 90th percentile minus median as measures of reliability.

Another set of similar route choice studies used State Route 91 (Small et al. 2005) (Small et al. 2006). These studies combined RP and SP surveys to enrich their estimation, and they calculated value of time and value of reliability. (Ghosh 2001) used RP data from another route with High Occupancy Toll (HOT) lanes in Interstate 15, San Diego. The study surveyed the respondents about the ramps they used to enter and exit the lanes, and used speeds from loop detectors to calculate travel times. The study also estimated a mode choice model with the choice set of subscriber, non-subscriber, carpooler and other similar alternatives and estimated value of time and value of reliability. (Bhat and Sardesai 2006) also incorporated reliability in their mode choice model. Although the travel times in their model were from a RP survey, travel reliability data was based on a SP survey. A more recent study (Carrion and Levinson 2010) used GPS data for travel time and reliability, and incorporated a RP survey for socio-demographics to observe travelers' route choice between an un-tolled lane, a tolled lane and a signalized arterial parallel to them in Minneapolis. Carrion and Levinson estimated a mixed logit model, and calculated value of time and value of reliability, but unfortunately their data suffered from high attrition and some data loss due to the GPS devices. They also estimated a bridge choice model (Carrion and Levinson 2012b) where they used another set of GPS data for Interstate 35W bridge to explore how travelers shifted from other available alternatives to using the bridge, and calculated the reliability ratio (marginal rate of substitution between travel time and travel reliability).

In terms of the reliability measure 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 2013). 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). Even though many studies have focused on reliability and its value in different contexts, their application in planning is very limited. To investigate the use of travel time reliability in transportation planning, (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. 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) (Levinson et al. 2004) (Rakha et al. 2006) (Sumalee and Watling 2008) (Zhang 2012). 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.

In reviewing the previous literature, it is evident that a model using a reliable source of travel time measurement data supplementing a RP survey (e.g. household travel survey) for TTR that can be utilized in planning process is not available in the literature. Besides, none of the studies have considered OD-level TTR. In this thesis, empirically observed travel time data from INRIX are used to estimate OD level TTR measures. The OD level TTR measures are combined with the 2007-2008 TPB-BMC household travel survey to provide a comprehensive RP dataset, which is used to develop discrete choice models to find the value of reliability. The reliability data are also combined with INRIX travel time data to explore the relationship between travel time and travel time reliability in order to forecast the reliability. All these findings are combined with MSTM to demonstrate how OD-Based reliability can be incorporated in planning and decision making.

Section 3: Methodology

3-1 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. The VoTR obtained in this study is unique because it is based on empirically observed travel times from INRIX, and it is OD-based. Details of calculating VoTR can be found in section 4. The second part of the figure contains calculating OD-based travel time reliability measure and developing relationship between reliability and travel time.

The INRIX data are in TMC (Traffic Message Channel) format. A step by step framework is introduced in this part to obtain OD-based reliability from INRIX data. OD specific travel time reliability data is not available readily and the second step helps obtaining it. OD specific reliability data are used in a random utility model estimation. They are also used in estimating the relationship between congestion and reliability to forecast future reliabilities. In a planning model the path travel times are static, so in order 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. Section 5 discusses OD-based travel time reliability and reliability forecasting in detail. The third part of flowchart shows how one can 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 due to travel time reliability can be captured at system, county, zone, and corridor level as desired by the user. These are all demonstrated in section 6.

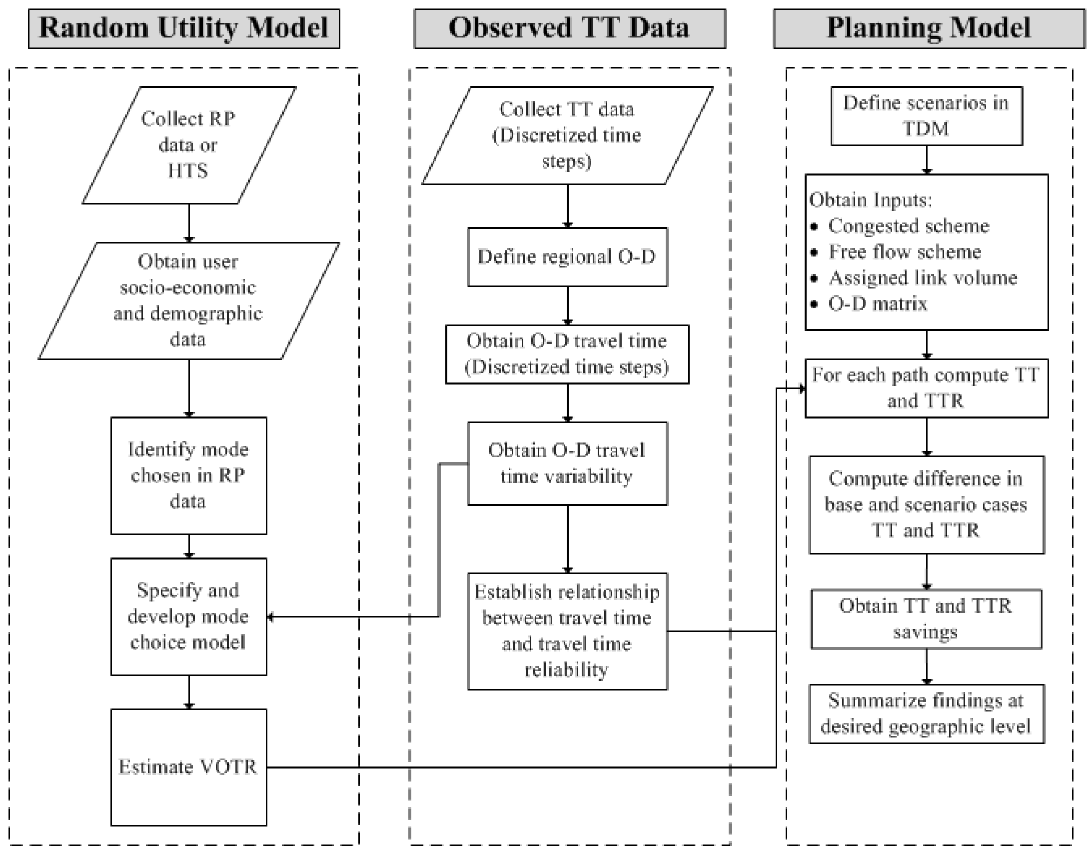

Figure 1: Proposed methodology for VoTR estimation and integration in planning models

3-2 Data

The following datasets are used in this framework:

<u>2007-2008 TPB-BMC Household Travel Survey</u>

2007-2008 Household Travel Survey data conducted by Metropolitan Washington Council of Governments (MWCOG) and Baltimore Metropolitan Council (BMC) is used in the thesis 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.

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 such as 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. 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.

MSTM outputs

Maryland Statewide Transportation Model (MSTM) is considered as the travel demand model to demonstrate the benefits 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 are 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 relationship is used with skim values to estimate the OD-based reliability matrices to calculate reliability savings.

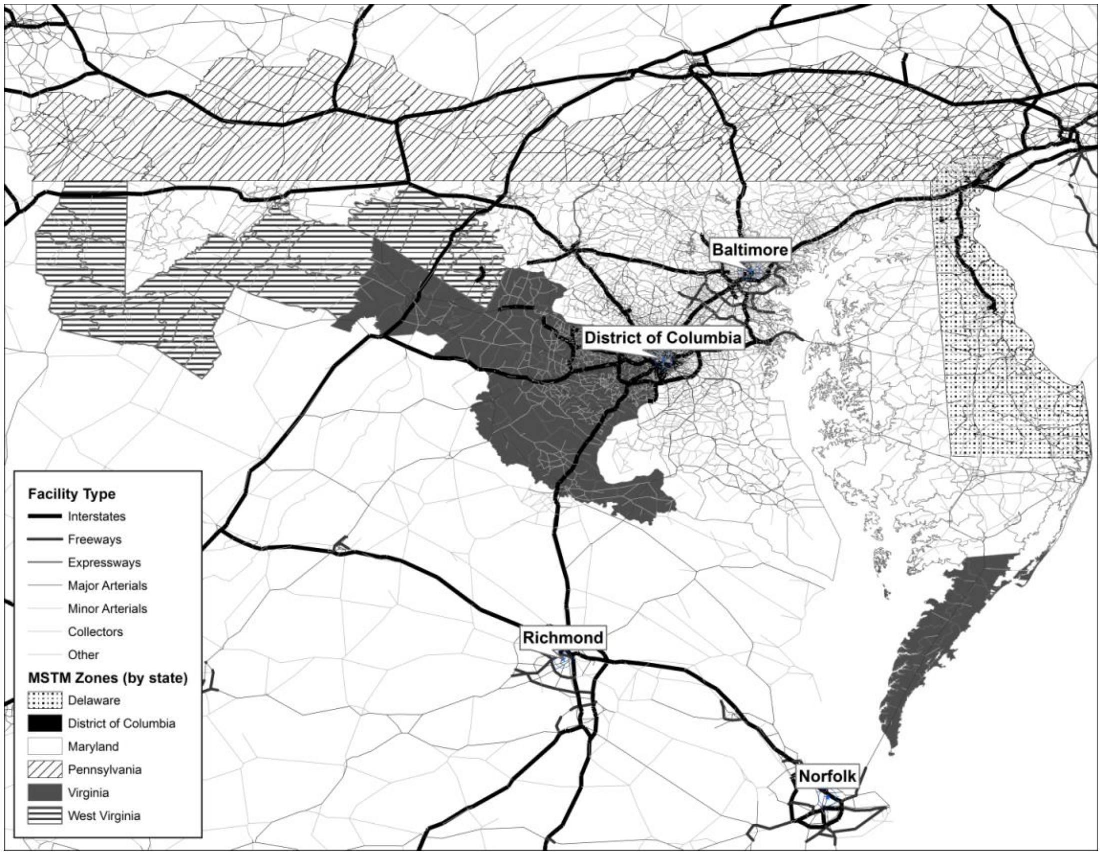

Figure 2: Topological map showing zone system and network of MSTM study area

MWCOG travel model outputs

MWCOG model is a model developed by Washington DC metropolitan area planning organization to model travels inside Washington DC metropolitan area, and it includes parts of Maryland and Virginia. Cost information such as transit fares between zones, parking costs, and vehicle maintenance cost are available in the MWCOG model and they are used for cost variable. The MWCOG model is consistent with the TPB HHTS and they have the same zoning structure.

Section 4: Value of Reliability

Drivers tend to dislike high travel time variations because of various reasons, such as accidents, bad weather, roadwork, fluctuation in demand, etc. On the other hand, rail usually has much more reliable travel times since it operates following a fixed schedule. So it would be very interesting to explore how this difference in TTR would affect traveler's choice between these two modes. In this study, OD pairs that have both rail and driving trips recorded in 2007-2008 TPB-BMC travel survey in Washington DC area are selected and studied since in these OD pairs both travel modes are available and are competing with each other. In total, there are 161 OD pairs with both rail and driving trip records. For two of these OD pairs, INRIX data are not available. The remaining 159 OD pairs form a major component of this study. In these 159 OD pairs, 261 rail trips, 291 driving trips, and only 2 trips of other travel modes can be observed, as shown in Table 1. Thus, in these OD pairs, it would be appropriate to assume that rail and driving are the only available alternatives.

Table 1: Trips records in the 159 OD pairs in HHTS

Travel Mode	Rail	Driving	Other	Sum
Number of Trips	261	291	2	554
Percent	47.1%	52.5%	0.4%	100.0%

In order to explore the impact of TTR on mode choice between rail and driving, both socio-demographic information and alternative-specific variables are needed. TPB-BMC household survey data provides a number of socio-demographic information such as income, gender, age, driver license, car ownership and so on. Alternative-specific variables in this study include travel time, cost and TTR measures. Similar to other RP surveys, the TPB-BMC household survey does record travel time for the actual taken mode, but travel time for the other alternative will remain unknown. In this thesis, since all studied OD pairs have both rail and driving trips reported, the travel time of the alternative mode is estimated by averaging the reported travel time of all the trips in the same OD pair using that mode. Travel cost information can be calculated from the MWCOG travel demand forecasting model. For the travel time reliability of driving trips, the estimated TTR between the origin and destination zones by INRIX data is used. The details of calculating OD-based reliability are described in section 5. Rail is assumed to be highly reliable and has no variation in travel time. Since the origin and destination TAZ numbers and trip start time are recorded for each trip in HHTS data, OD-level TTR can be easily linked with each trip. Trip start time is used to link reliability with each trip because TTR is calculated for different hours of the day. Thus, by incorporating HHTS data, MWCOG model travel cost information and estimated OD-level TTR, a comprehensive dataset is generated which includes both demographic information and alternative-specific variables such as travel time, cost and TTR. Some of the explanatory variables in the dataset are summarized in Table 2.

Table 2: Explanatory variables

Variable	Definition	Values
Veh	Number of household vehicles From HHTS	0 = 0; 1 = 1; 2 = 2; 3 = 3+
Lic	Have driver license?(Persons 16+) From HHTS	1 = YES; 2 = NO; -9 = Not Applicable
Age	Age in years From HHTS	Continuous (years)
Disc	Is the trip a discretionary trip or not (Trips with trip purpose other than home, work and	1 = YES; 2 = NO

	school are considered discretionary trips) From HHTS	
TT	Travel time From HHTS	Continuous (min)
Cost	Travel cost From MWCOG	Continuous (cent)
TTR	Travel time reliability	Continuous (min)

OD-level TTR can help to explore the impact of TTR in different choice dimensions, such as mode choice, departure time choice, etc. In this study, OD-level TTR will be incorporated with a traditional household travel survey to explore how TTR affects traveler's mode choice. A discrete choice model consistent with Random Utility theory is used in this study, where linear utility functions are assumed:

$$U_m = \beta_{0,m} + \sum_{i=1}^{n} \beta_{i,m} + x_{i,m} + \varepsilon_m \qquad \textbf{(Equation 1)}$$

where U_m is the utility of mode m. $\beta_{0,m}$ denotes a mode-specific constant. $\beta_{i,m}$ is the coefficient of the ith explanatory variable in the utility function of mode m. $x_{i,m}$ is the ith explanatory variable of mode m. ε_m represents the random component of the utility which is assumed as an independently distributed random variable with a Gumbel distribution (with location 0 and scale parameter 1). Explanatory variables include alternative-specific variables such as travel time (TT), travel cost (Cost) and travel time reliability (TTR), as well as other variables such as age (Age), number of vehicles (Veh) and trip purpose (Disc).

After trying different model specifications, the model specification adopted in this thesis is shown in Equation 2:

$$U_d = \beta_0 + \beta_{veh} * Veh + \beta_{age} * Age + \beta_{disc} * Disc + \beta_{TT} * TT_d + \beta_{cost} * Cost_d + \beta_{TTR} * TTR + \varepsilon_d$$

$$U_r = \beta_{TT} * TT_r + \beta_{cost} * Cost_r + \varepsilon_r \qquad \textbf{(Equation 2)}$$

where U_d is the utility of driving and U_r is the utility of rail. *Veh*, *Age* and *Disc* are explained in Table 2. TT_d *and* TT_r denote travel time for driving and rail. $Cost_d$ *and* $Cost_r$ represent travel cost for driving and rail. *TTR* is the TTR for driving. β_0 denotes mode-specific constant. β_{Veh}, β_{Age}, β_{TT}, β_{Cost}, β_{TTR} are coefficients for corresponding explanatory variables.

Based on the model specification, value of reliability (VOR) can be calculated:

$$VoR = \frac{\beta_{TTR}}{\beta_{cost}} \qquad \textbf{(Equation 3)}$$

Reliability ratio (RR) can be calculated by using VOR divided by value of time (VOT):

$$RR = \frac{VOR}{VOT} \qquad \textbf{(Equation 4)}$$

Model results are shown in Table 3. Since driving is not a possible choice for people without a driver license, those trips are not included in the model. This consideration excludes 32 trips.

Table 3: Model estimation results

Variable	Standard Deviation	
	Coefficient	t-Stat
Constant (driving)	-1.660	-3.54
Veh	0.757	5.63
Age	0.203	2.90
Disc	0.869	3.98
TT	-0.007	-1.57
Cost	-0.001	-4.94
TTR	-0.122	-2.48
Number of obs	521	
Likelihood Ratio Test	125.51	
Final log-likelihood	-298.37	
Rho-square	0.174	
AIC	610.75	
Correlation between T and TTR	0.37	

P-value of the correlation	9.37
VOR	56.31$/h
95% CI of VOR	(54.14$/h, 58.51$/h)
Estimated RR	17.42

The coefficients of the variables Veh, Age, Disc are significant with positive sign, which means that older people owning more cars tend to drive more. Besides, people will drive more for discretionary trips. The coefficients of TT and Cost are negative which shows that people will drive less if driving will take longer or cost more compared to rail. TT is not significant, which may be caused by the method how travel time is calculated. As described earlier, travel time of the alternative mode is estimated by averaging the reported travel time of all the trips in the same OD pair using that mode. However, there is a gap between the calculated travel time and the real travel time, which may lead to the insignificance of travel time in the model.

The coefficient of the TTR variables is significantly negative, which shows that people tend to drive less when travel time variation of driving increases.

The value of travel time reliability (VOR) and its 95% confidence interval (CI) are also calculated and shown in Table 3. Reliability ratio is 17.42. It is larger than RRs in the previous literature which usually vary from 0.10~ 2.51 (Carrion and Levinson 2012a) This may be caused by several reasons. First of all, reported travel times in the survey do not show significant difference between rail and auto. But in reality, rail has longer travel time with higher reliability. This is the reason why the model relates auto travels to lower cost of auto, and relates rail travels to higher reliability of rail; but it cannot find a significant effect of travel time, because travel time is not significantly different between alternatives. As a result, travel time becomes insignificant, and value of time is estimated very low. Second, the mode choice model in this study only considers rail and driving, while other modes exist in reality, such as bus, carpool, bike, etc. Thirdly, 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 (Ghosh 2001). Moreover use of different time intervals will lead to different travel time variations. Since a 1 hour time interval is used in this study for reliability, 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. For these reasons, the RR value may vary a lot when using different reliability measures or different estimation methods.

Section 5: Measuring and Forecasting OD-based Reliability

5-1 Measuring OD-based Reliability

This section describes how OD travel time reliability can be obtained from INRIX travel time data and how these data are used to explore the relationship between travel time and travel time reliability. The proposed approach to estimate OD-level TTR measures for a given OD pair is shown in Figure 3. The five steps in the proposed methodology are discussed next.

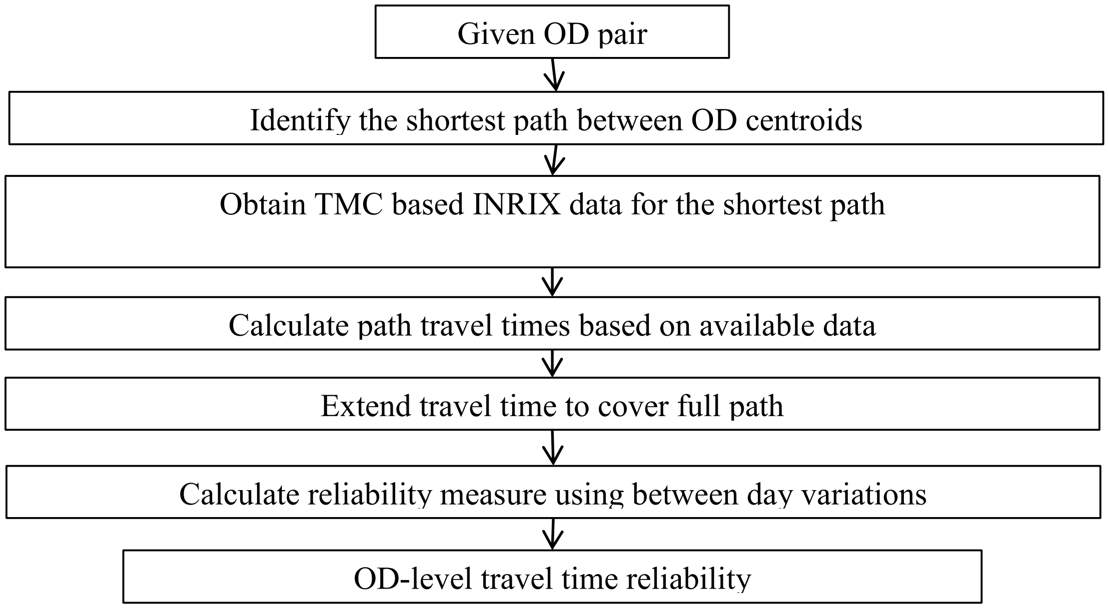

Figure 3: Proposed OD level TTR estimation method

Step 1: Identify the shortest path between OD centroids.

In order to estimate travel time and reliability for a given OD pair, the first task is to determine possible routes that people may take between this OD pair. For this purpose, two assumptions are made: 1) Trips between OD centroids are representative of all the trips between the OD pair. 2) The traffic condition of the shortest path is representative of all possible routes between the same origin and destination. The second assumption is valid under the assumption of the user equilibrium condition. Since this thesis is not focused on route choice, user equilibrium condition is assumed, meaning all the used paths between a given OD pair have equal generalized cost, and path selection does not affect the results. Since the INRIX network is based on TMCs and is not routable, the shortest path was identified using other routable networks, such as planning network models or Google Maps. Two shortest paths were selected for each OD pair representing the trips from origin to destination and from destination to origin, respectively.

Step 2: Obtain TMC based INRIX data for the shortest path

After specifying the shortest path, all the segments on the path available in INRIX network were selected and data for a specific time period was requested. Average travel time for each hour of the day (24 values) for one year (365 days) was collected. Weekend data were deleted at this point since the respondents were required to record activities on a weekday in the TPB-BMC household survey. Between-day variations will be used to calculate travel time reliability for each alternative.

Step 3: Calculate path travel times based on available data

All available TMC based travel time data along the shortest path were added to form path travel times for each hour of the year.

Step 4: Extend travel time to cover full path

INRIX data does not cover all the road segments. Generally speaking, INRIX has better coverage for freeways than for local roads. Also, missing observations were observed in INRIX data, for instance the travel time for some time periods were missing for some specific road segments. Therefore, an estimation method is proposed by the author to use the available INRIX data in order to estimate the average travel time of the whole path. The method starts by dividing the paths into two groups: freeway and non-freeway. This is mainly because these two types have different speeds, and since available average speed is used to estimate missing data, paths were divided into these two categories. In this way, each missing data point was estimated using its similar available data. Figure 4 shows the Gaussian kernel density function of the speed, with the optimal bandwidth computed from the variance of the data, for one selected OD pair. In this graph two peaks can be observed, one representing non-freeway segments with lower speed, and the other representing freeway segments with higher speed. Other OD pairs show similar peaks.

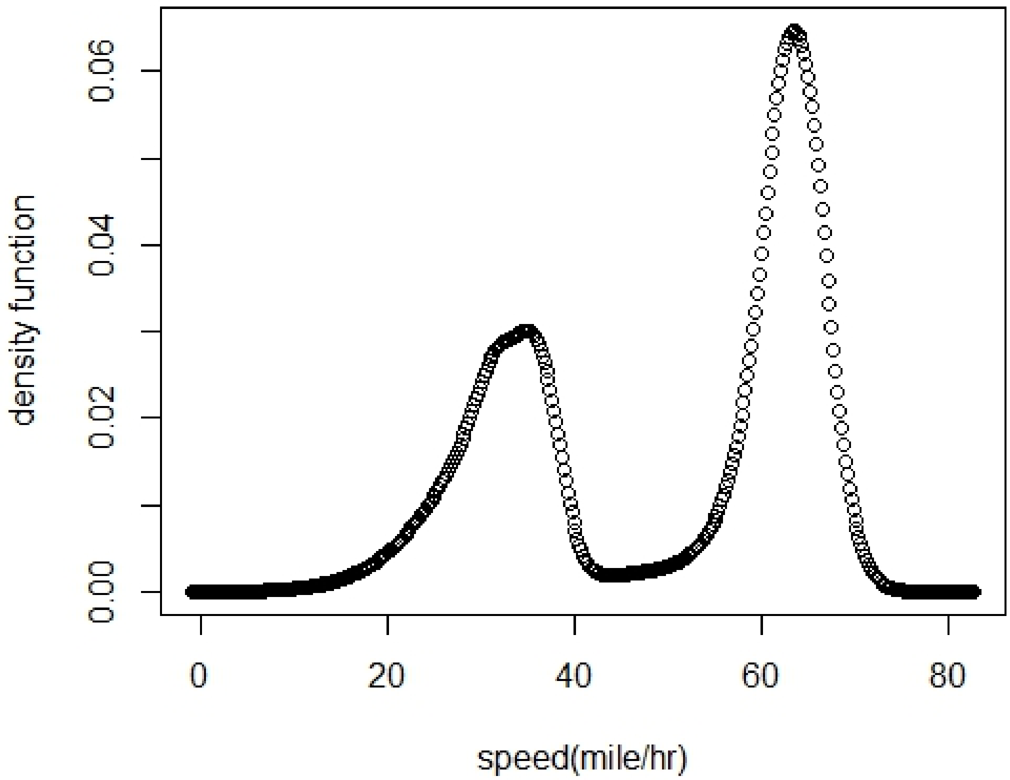

Figure 4: Kernel density function of speed for one OD pair

The length of available freeway and available non-freeway data were calculated and combined with the full length of the freeway segments and the full length of the non-freeway segments in the path to estimate the whole paths travel time. The extended travel times are based on the assumption that freeway segments with missing data are driven with the average speed of freeway segments with available data, and non-freeway segments with missing data are driven with the average speed of non-freeway segments with available data. Using these assumptions, extended travel times can be calculated with Equation 5:

$$Extended\ fw\ tt = Available\ fw\ tt * {}^{real\ fw\ length}/_{available\ fw\ length}$$

$$Extended\ nfw\ tt = Availablenfw\ tt * {}^{real\ nfw\ length}/_{available\ nfw\ length}$$

$$Extended\ total\ tt = Extended\ fw\ tt + Extended\ nfw\ tt \quad \textbf{(Equation 5)}$$

<u>Step 5: Calculate reliability measure using between day variations for each hour</u>

At this part all travel time data for 24 hours during a year were available. Between day travel time variation was used for reliability measure of each hour. The distribution of the travel time data using daily observations for each hour was used to calculate the reliability measures for the intervals to reflect the day-to-day travel time variation. It should be noted that weekends were excluded. Also, travel time observations that were 10 times greater than the average travel time for each segment were considered outliers, and thus excluded as well.

5-2 Forecasting Reliability

Typical planning models report static travel times at each time of day. They do not report the variation of travel times. The estimated OD level travel times and travel time reliabilities were used to establish the relationship between travel time and travel time reliability. This relationship is useful, because it can be incorporated with OD travel time matrices to find out the OD reliability matrices. Network-wide value of reliability savings can be easily calculated using OD reliability matrices.

To establish this relationship 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 per mile is regressed with percent deviation of congested travel time from free flow travel time. The result is shown in Figure 5. A number of outliers were removed from the regression estimation. The Logarithmic relationship was found to provide the best goodness of fit. The resulting 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.

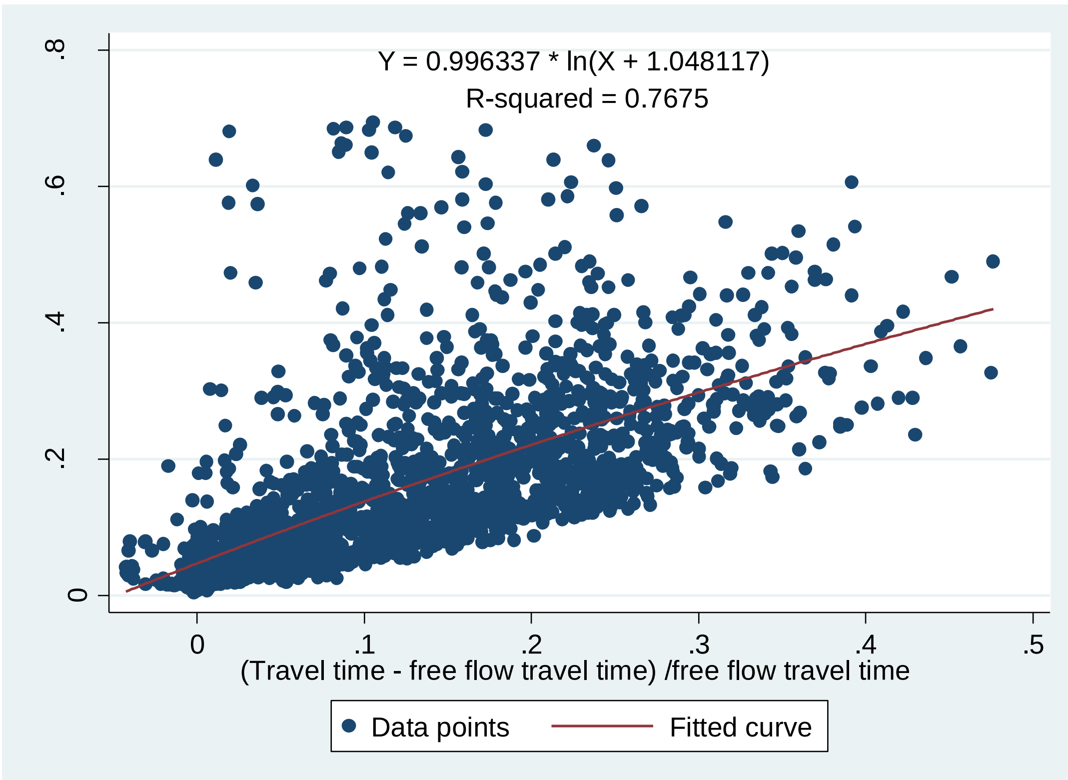

Figure 5: Regression of standard deviation per mile on a percent deviation from free flow time travel time

Section 6: Case Study

This section demonstrate how OD reliability and VoTR can be utilized to find the value of reliability savings by an investment. To estimate reliability savings due to recent network investment the 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 6 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). The ICC opened to traffic in the year 2011. One of the goals of the thesis is to evaluate the reliability savings on other major facilities due to the 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.

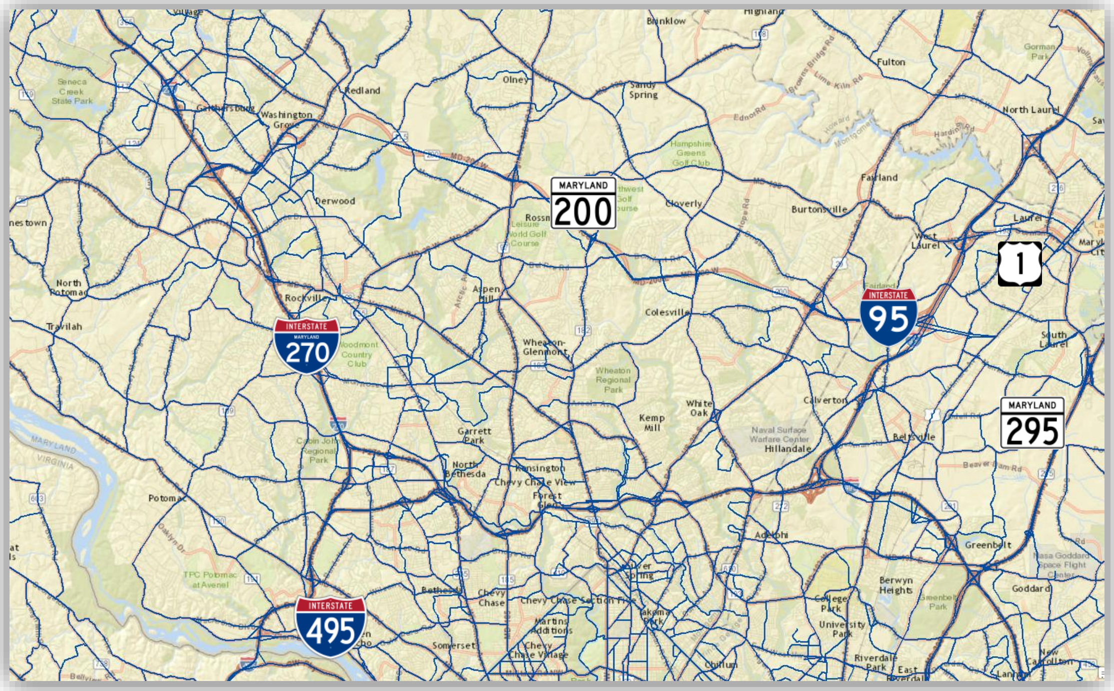

Figure 6 ICC and I270

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 the model summary, congested skim matrix needed to be developed to represent congested travel times for each O-D pair. Similarly, corresponding trip matrices had to be obtained. Reliability matrices were obtained using the relationship described in section 5. 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 section 4 it was explained in detail 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.

6-1 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 the statewide level travel time reliability savings are approximately ten percent of that of travel time for base year. Table 4 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 4: Statewide peak hour savings for base and future years

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

6-2 County Level Findings

Travel time savings for the base and future years are shown in Figure 7, and travel time reliability savings are plotted at county level in Figure 8. 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 due to the 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.

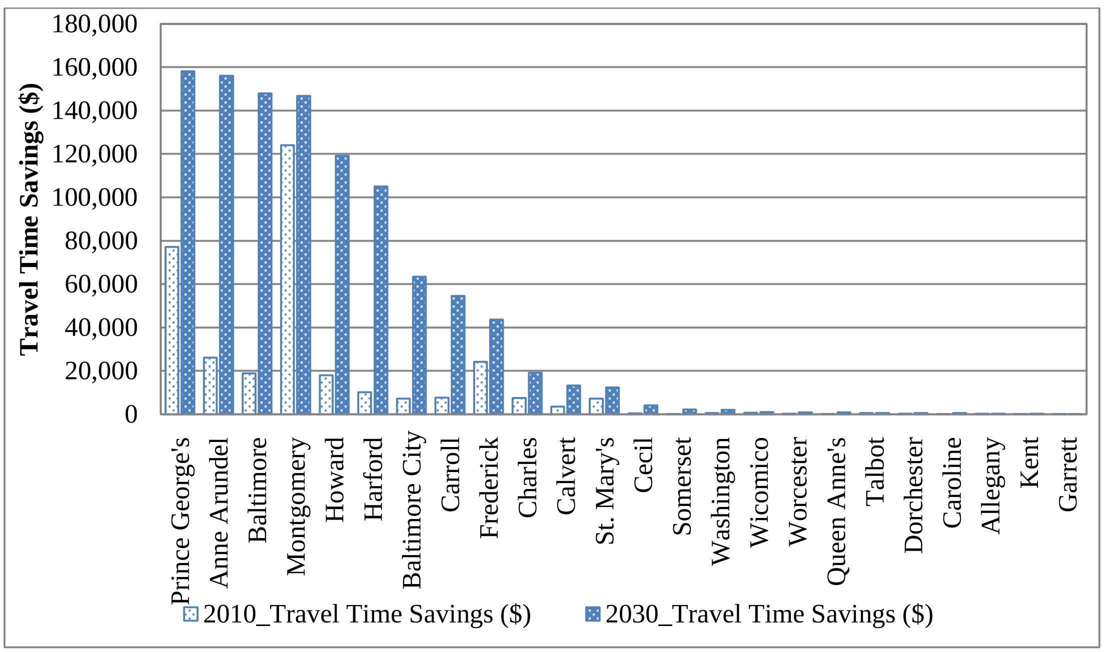

Figure 7: County level travel time savings comparing build and no-build scenarios

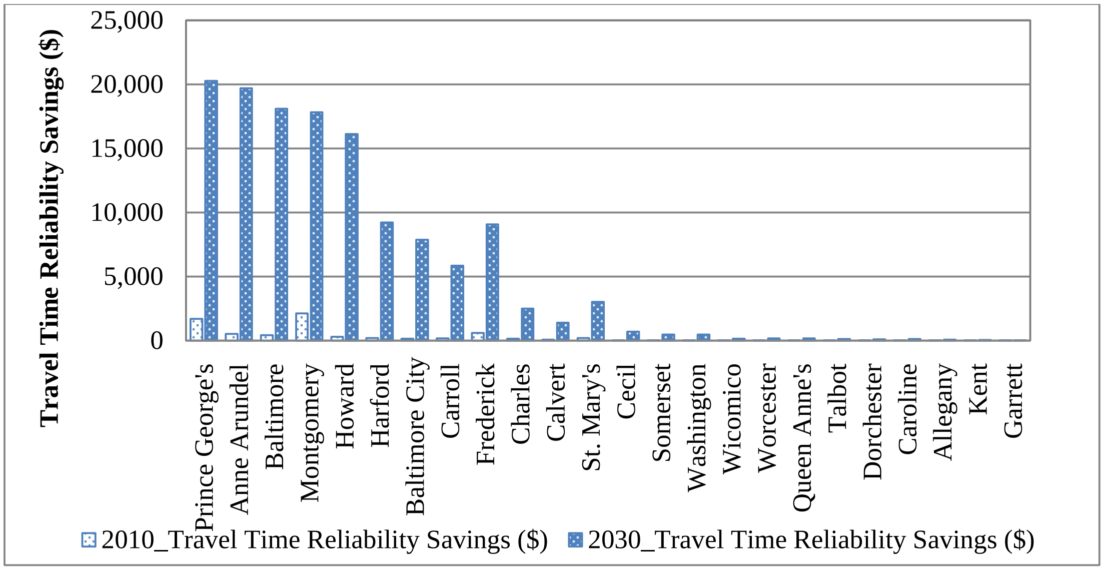

Figure 8 County level travel time reliability savings comparing build and no-build scenarios

6-3 TAZ Level Findings

TAZ level findings are shown in Figures 9 through 12. 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 9 and 11 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 10 and 12 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.

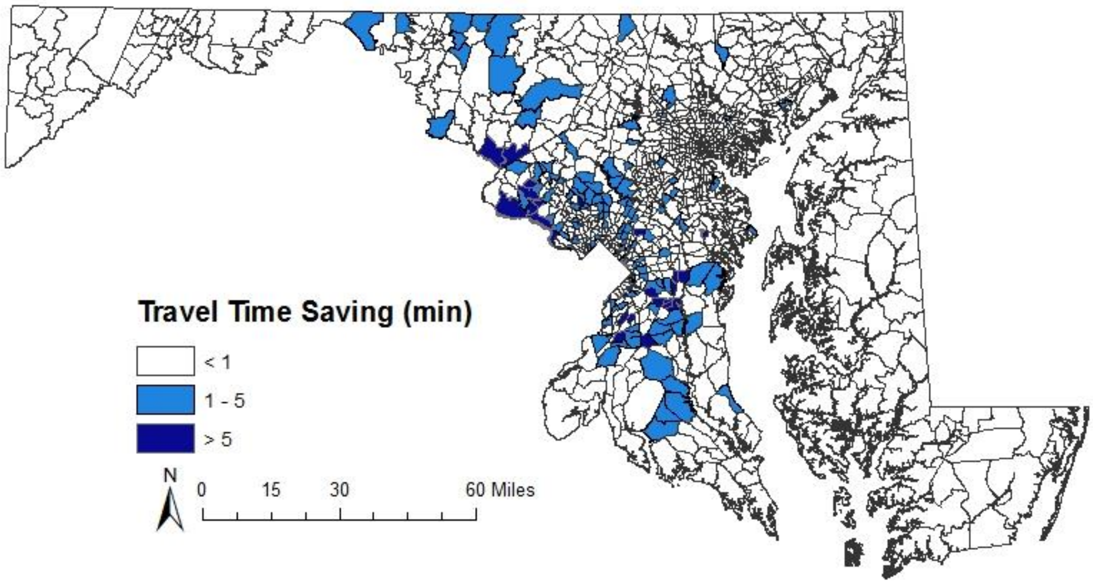

Figure 9: Travel time saving per trip comparing base year build with base year no-build

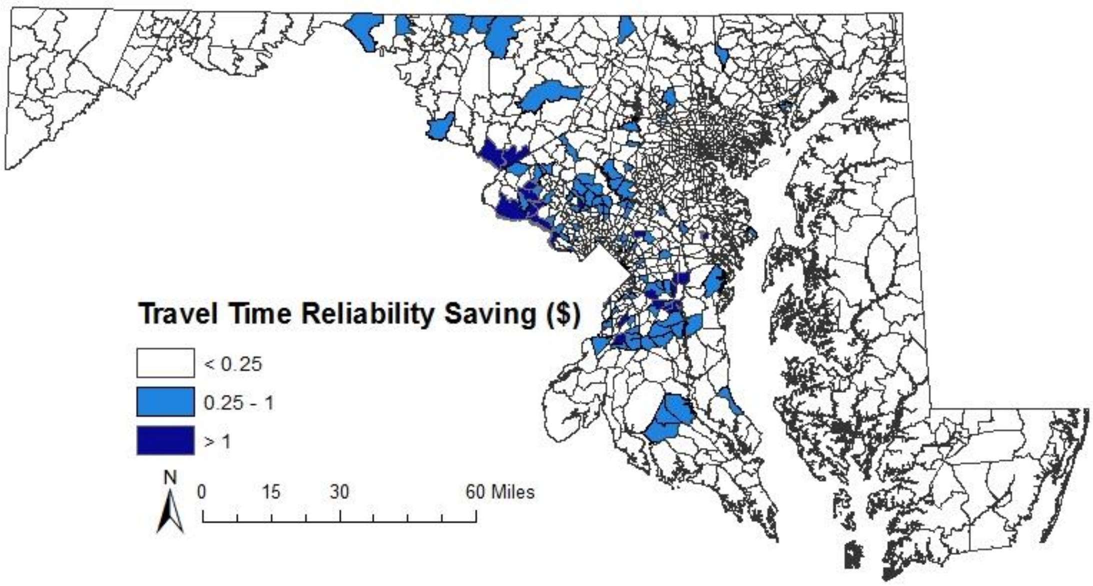

Figure 10: Travel time reliability savings per trip comparing base year build with base year no-build

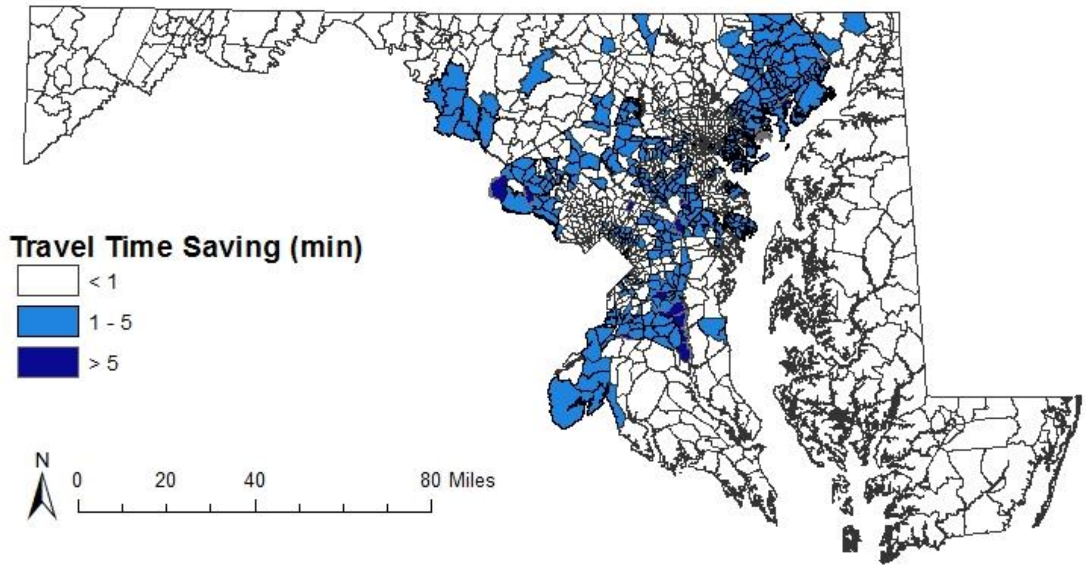

Figure 11: Travel time savings per trip comparing future year build with future year no-build

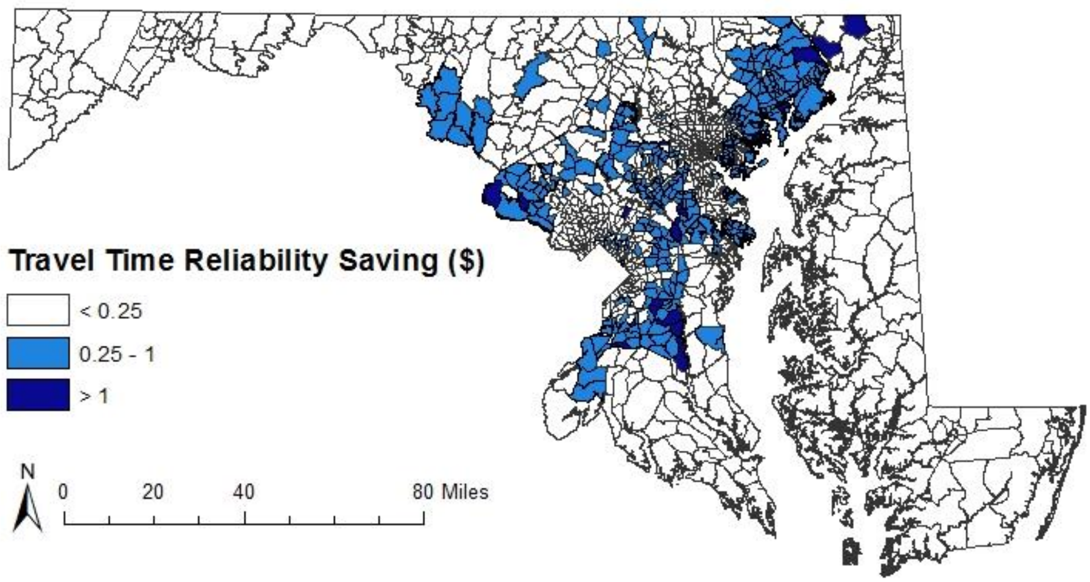

Figure 12: Travel time reliability savings per trip comparing future year build with future year no-build

6-4 Corridor Level Findings

Travel time and travel time reliability savings are estimated for the I-270 corridor using link level congested travel times for each scenario. Table 5 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 13. 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 5: 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				

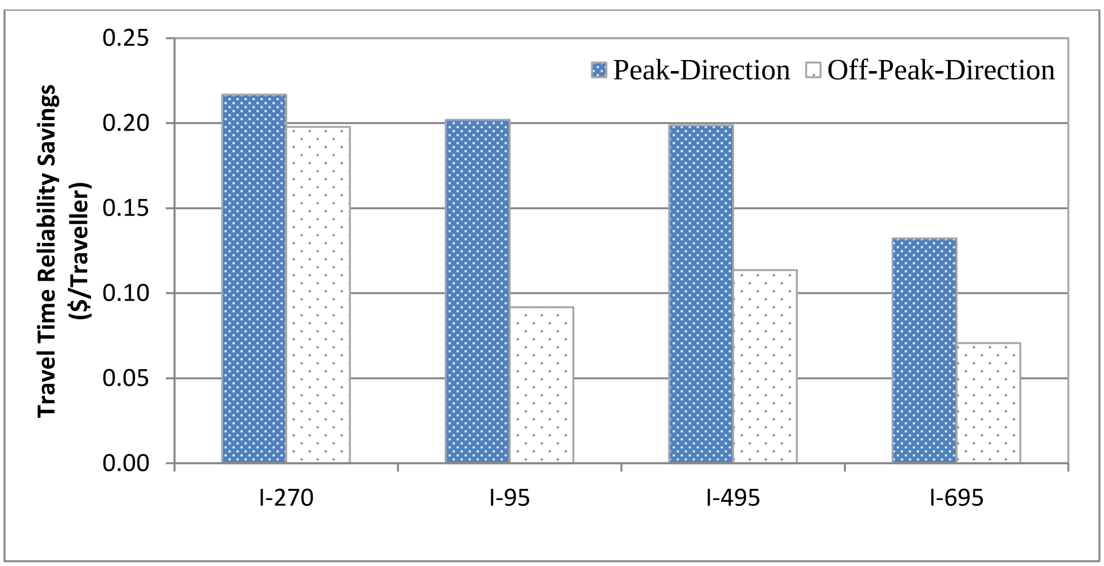

Figure 13: Travel time reliability savings for sample interstate corridors comparing future year build and future year no-build

Section 7: Summary and Conclusions

Reliability is one of the major parameters that describe the performance of transportation network. When the 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 the value of reliability savings can affect the results. In this chapter a framework was proposed to measure the value, to forecast, and to incorporate reliability in the transportation planning process. Measuring reliability of trips between origin destination pairs was done using empirically observed 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. Origin-Destination reliability introduced in the thesis is very useful and important, because it can be easily incorporated in travel models. Afterward, these data were used to estimate a mode choice model between two competing alternatives with reliability as an independent variable. The estimated coefficient of reliability made it possible to find reliability ratio and value of travel time reliability (RR and VoTR). This value is unique, since it is based on empirically observed OD-based reliability in mode choice context. The reliability data were 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 was useful for obtaining 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.

This thesis explained how observed travel time data can be used to measure reliability at the OD level. It showed how OD-based reliability can be easily calculated and incorporated in transportation planning process. It also presented how value of reliability can be estimated using the data, and why the estimated reliability ratio is not comparable with previous studies. The case study findings showed considerable amount of reliability savings that should not be neglected. State level findings illustrated that reliability savings were about 10 percent of travel time savings. It also displayed that more comprehensive improvements in year 2030 will result in larger value of reliability savings. County level results demonstrated 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 models based on utility maximization. Results from different choice models can be compared, to see how value of reliability differs in different choices. Another interesting comparison is comparing the model estimated with reported travel times versus the model with MWCOG travel times. 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. The mode choice model itself has many aspects to be improved. Reliability of rail can be added if required data become available. Other modes such as bus may also be added in the future by collecting bus reliability data. By adding more modes, other types of discrete choice models such as mixed logit or nested logit should be tried to consider correlation between modes.

Regarding incorporation with planning process, this study used 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.

Chapter 2: Peak Spreading

Section 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 the 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.

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 affecting travelers' 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. A 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

These methods are all explained and reviewed in the literature review section. One major weakness of four step models is that they usually suffer from elementary time of day components such as hourly factors or link and trip based adjustments. Discrete choice models are usually utilized in more advanced travel models such as tour or activity based models. Data on preferred arrival times are usually unavailable for trip based four step models, and these models are limited to use post processing techniques. Besides, most of four step models have static traffic assignment which does not have a time component.

This chapter of thesis introduces a framework that can be used with a typical trip-based four-step model to incorporate time of day modeling using discrete choice models. This framework is unique in terms of data requirement. It only requires a household travel survey, four step model outputs such as skim matrices and trip tables, and traffic count data. All these data are readily available for modelers and practitioners. Two iterative frameworks are proposed that can estimate departure time choice model, and predict future demand distribution using aforementioned data for any trip based four step model.

One major research gap in this area is estimation of preferred time. Preferred time is not recorded in most RP surveys. Besides SP surveys including preferred times are not always available. Estimating demand distribution for future scenarios also require preferred time information which is not available in any survey. This thesis proposes a method to estimate preferred departure time by assuming rational behavior of travelers. This method is unique in the literature, and it can fill a very important research gap.

Another contribution of this chapter is related to OD-based reliability which was discussed in the previous chapter. The models that will be explained in this chapter are estimated with OD-based reliability as an independent variable to explore the effect of reliability on departure time choice. To the best of author's knowledge, this is the first study that uses reliability in four step models. The advantage of introduced OD-based reliability is in its compatibility with travel models such as MSTM. This advantage is again demonstrated in this chapter, where OD-based reliability is estimated from skim matrices, and used in model estimation and prediction.

In this study discrete choice models are selected as the best approach to model time of day. In the next section the previous literatures on time of day models are reviewed. The following section discusses the methodology in detail. Section 4 explains how MSTM is used to obtain alternative specific skims. Section 5 discusses how preferred departure time is estimated using skim matrices, and Section 6 presents departure time choice model estimation results separated by trip purpose. In Section 7, estimated models are used to predict the demand distribution of the base and future year to show how peak spreading occurs. The peak spreading chapter finishes with summary and concluding remarks.

Section 2: Literature review

A temporal component is usually modeled with 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), similar to 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) in which homogeneous users traveling from one origin to one destination using one link are assumed. 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.

$$V(t) = \alpha\, C(t) + \beta\, Max(0, (PAT - t - C(t))) + \gamma\, Max(0, (t + C(t) - PAT)) \qquad \textbf{(Equation 6)}$$

$$L(t) = \int_{t1}^{t} q(w)dw - h * (t - t1) \qquad \textbf{(Equation 7)}$$

In equilibrium scheduling theory Vickrey's model is extended in number of aspects such as 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 Preferred Arrival Time (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 1982), and they are based on random utility theory. Such models categorize the time span into discrete intervals, and usually assume a similar specification to Vickrey's utility with an added error term. Socio-economics, or demographics, effects can be easily included in the utility function. Many types of discrete choice models are introduced by researchers for a 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 1978). For instance multinomial logit (MNL) is a simple type of GEV model that assumes error terms are IID Gumbel, which results in no correlation between error terms. An example can be seen in (Zeid et al. 2006). Abu-Zeid et al. 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 model, which is usually used when two choices are being modeled together. Nests may represent different choice dimensions, or they may 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 distance, 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, for instance work by (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) and (Bolduc and Ben-Akiva 1991) as a 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 an error component mixed multinomial logit for the analysis of travel mode and departure time choice for home based social-recreational trips using 1990 data from 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 similarly 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 such as 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) used a 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.

After reviewing all these models, an advanced model compatible with trip based four step model without extensive data requirement could not be found. Discrete choice models are used in this study as an initial step toward integration of trip based four step models and time of day models. Future steps can be toward continuous choice models.

Section 3: 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 realistically model travelers' preferences. Peak spreading can be observed by comparing distribution of travel demand for any two scenarios. This thesis chapter compares travel demand distribution for base year (2007) and future year (2030) in the study area; which is 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 the morning peak (5 a.m. to 10 a.m.) which is divided to 5 one hour periods, and the 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. The six purposes utilized in this study are as follows:

1- Home-Based Work
2- Home-Based Shopping
3- Home-Based School
4- Home-Based Other
5- Non- Home-Based Work
6- Non-Home-Based Other

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

3-1 Data

The dataset used in this study contains household travel survey which forms the basis of 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:

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, socioeconomics 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 for model estimation. This dataset contains 15956 trips related to Montgomery County.

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 the principal outputs 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 chapter, 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 study 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. Section 4 describes the method used to obtain skim values corresponding to alternatives.

MSTM trip tables

Trip matrices are the 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.

3-2 Framework

The framework for obtaining a 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 any given scenario.

Model estimation framework

A 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 travelers, and lacks the generalized cost information of the other alternatives they could choose. MSTM skim matrices are used as a source for information about the other alternatives. The way MSTM's alternative specific skim matrices obtained will be explained in Section 4. The estimation process is summarized in Figure 14.

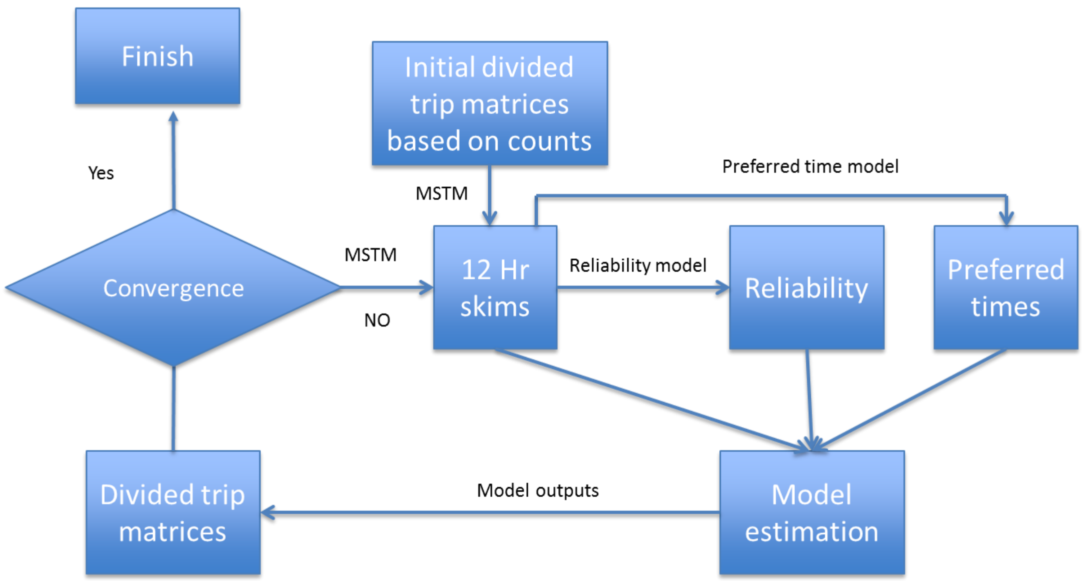

Figure 14: Departure time choice estimation framework

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. By doing so, MSTM can provide alternative specific skim matrices. This process will be explained in greater details in Section 4. In subsection 5-2 of the reliability part, regression of reliability based on the travel time was explained. Using the same method, reliability data can be derived from the skim matrices for each alternative. Other important data type for model estimation is information about travelers' preferred times. Such data are not available in the household travel survey, and it is required to calculate scheduling terms of the departure time choice model. Skim matrices are used to estimate preferred departure time information by a method which is proposed and used in this study for the first time. This is a very critical part which is described in section 5. 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).

$$U_i = ASC_{\ i} + \beta_{skim} * skim_i + \beta_{late} * La_i + \beta_{early} * E_i + \beta_{dist-skim} * dist * skim_i + \beta_{reliability} * R_i + \varepsilon_i \qquad \textbf{(Equation 8)}$$

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

ε_i : error term

The form described is the general form of the utility function that is tried for different trip purposes. Specific terms may show insignificant effect on some purposes and be removed from their corresponding model. 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 shown in Equations 9 and 10.

$$E_i = Max[\, preferred\ departure\ time_i - departure\ time_i, 0\,] \qquad \textbf{(Equation 9)}$$

$$La_i = Max[departure\ time_i - preferred\ departure\ time_i, o] \qquad \textbf{(Equation 10)}$$

Different types of discrete choice models such as Multinomial Logit, Nested Logit, and Mixed logit are estimated for each trip purpose and the best model in terms of performance is chosen. The main difference between these types of model 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 demand distribution; 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 match 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 step, only one iteration of the loop is performed, and continuing the same steps in additional iterations may lead to better results. More iterations will be conducted in the future to improve the model estimation part.

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 study uses total trip tables and divides them into 12 separate trip matrices for 12 intervals. The prediction process is summarized in Figure 15.

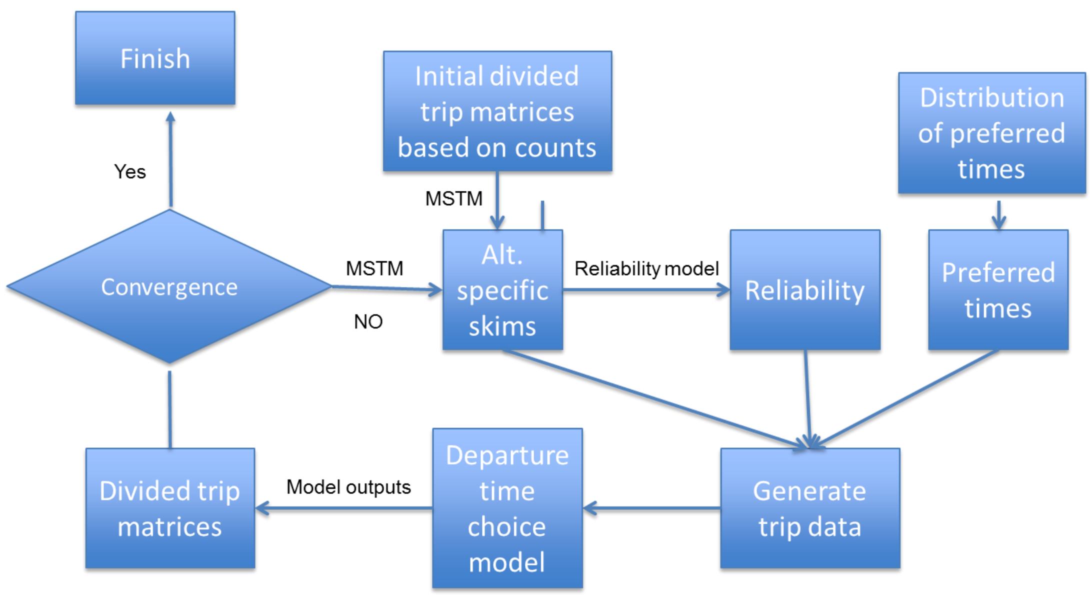

Figure 15: Framework to forecast demand distribution for any given scenario using estimated departure time choice model

In order to predict the demand distribution of any given scenario, initial trip tables and skim matrices are needed. Section 4 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 modeling framework, each trip has a preferred deaparture time, which should be generated. This is done by generating a random number from preferred departure time distribution of each trip purpose.

It is assumed that the distribution of preferred departure times stays the same for any scenario. This distribution is obtained from the model estimation data for which preferred departure time of each trip was previously estimated. The estimation of preferred departure time is explained in detail in Section 5. It is assumed that the same distribution applies to any other scenario, and preferred departure 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 departure times, and reliability data are all combined 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.

Section 4: Alternative Specific Skims

Figure 16 shows the step-by-step procedure of the data preparation for the peak spreading model development

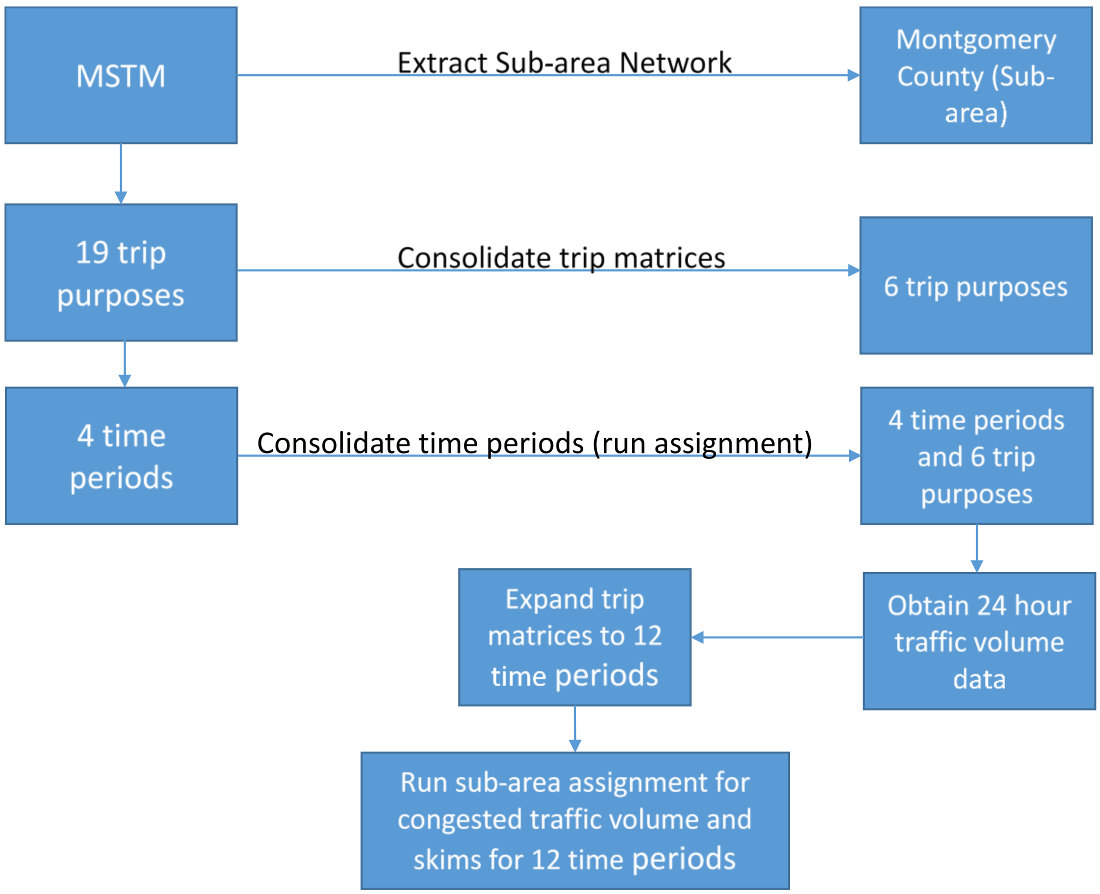

Figure 16: Step by step procedure to obtain trip tables and skim matrices for 12 alternatives

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) (Mishra et al. 2011). 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 17 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 were 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. The outputs of this process are the 6 trip matrices for each of the 4 time-periods. In this process, Equation 11 is formulated to calculate the generalized link cost for all user classes:

$$cost = t + (toll/vot) + \pi \times distance \qquad \textbf{(Equation 11)}$$

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).

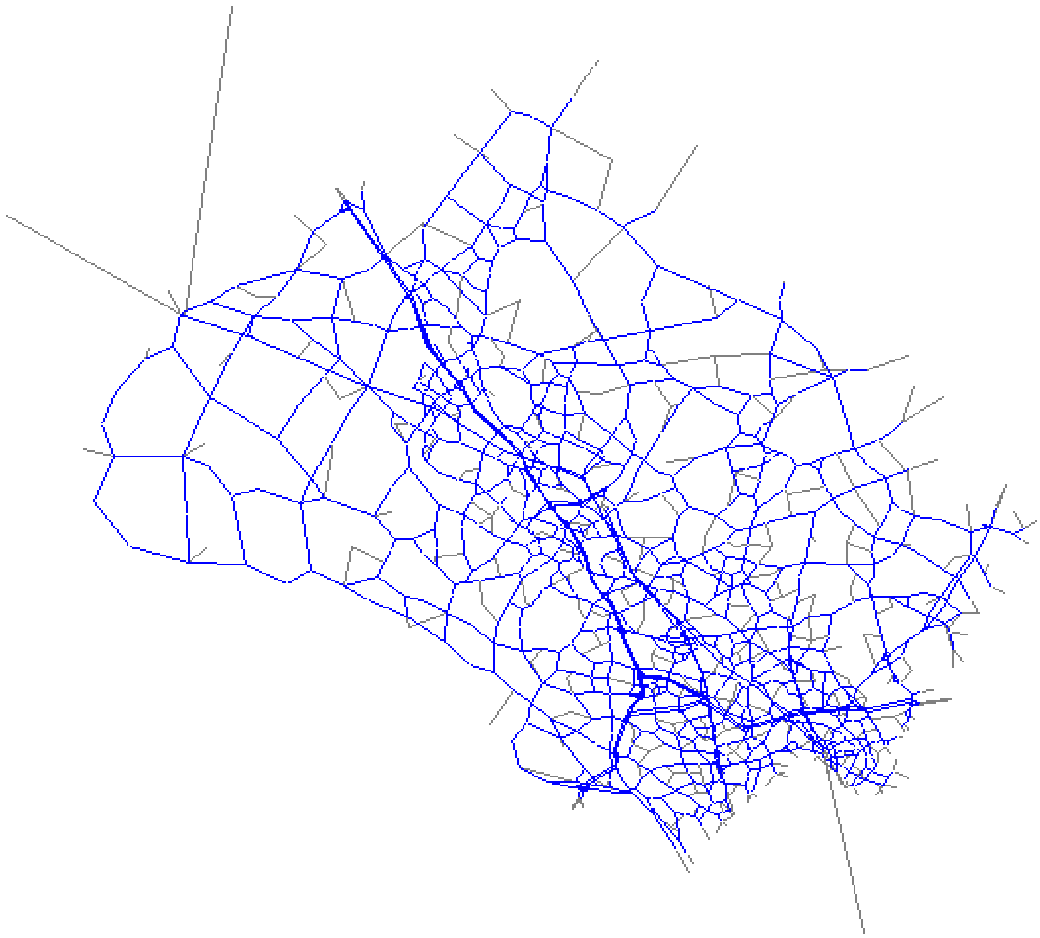

Figure 17: Extracted Montgomery County network from MSTM

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

$$t = t_0 [1 + \alpha (v/c) \beta] \qquad \textbf{(Equation 12)}$$

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 running the script, a specific file 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 into 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. Then alternative specific trip matrices were obtained by multiplying the daily O-D trip matrices with the 12 time period factors obtained from traffic counts data.

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 for Highway Assignment of 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. 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 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 Equation 13:

$$TT = 60 * Distance / (CSPD) \qquad \textbf{(Equation 13)}$$

where,

TT = Travel time in Minutes

Distance = Distance or Length of the links in miles

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

Section 5: Preferred Departure Time (PDT) Estimation

The departure time choice model used in this thesis 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 such as 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. Previous preferred time estimations are based on regression on traveler and trip characteristics which needs huge amount of data. These data are not always available in four step modeling context. Estimating preferred times based on skim values has not been done before to the best of author's knowledge.

Any assumption on preferred times, strongly affects model estimation result. For instance, it can be assumed that preferred departure time is equal to actual departure 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.

This thesis introduces a method to estimate PDT based on skim values. It assumes rational behavior of users who are trying to maximize their utility. This approach estimates preferred departure time based on actual departure time. It is assumed that the actual departure 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 departure interval j is observed, the preferred departure 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. Equations 14 and 15 assumed to calculate the probability that observed trip at interval *j* has PDT at interval *i*:

$$P(PDT = i|ADT = j) = \alpha/k * \frac{S_i - S_j}{|i-j|} \qquad \textit{If } S_i > S_j \qquad \textbf{(Equation 14)}$$

$$P(PDT = i|ADT = j) = 0 \qquad \textit{If } S_i <= S_j \qquad \textbf{(Equation 15)}$$

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 of the P values over all intervals should be 1. Or:

$$0 \leq \sum_{i \neq j} P\left(PAT = i \,\middle|\, AAT = j\right) \leq 1 \qquad \textbf{(Equation 16)}$$

Sigma in Equation 16 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 doing so 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 as:

$$k = \frac{CDF(\sum_{i \neq j} \alpha * \frac{S_i - S_j}{|i-j|})}{\sum_{i \neq j} \alpha * \frac{S_i - S_j}{|i-j|}} \qquad \textbf{(Equation 17)}$$

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 is estimated using Home-Based Work dataset. For HBW trips PDT can be obtained using work start time and work end time, by assuming that work start time is the preferred arrival time of home to work trips, and work end time is the preferred departure time of work to home trips. Knowing the probability of PDT being in each interval as a function of α, and actual preferred interval, α can be estimated using maximum likelihood estimation. Doing so, α is estimated to be equal to 5.56, with standard deviation equal to 0.181, and t-value equal to 30.659. Alpha is assumed to be the same for other trip purposes.

The method described can estimate the PDT for model estimation dataset without requiring any further data collection. The distribution of PDTs 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 PDT of travels are randomly drawn from the PDT distribution. It is a fairly good assumption, because PDTs are dependent on traveler's schedules and preferences, not necessarily on network conditions.

Section 6: 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 variances of random coefficients were 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. The 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 shows 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, the 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.

6-1 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 6 to 8 summarize the results of model estimation:

Table 6: 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 7: 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 8: HBW model nest coefficients estimation results

Name ▼	Value	Std err	t-test	p-value	Robust Std	Robust t-	p-

					err	test	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 departure time estimation.

The model is estimated on 70 percent of the data, and the remaining 30 percent is used for validation purpose. The estimated share should be compared with real share for validation. Figure 18 shows the result of model validation:

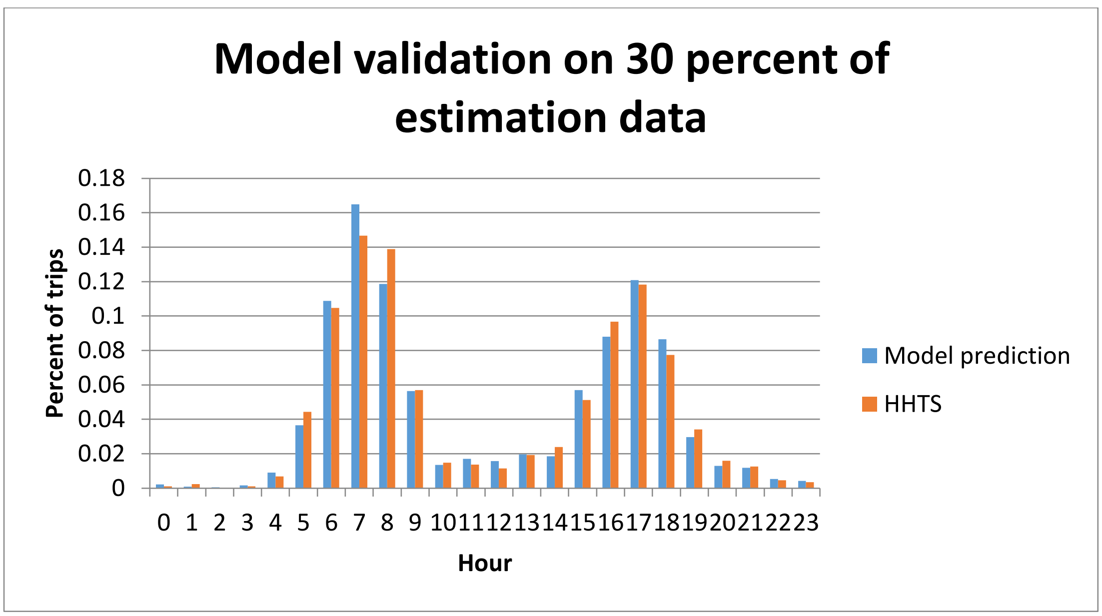

Figure 18: HBW model validation using 30 percent of data

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.

6-2 Home-Based Shopping (HBS) Trips

Similar by HBW model, the 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 9 to 11 summarize the results of model estimation:

Table 9: 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 10: 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 11: 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 departure 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 that travelers prefer to have shorter travel times. The results of model validation are presented in Figure 19:

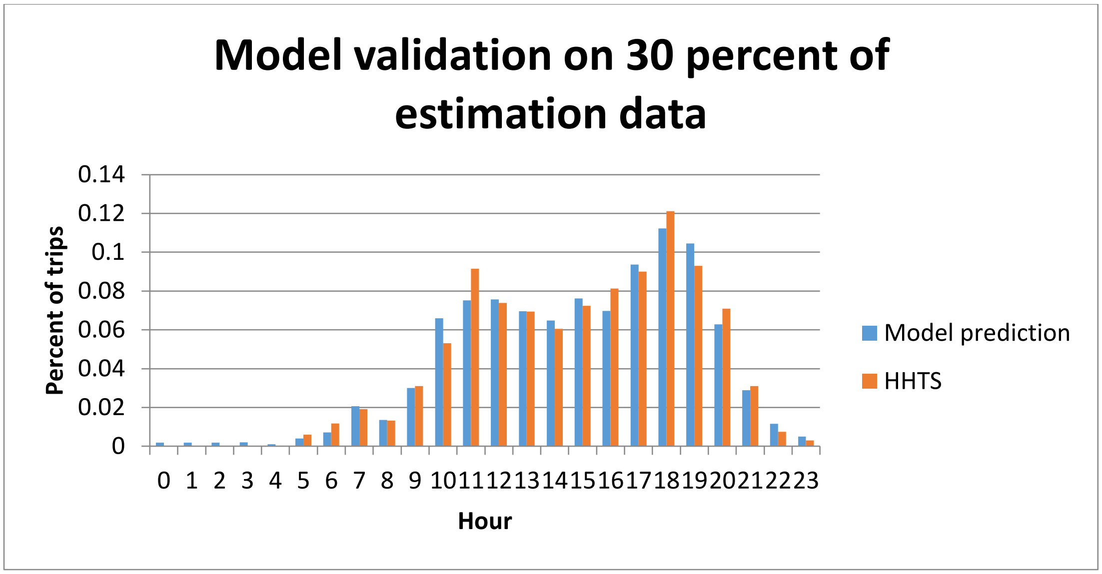

Figure 19: HBS model validation with 30 percent of data

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.

6-3 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 12 to 14 summarize the results of model estimation:

Table 12: 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 13: 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 14: 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 departure 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 Figure 20:

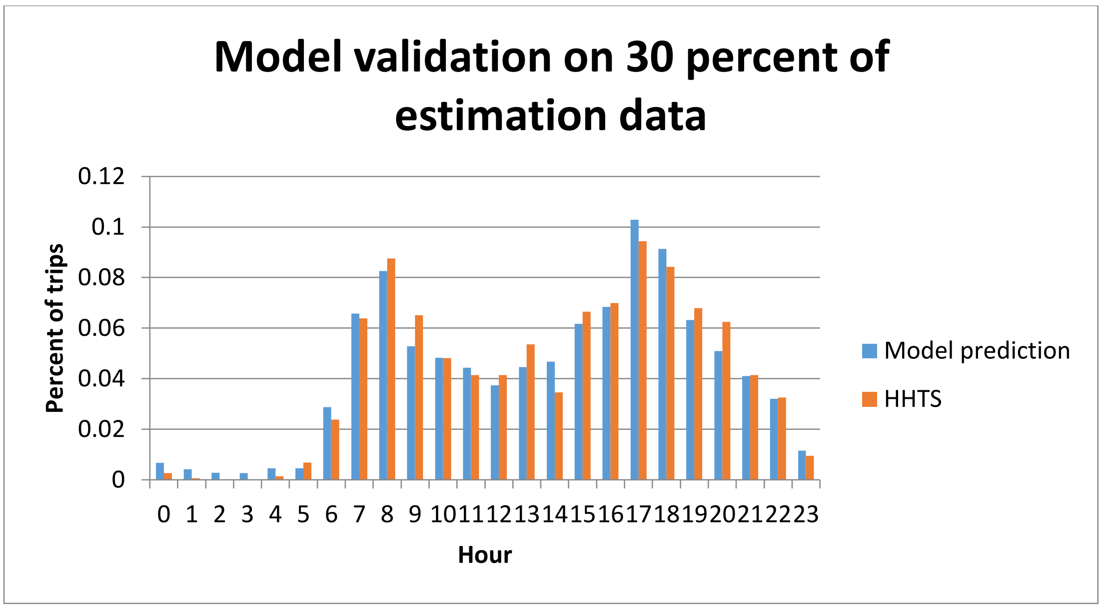

Figure 20: HBO model validation with 30 percent of data

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.

6-4 Home-Based School (HBSCH) Trips

Similar to previous models, HBSch model follows nested logit structure with the same nests. Tables 15 to 17 summarize the estimation results:

Table 15: 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 16: 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 17: 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 departure time estimation. The validation results are presented in figure 21:

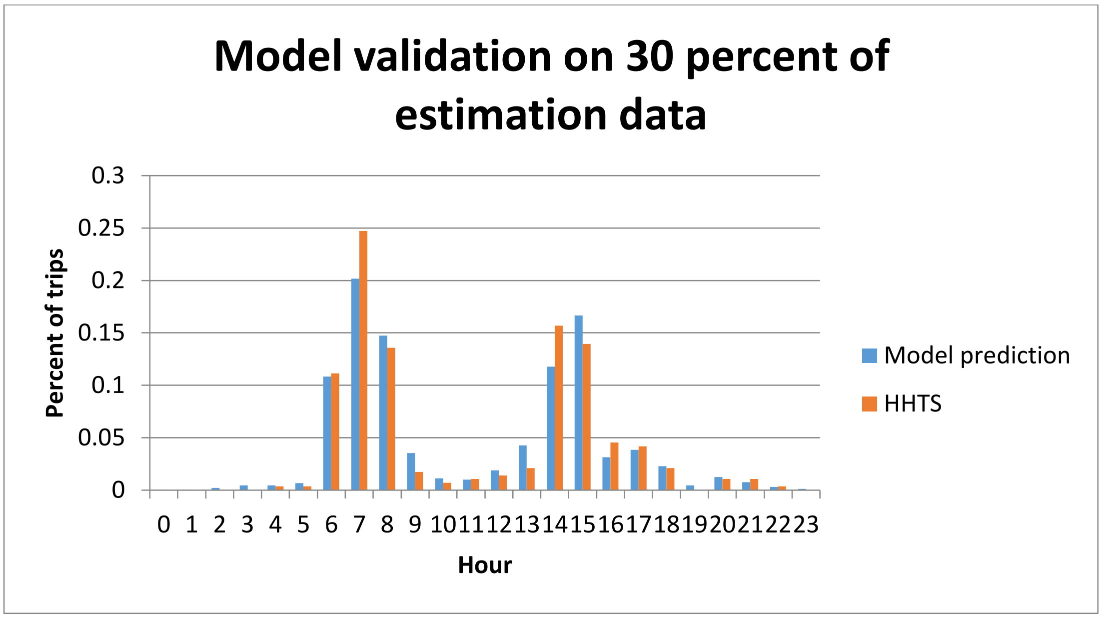

Figure 21: HBSch model validation with 30 percent of data

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

6-5 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 a considerable number of midday trips. 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 variables show significant effect if they are in the model alone, but the model with reliability had higher Rho-square and it was preferred. Tables 18 to 20 summarize the estimation results:

Table 18: 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 19: 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 are as expected, and Rho-square is high because of preferred departure time estimation. The result of model validation can be seen in Figure 22:

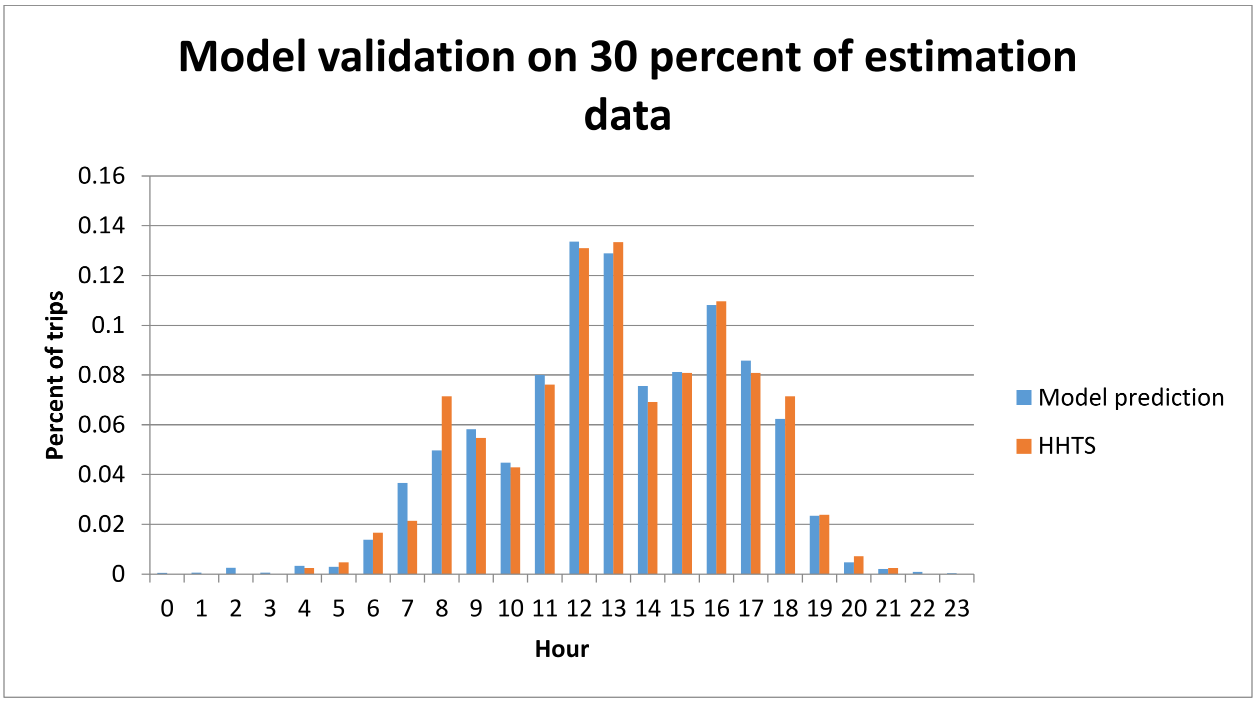

Figure 22: NHBW model validation with 30 percent of data

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

6-6 Non-Home-Based Other (NHBO) Trips

The 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 20 to 22 summarize the results of model estimation:

Table 20: 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 21: 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 22: 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 departure time estimation. The result of model validation can be seen in Figure 23:

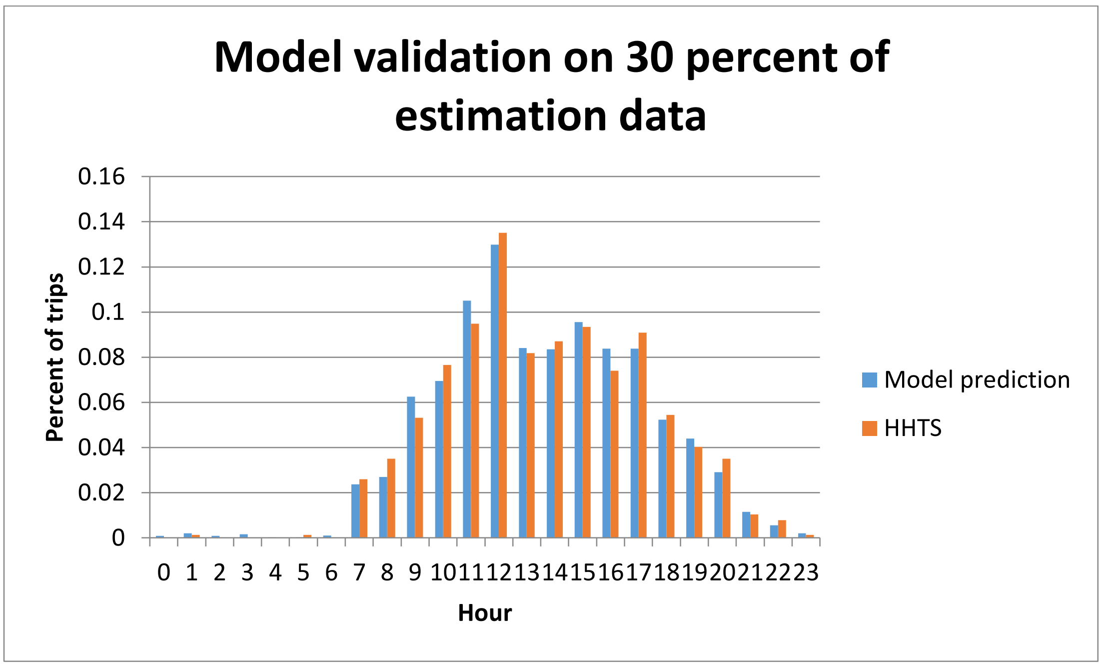

Figure 23: NHBO model validation with 30 percent of data

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 a 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 section. The result is compared with the observed distribution of demand from household travel survey. Figure 24 shows this comparison:

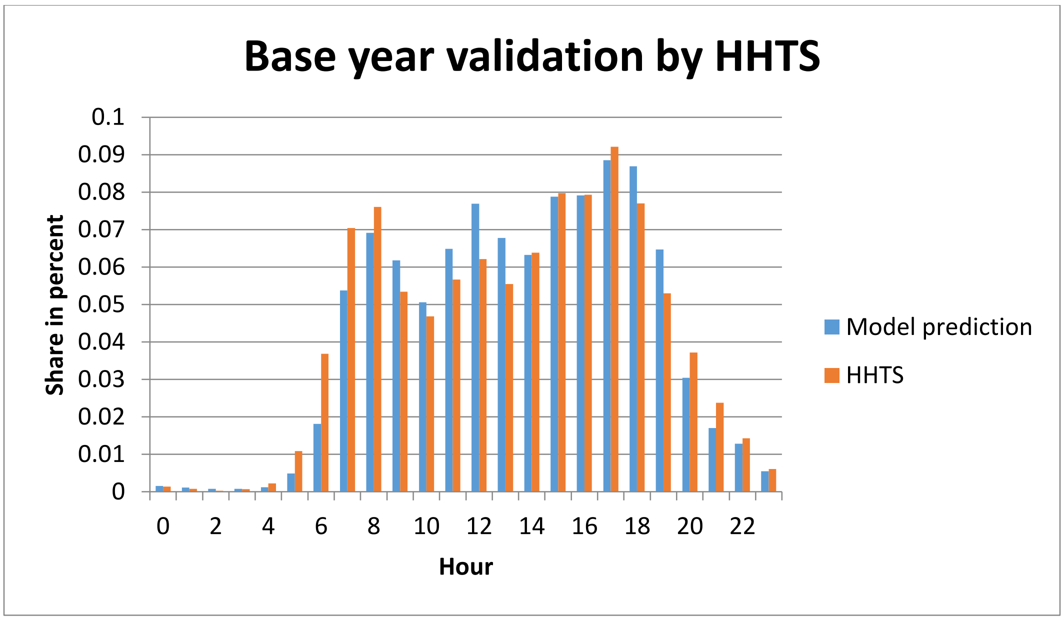

Figure 24: Model validation by comparing predicted distribution versus HHTS distribution

Normalized root mean square for this comparison is 0.09.

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

Section 7: Peak Spreading Prediction

In the methodology section, the way in which the 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.

7-1 Home-Based Work (HBW) Results

Initial run of the MSTM shows changes in the network-wide average skim values from base to future year as described in Figure 25:

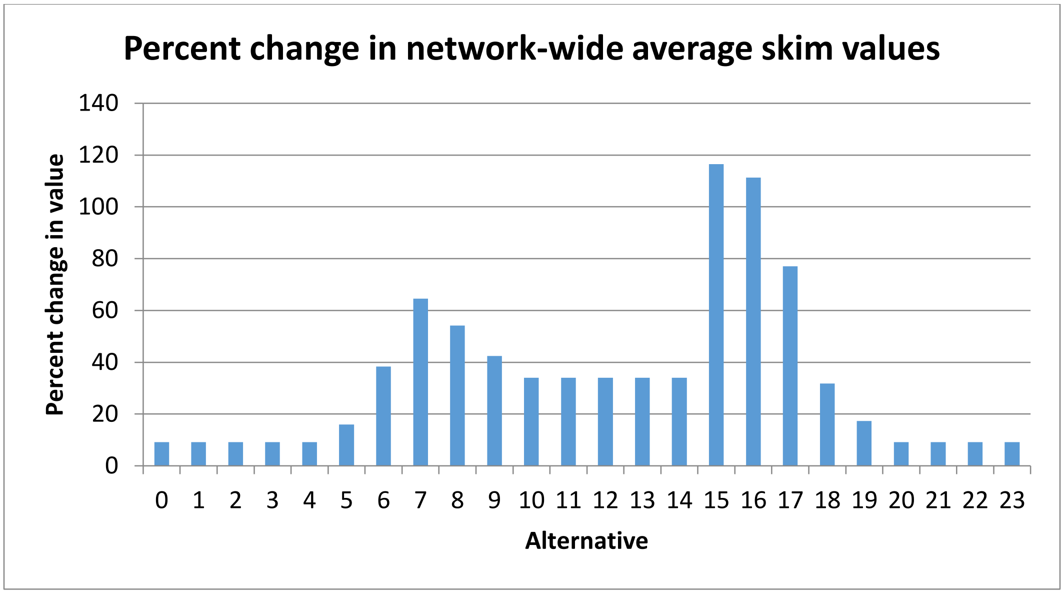

Figure 25: Percent change in network-wide average skim values for HBW trips

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. The total number of trips for the base year is 291425, and for the future year is 378032. Using these input data in the prediction process, the distribution of trips is obtained and depicted in Figure 26:

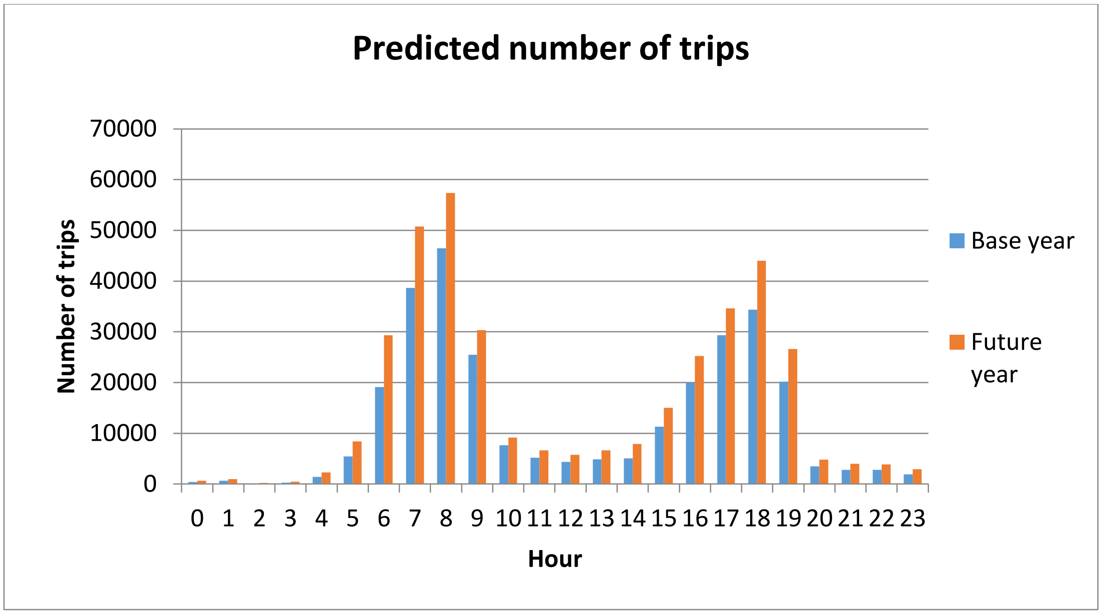

Figure 26: Predicted distribution of HBW trips

Figure 27 better shows the change in the distribution. It represents the change of share from total number of trips in percent by comparison of base and future year:

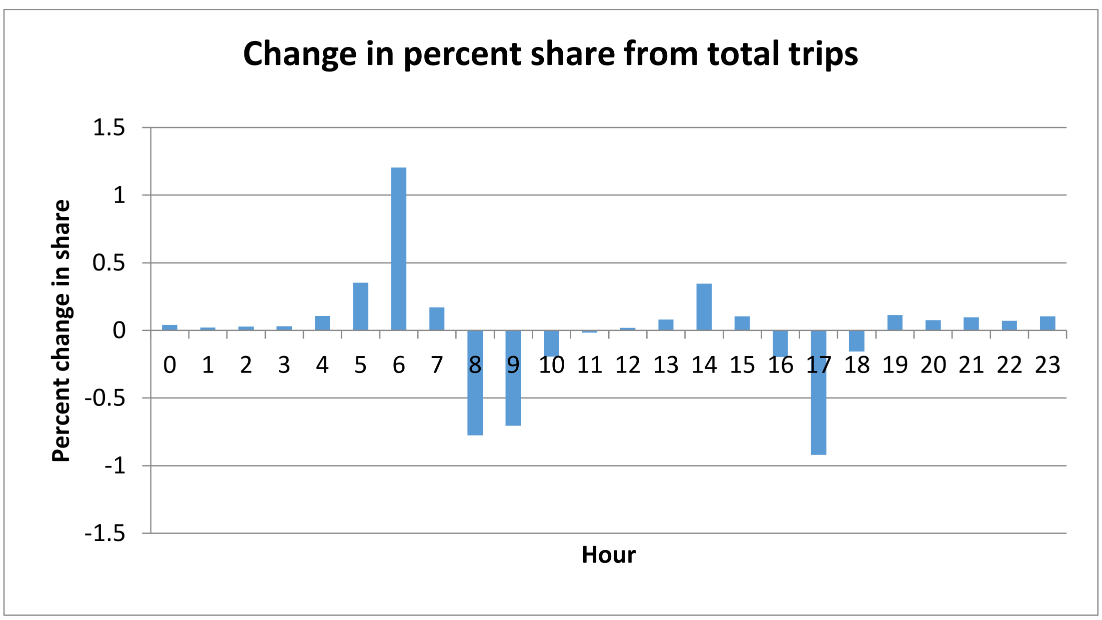

Figure 27: Change in percent share from total HBW trips

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 shares of the peak hours are decreasing.

7-2 Home-Based Shopping (HBS) Results

Percent change in network-wide average skim values can be seen in Figure 28:

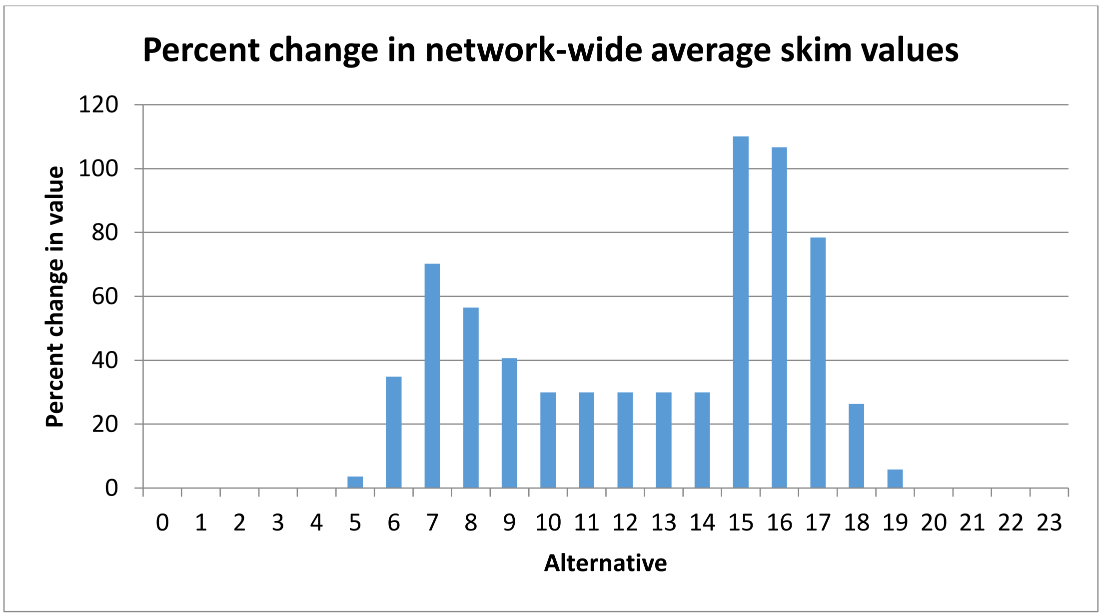

Figure 28 Percent change in network-wide average skim values for HBS trips

It can be seen that MSTM shows higher skims for future year, and the increase is more significant at the afternoon peak hours. The 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 29 and 30:

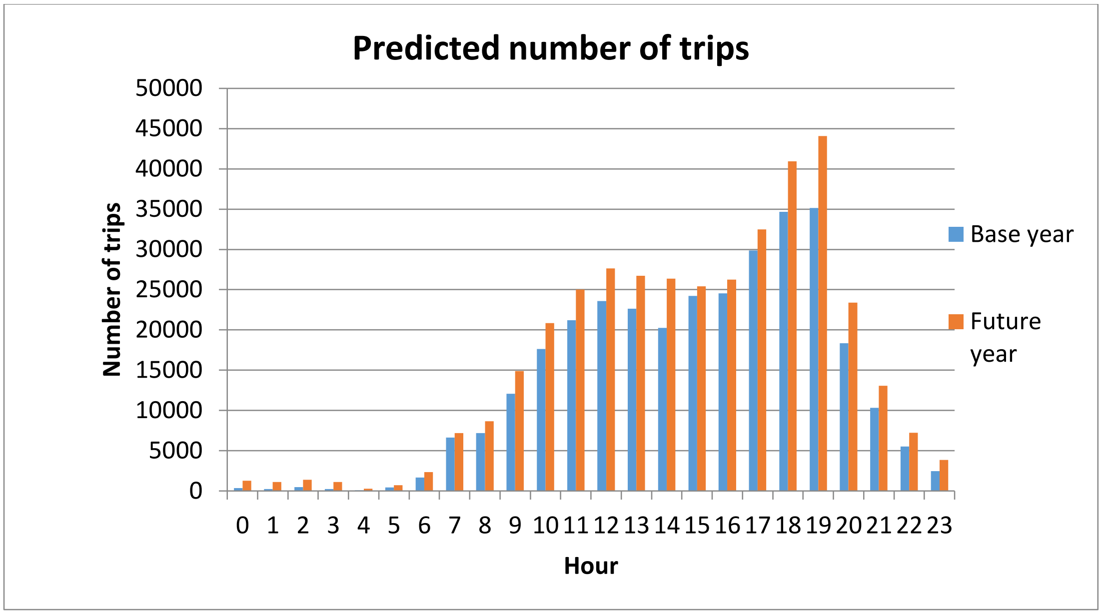

Figure 29: Predicted distribution of HBS trips

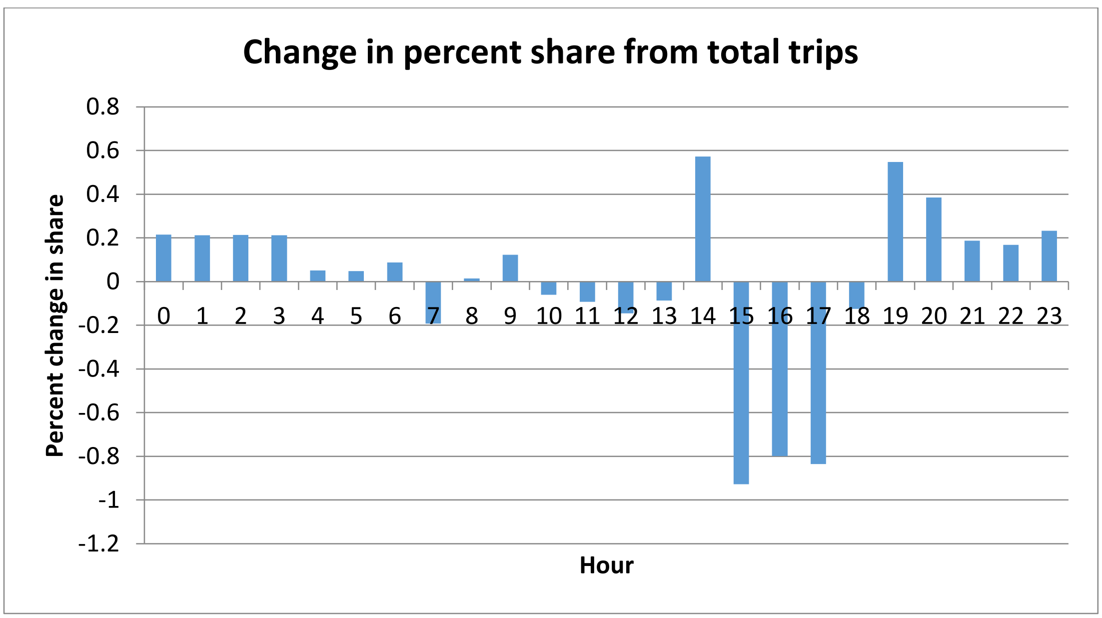

Figure 30: Change in percent share from total HBS trips

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

7-3 Home-Based Other (HBO) Results

Figure 31 shows the percent change in network-wide average skim values obtained from MSTM outputs:

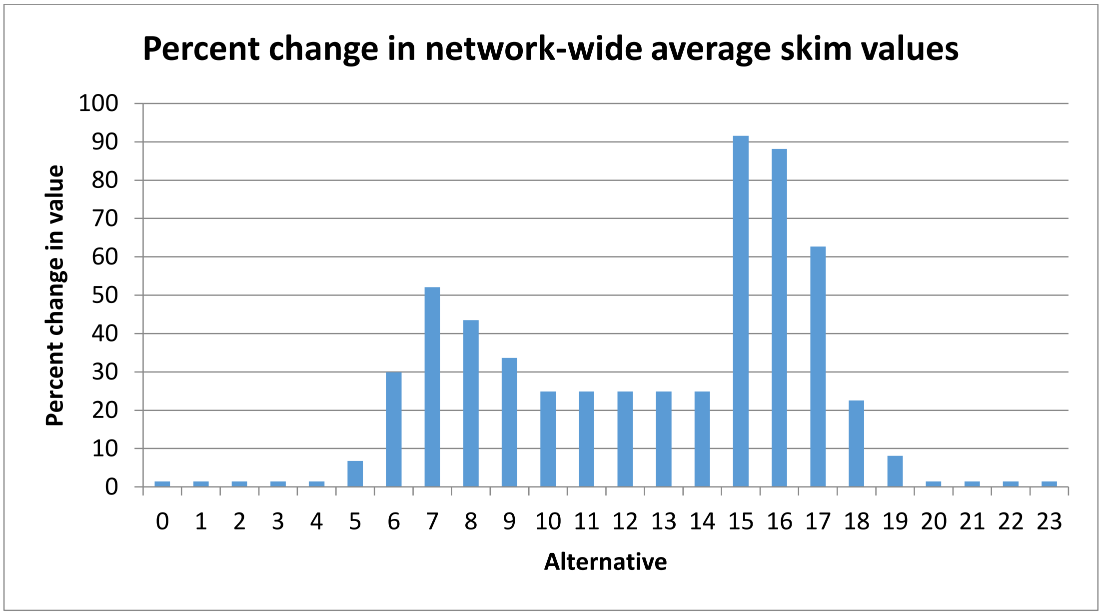

Figure 31: Percent change in network-wide average skim values for HBO trips

Congestion gets more severe all along the day, especially in the afternoon peak. The number of trips in the base year is 486430, and in the future year is 644947. The results of prediction are presented in Figures 32 and 33:

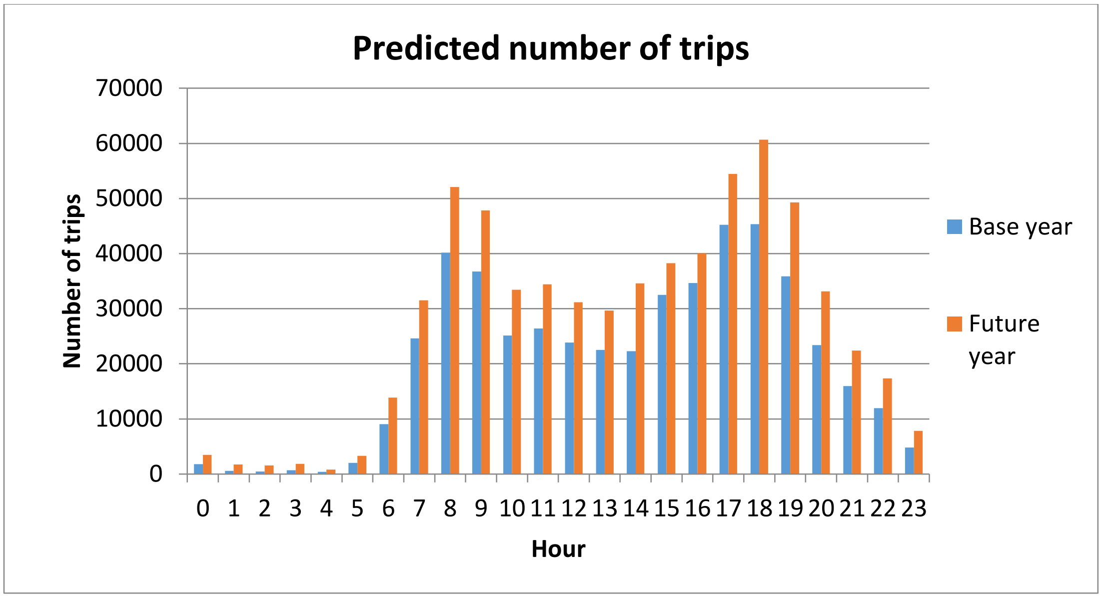

Figure 32: Predicted distribution of HBO trips

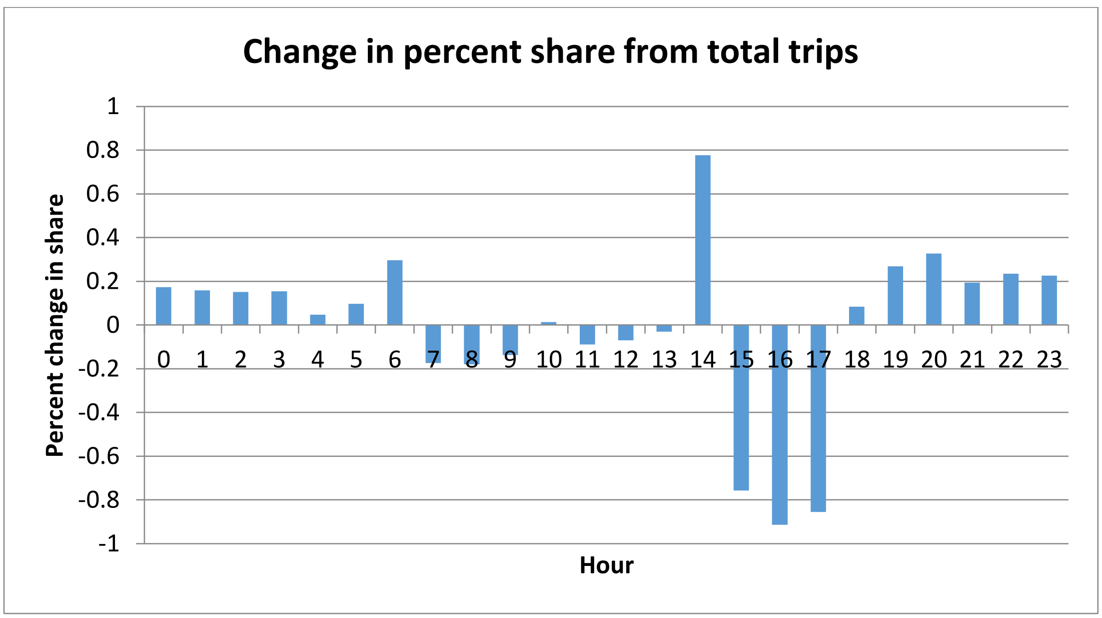

Figure 33: Change in percent share from total HBO trips

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

7-4 Home-Based School (HBSch) Results

Figure 34 shows the percent change network-wide average skim values:

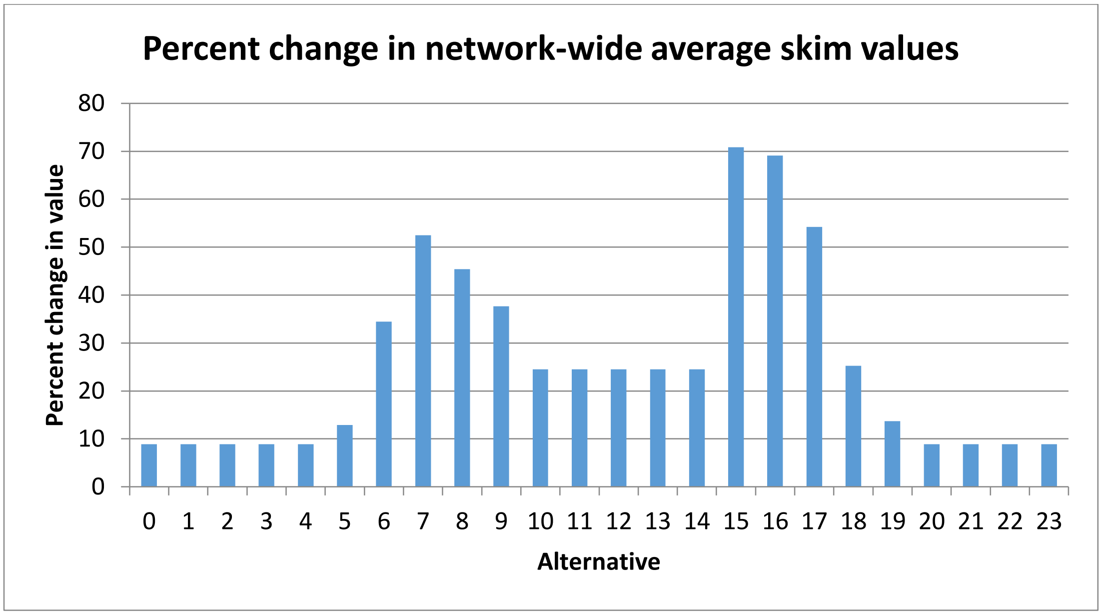

Figure 34: Percent change in network-wide average skim values for HBSch trips

More severe congestion is observable similar to previous purposes. The base year number of trips is 94359, and future year number of trips is 113022. The prediction outputs are presented in Figures 35 and 36:

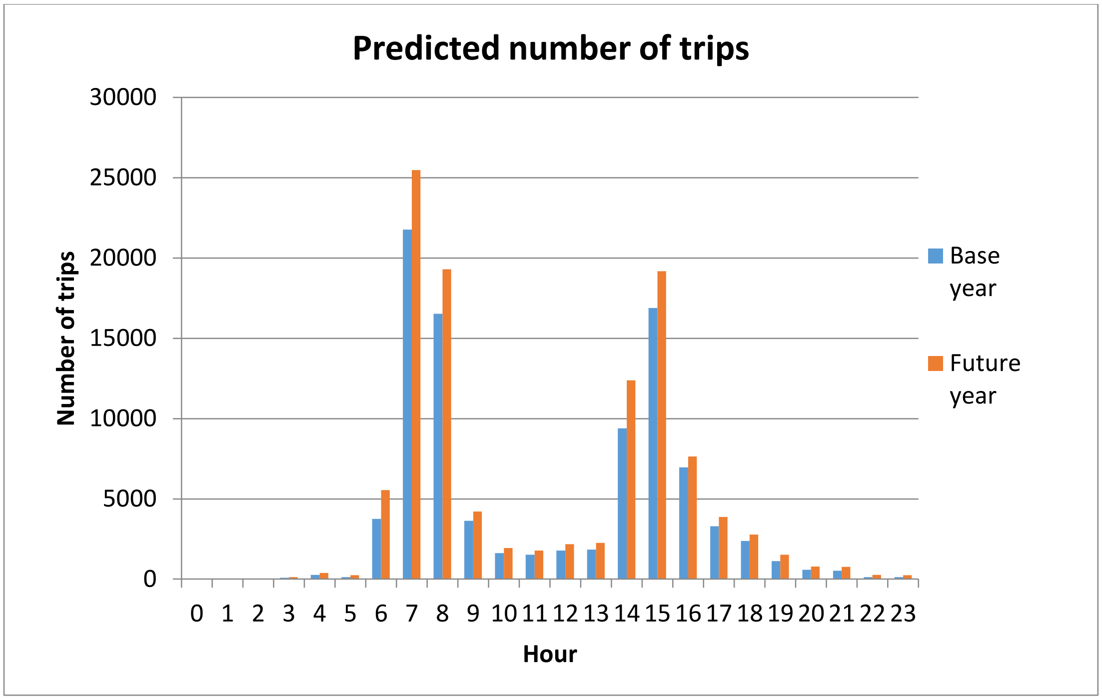

Figure 35: Predicted distribution of HBSch trips

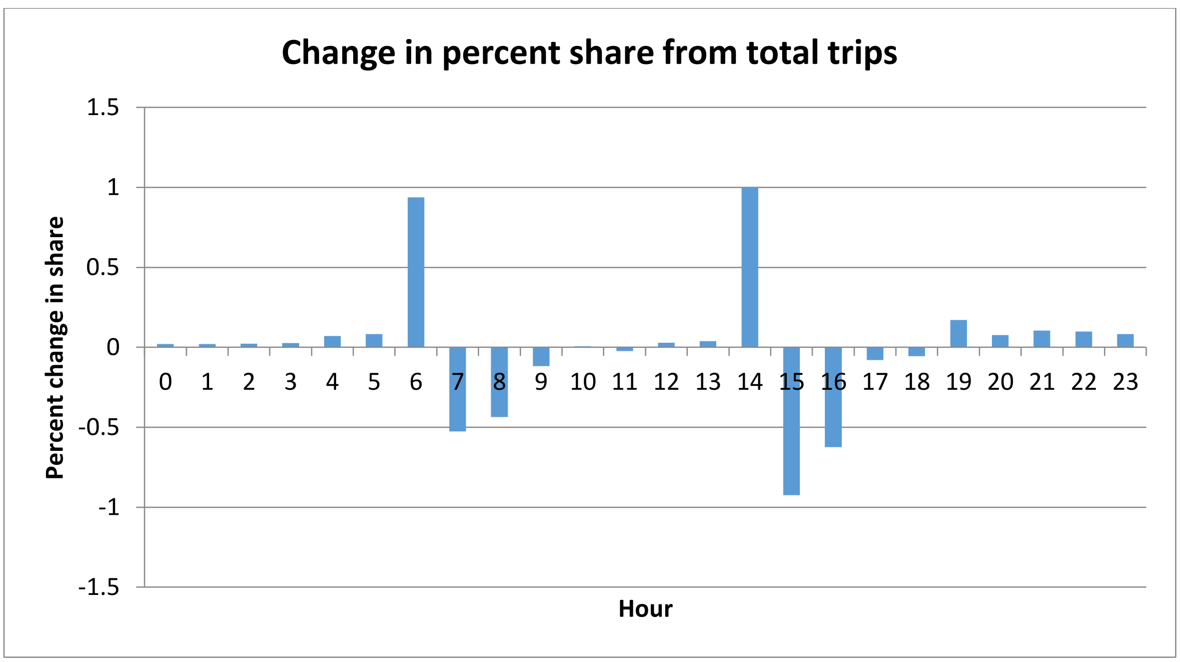

Figure 36: Change in percent share from total HBSch trips

School trips are being shifted to the earlier time periods in which roads are less congested.

7-5 Non-Home-Based Work (NHBW) Results

Similar by previous models, skim values get higher for the future year as can be seen in Figure 37.

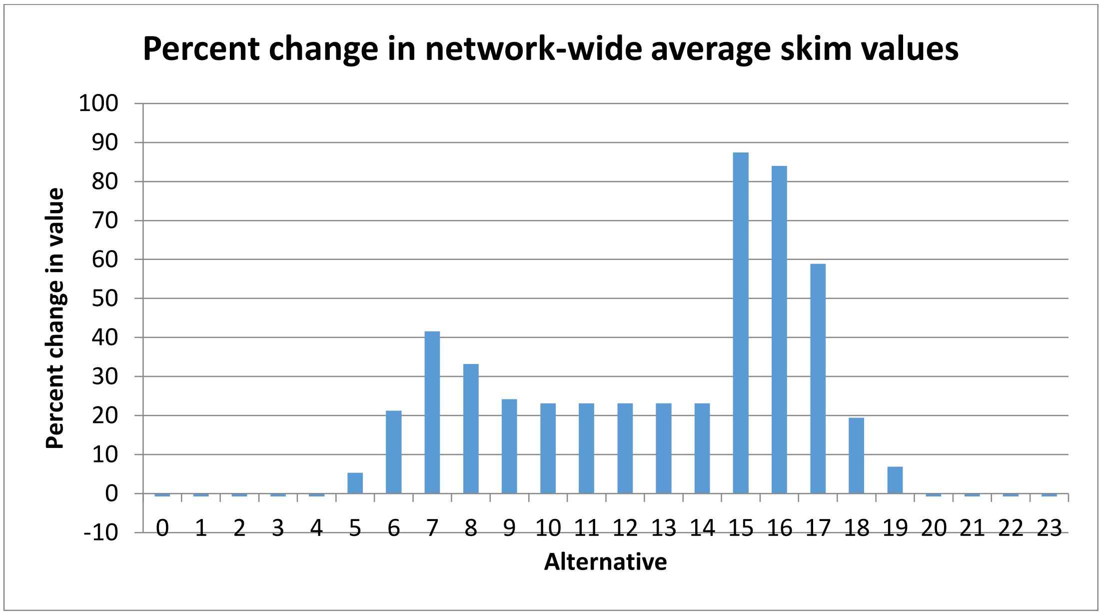

Figure 37: Percent change in network-wide average skim values for NHBW trips

The number of trips for the base year is 378896, and for the future year is 497827. The prediction outputs can be seen in Figures 38 and 39:

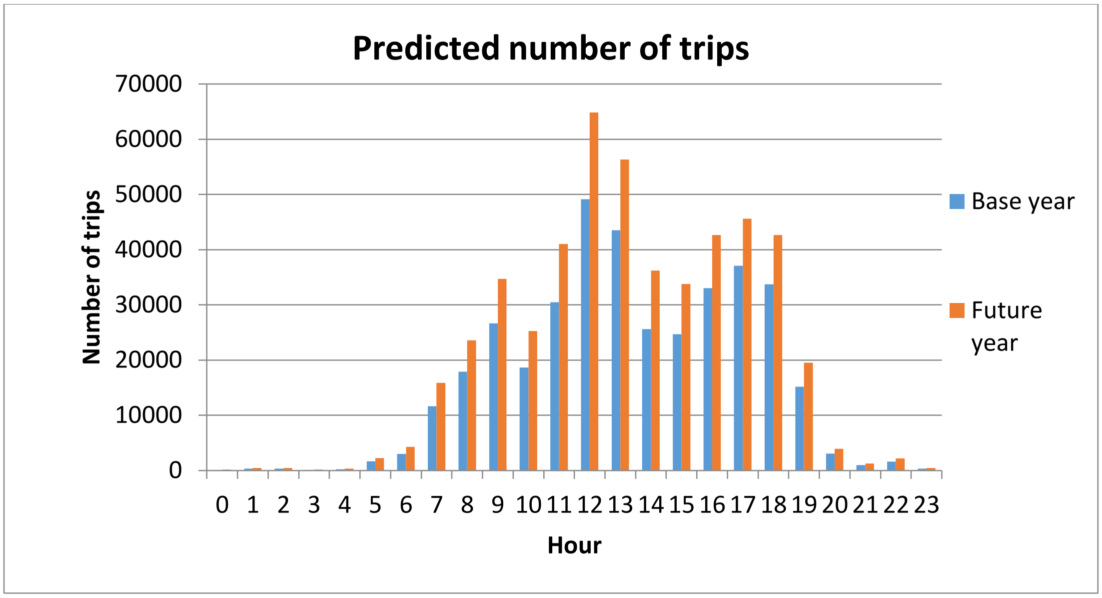

Figure 38: Predicted distribution of NHBW trips

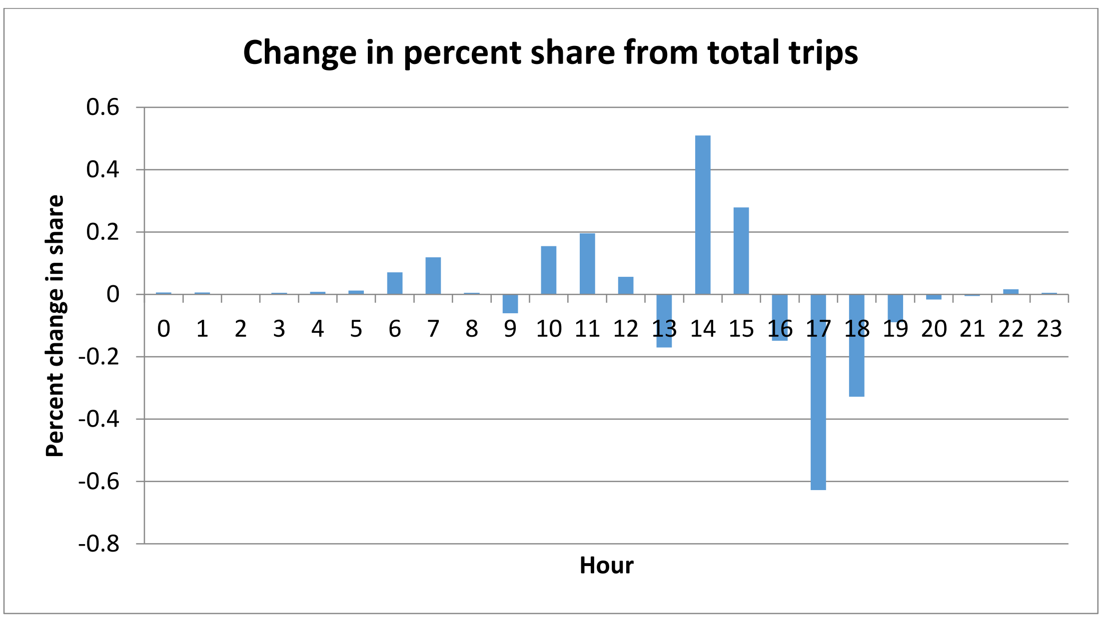

Figure 39: Change in percent share from total NHBW trips

For this trip purpose the afternoon peak shifts to earlier less congested intervals.

7-6 Non-Home-Based Other (NHBO) Results

Figure 40 shows trends similar to previous figures. The only difference is the lower skim value for future year during night time, which should be a bug in the input data.

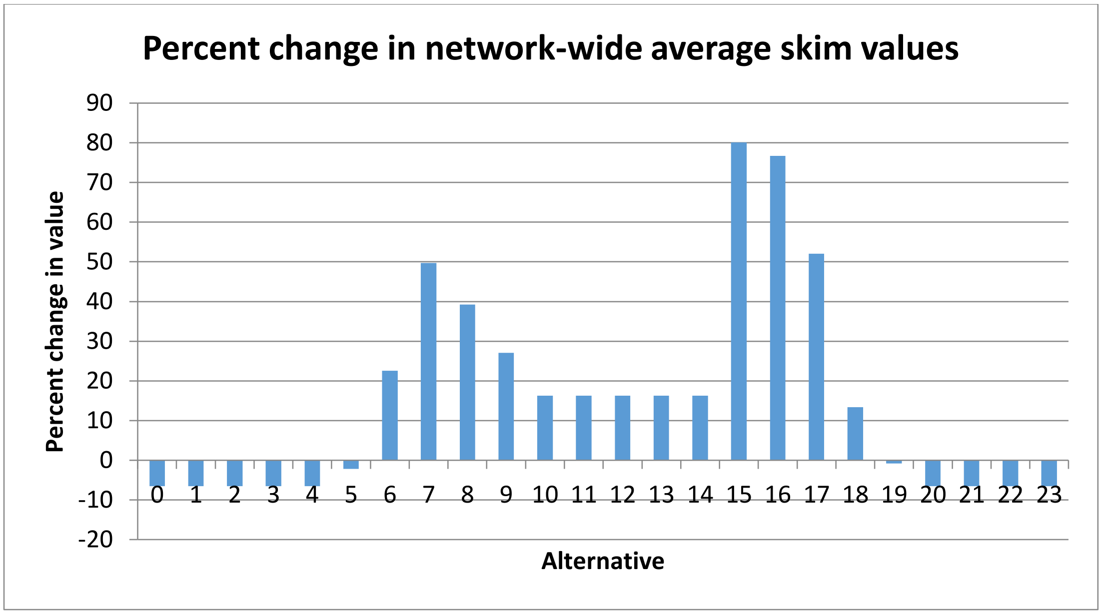

Figure 40: Percent change in network-wide average skim values for NHBO trips

The 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 shown in Figures 41 and 42.

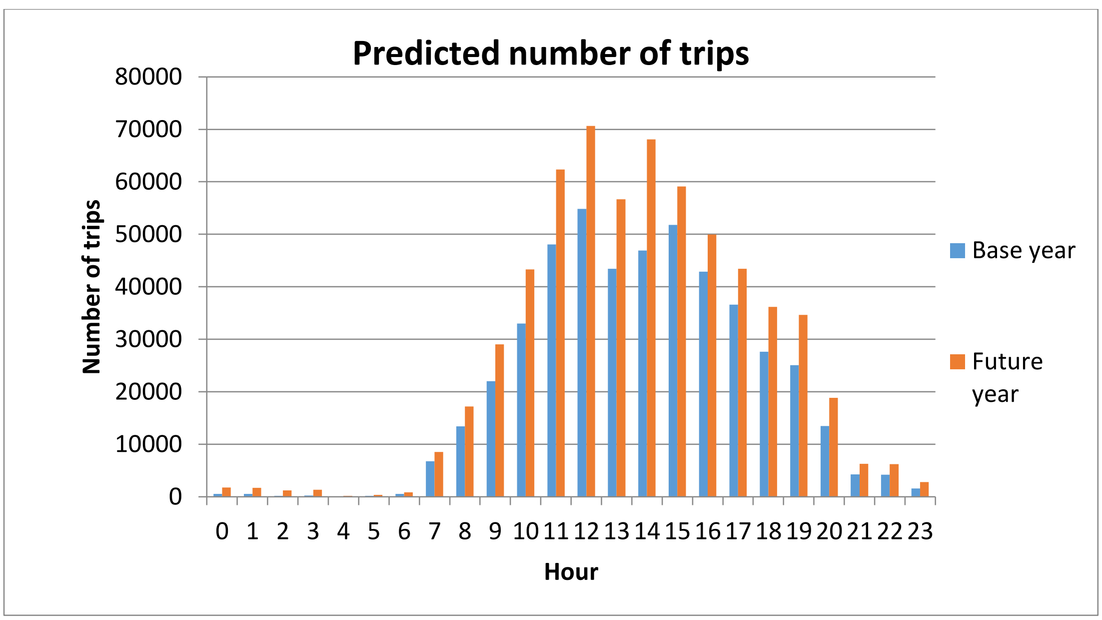

Figure 41: Predicted distribution of NHBO trips

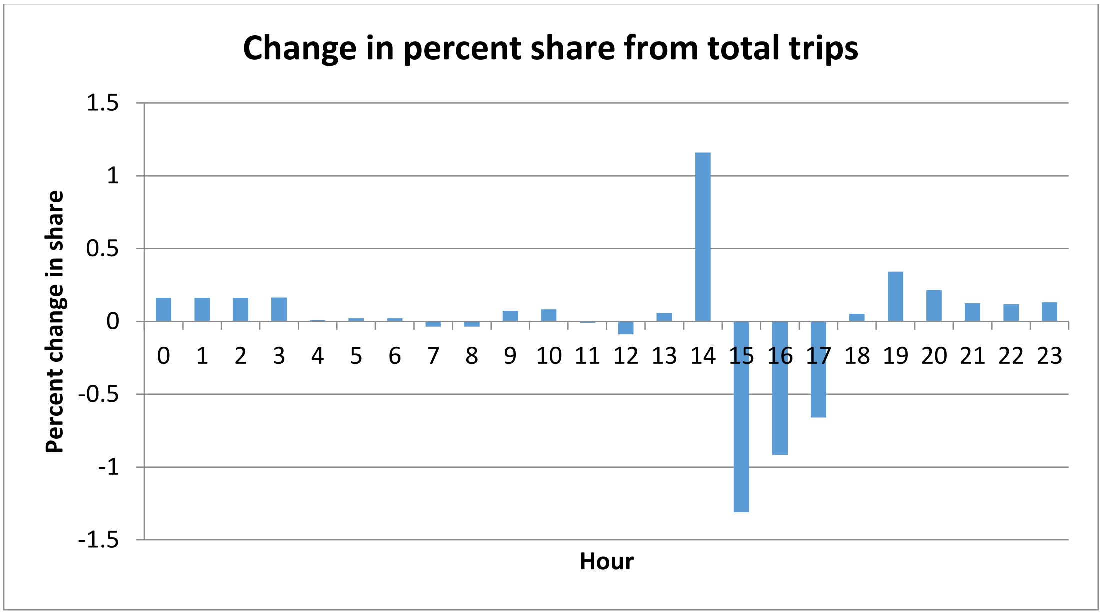

Figure 42: Change in percent share from total NHBO trips

7-7 Overall Peak Spreading Results

Results of comparison between base year and future year demand profiles for different trip purposes were presented separately in previous sections. Now they are combined to show the overall demand profile. The change in skim values is presented first in Figures 43 and 44:

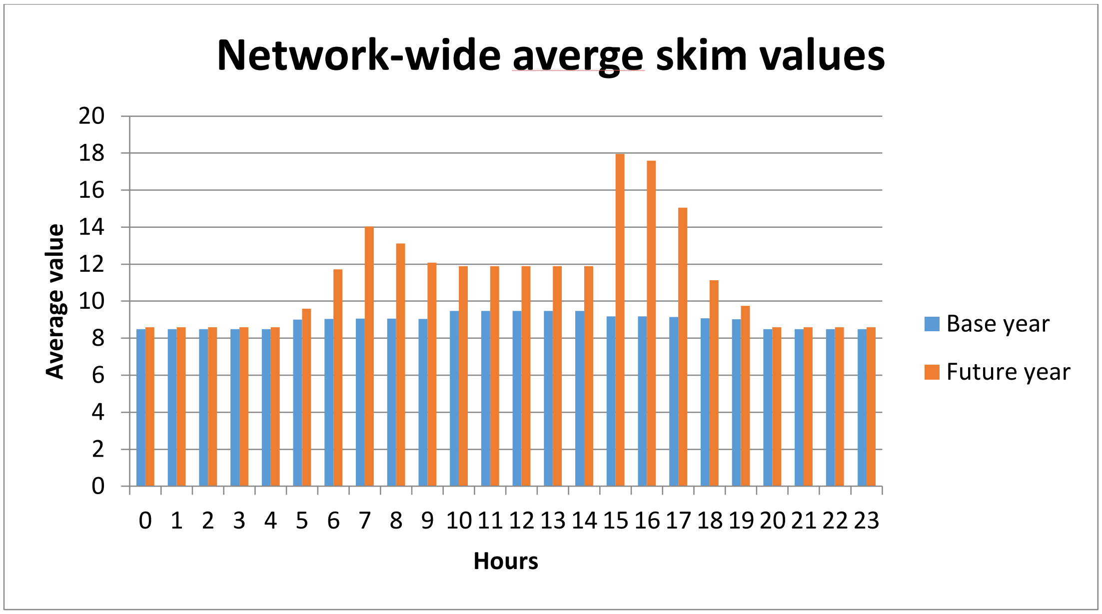

Figure 43: Overall network-wide average skim values

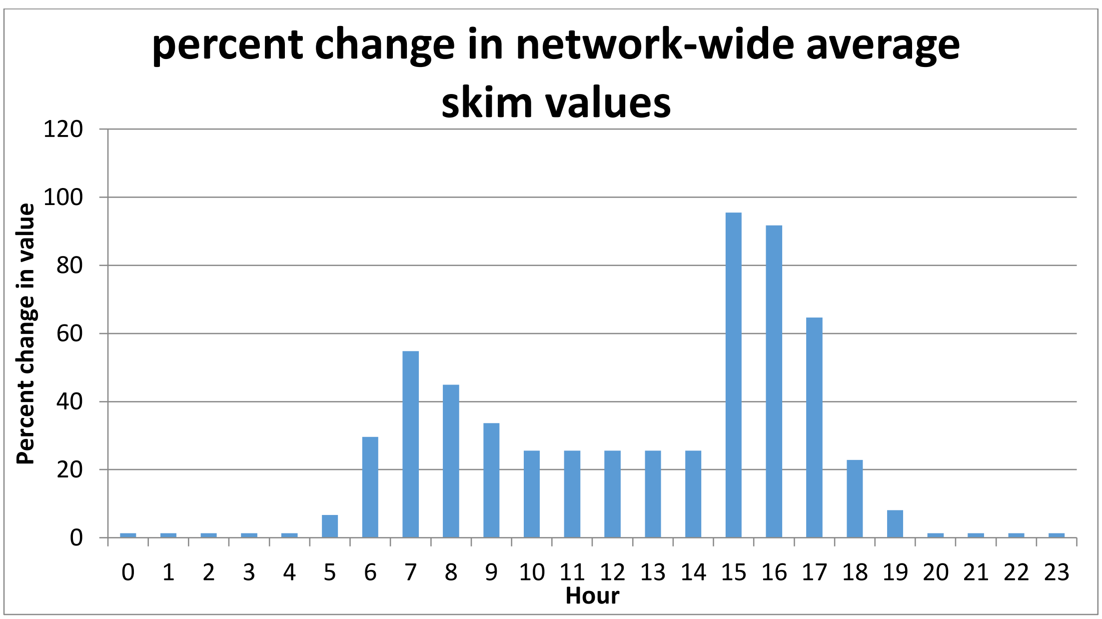

Figure 44: Percent change in overall network-wide average skim values

Based on these inputs, the overall prediction results are obtained and presented in Figures 44 and 45:

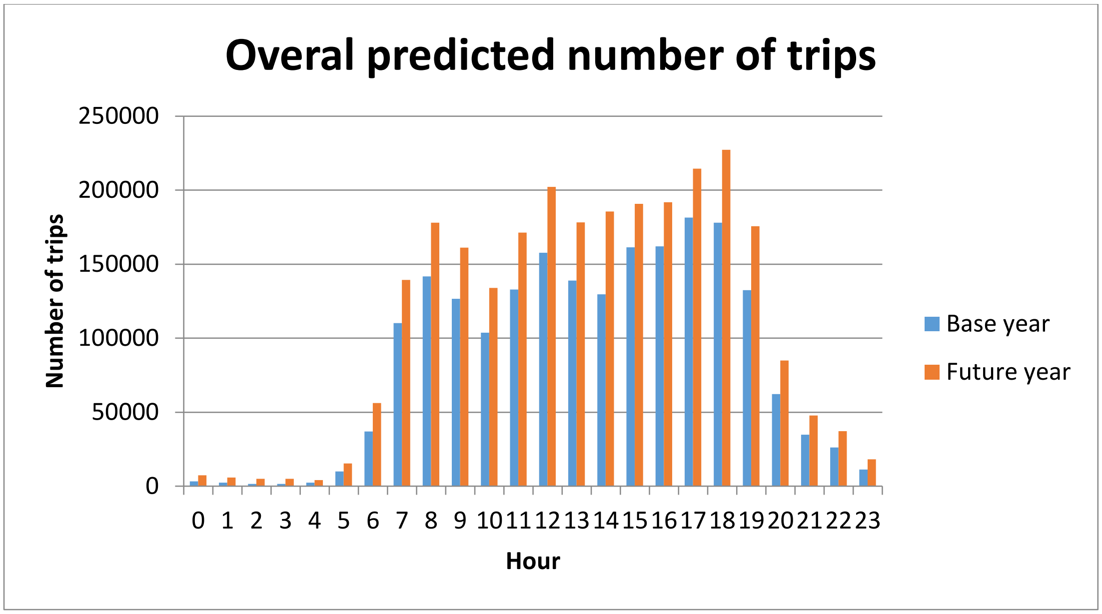

Figure 45: Overall predicted distribution of trips

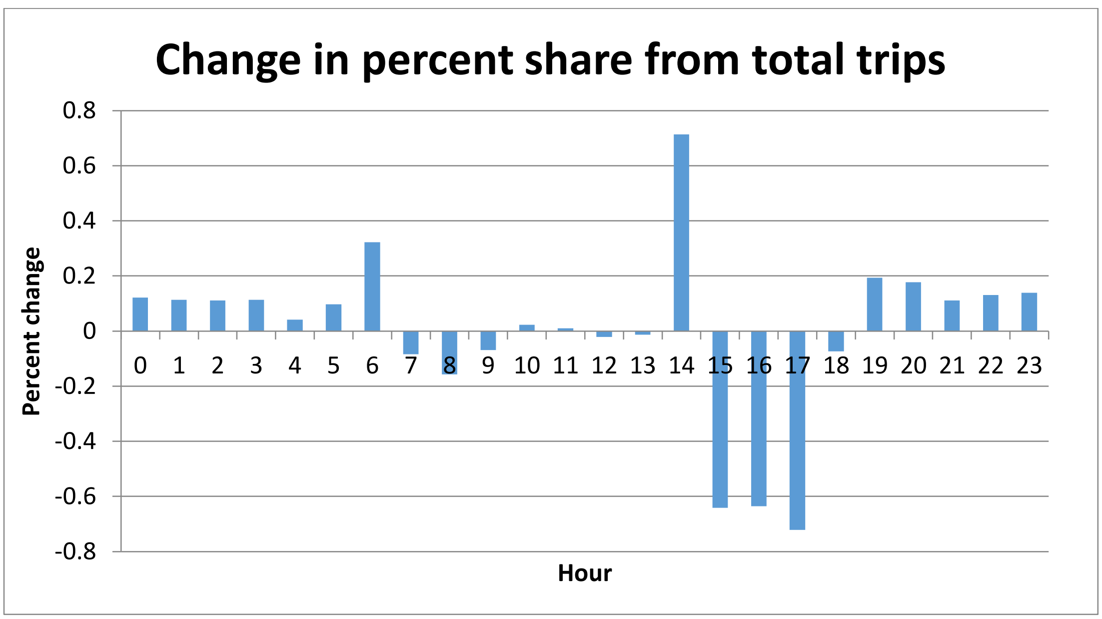

Figure 46: Change in Percent share from total trips

The overall result show that afternoon peak hour share will decrease in the future year. A considerable amount of this shifted demand goes to the left peak shoulder. A 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.

Section 8: Summary and Conclusions

This chapter proposed a framework that can be incorporated with trip-based four-step models to account for time of day. The framework estimates reliability and preferred departure times based on skim values, which makes it easily usable without additional data requirements. In this study discrete choice models were combined with MSTM to model departure time choice of 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. Each of the attributes were obtained in a unique way introduced in a separate section. Separate models were estimated for each trip purpose. 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. Alternative specific skims were combined with TPB-BMC Household Travel survey data to estimate a departure time choice model. No data were available on preferred departure time of travelers and a method was introduced to estimate it based on skim values. The estimated models showed negative effect of longer travel time, unreliability, and scheduling delay, as expected. Scheduling delays turned out 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 in the future. First, 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 expanded to cover the entire state of Maryland. Another idea for improvement is about estimation of PDT. A travel survey that includes PDT information can be conducted, and it can be used in model estimation instead of HHTS. The reliability model is another part that can be improved. Incident and weather data can be added to 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.

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