SIMULATION BASED EVALUATION OF DYNAMIC CONGESTION PRICING ALGORITHMS AND STRATEGIES

by

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ABSTRACT OF THE THESIS

Simulation Based Evaluation of Dynamic Congestion Pricing Algorithms and Strategies

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Congestion pricing is defined as charging motorists during peak hours to encourage them to either switch their travel times or to use alternative routes. The theory behind road pricing suggests that, in order to reach social optimum conditions, a toll needs to be charged which is equal to the difference between social marginal costs and private average costs of users.

In recent years, with the help of technological developments such as electronic toll collection system, pricing can be done dynamically, that is, tolls can be set in a real-time fashion according to the on-line measured traffic conditions. Dynamic pricing is only being used in High Occupancy Toll (HOT) lanes. However time-dependent pricing idea can be used in a network setting where drivers have to make route choices that are relatively more complex than the choices they make in the case of HOT lanes. This thesis proposes a simulation-based evaluation of dynamic congestion pricing on the crossings of

New York City where many of the limited number of crossings to the island of Manhattan are tolled and function as parallel alternatives. One of the key aspects of this study is the estimation of realistic values of time (VOT) for different classes of users, namely, commuters and commercial vehicles. New York region-specific VOT for commercial vehicles is estimated using a logit model of stated preference data. Two different simulation studies are conducted. First simulation study is performed using the software TransModeler by considering the Manhattan network with a simple step-wise dynamic tolling algorithm and modeling the driver behavior by taking VOT into consideration. In the second simulation study, a tolling algorithm which is applicable to two tolled alternative crossings is developed. The algorithm includes real time toll rate calculation depending on travel times on crossings and models the driver behavior in response to toll rates and real-time measured travel time information on alternative routes. The algorithm is tested in traffic simulation software Paramics on a network including the two tunnels between New Jersey and New York City with a microscopic simulation of the traffic entering Manhattan.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

1.1 BACKGROUND

Traffic congestion has become one of the most severe problems of many countries due to the increase in traffic demand. According to Texas Transportation Institute (2007), New York-New Jersey- Connecticut area is bearing the second worst traffic conditions in United States. Their study indicated that the congestion cost for this area is $8 billion and the excess fuel consumed is 238 million gallons. The overall numbers show that in the United States one urban driver spent 62 hours sitting in traffic in 2000, whereas this number was only 16 hours in 1982.

The problem of recurring traffic congestion arises when existing facilities cannot meet the increasing demand and it becomes a must to consider alternative techniques other than building new facilities or expanding the existing ones. Congestion pricing means charging users for using a congested road during peak periods when the traffic congestion is at its highest level to encourage them to either use an alternative route or to change their departure times. Several different applications of congestion pricing have been used by many cities suffering from traffic congestion and the successful results encouraged many other cities to consider using similar techniques to solve their traffic congestion problem.

1.2 PROBLEM STATEMENT

Congestion pricing has been considered as one of the most efficient methods to mitigate congestion in highways, crossings and even airports. The basic theory of congestion pricing has been significantly extended since Pigou (1924) by various economists and transportation researchers. One of the most recent developments is "Dynamic Pricing", which has a history of no more than 15 years in the United States. The idea of dynamic pricing enables congestion pricing applications to operate more "intelligently", as the system can respond to real-time traffic conditions, make users to be informed about the situation on the alternate routes and make them select the best alternative by making them paying a toll changing in-real-time.

Dynamic pricing has been used in only four HOT (High Occupancy Toll) lane facilities, which are managed lanes in a highly used freeway. They are the implemented on I-15 in California, I-394 in Minnesota, WA167 in Washington and I-95 in Florida. This system allows users to travel in high-speed lanes by paying a toll changing in real-time. Although these applications are successful in terms of day to day operations, the lack of theoretical background in tolling algorithms is one of the major concerns which can sometimes create highly fluctuating toll rates within short time intervals. Therefore theoretically more robust tolling algorithms are needed to get the real time toll rates to ensure smoother behavior.

Dynamic pricing has been successfully implemented in HOT lanes. The same idea of changing the tolls according to real time traffic conditions can be extended to a similar application of tolling the crossings between Northern New Jersey and New York City. This idea needs the development of a new tolling algorithm which is quite different than the one which is used for HOT lanes which only tries to keep free flow speeds on all the HOT lanes at any given time.

Dynamic tolling algorithm should also take driver value of time into account to make sure drivers respond positively to the estimated toll rates as well as keeping the system profitable. As indicated in the literature review section of this thesis although there are some studies conducted for estimating the commuters' value of time for New York-New Jersey region, there was no specific study for estimating commercial vehicles' value of time in the same region. It is thus important to estimate different value of times for different vehicle classes in a multi-class tolling environment to ensure all user classes are paying what they need to pay to change their behavior.

1.3 RESEARCH OBJECTIVES AND SCOPE

The objective of this thesis is to test the implementation of a realistic dynamic congestion pricing system for New York City Crossings, using a novel real-time tolling algorithm which takes value of time of different user classes into account.

To achieve this objective following steps have been identified:

- Conduct an extensive literature review to identify existing methodologies and real-world implementations for different types of congestion pricing applications.
- Develop a dynamic tolling algorithm that responds to traffic changes in real-time to ensure that users are reacting to real-time changes in toll rates in a realistic manner by changing their routes depending on their own value of time.

- Explore the dynamic pricing capabilities of two different traffic simulation packages namely, Paramics and TransModeler, for traffic simulations.
- Estimate the value of travel times of commercial vehicles using real-world data to use in the simulation models.

1.4 THESIS ORGANIZATION

This thesis consists of 7 chapters and is organized in the following manner:

Chapter 1 covers the introduction including the problem statement, research objectives and scope, and thesis organization.

Chapter 2 covers the literature review of congestion pricing, focusing on dynamic congestion pricing, review of real-world dynamic pricing implementations and literature review of value of time studies.

Chapter 3 describes the estimation of the value of time of commercial vehicles using the 2004 Port Authority New York New Jersey (PANYNJ) trucker survey data (Holguin-Veras et al., 2006).

Chapter 4 covers the case study using the large Manhattan network simulation for testing the scenario of dynamic pricing for New York City crossings using a step-wise dynamic tolling scheme.

Chapter 5 covers the dynamic pricing algorithm developed to be used for crossings.

Chapter 6 covers the simulation based test of the developed tolling algorithm using Paramics microsimulation software.

Chapter 7 presents the conclusions and the recommendations of the study along with the scope of research.

CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

Traffic congestion is one of the major concerns of modern life and several methods have been developed by numerous researchers to negative effects of mitigate congestion. Congestion pricing is a method which is being used by many countries and there are a number of reports showing that it can successfully manage traffic congestion when used effectively. This chapter reviews existing theoretical studies as well as real-world implementations of the idea of congestion pricing. Literature dealing with the value of travel time due to the strong relationship with congestion pricing is also reviewed in this chapter.

2.2 CONGESTION PRICING

Congestion pricing is defined as "*charging motorists during peak hours to encourage them to either switch their travel times or to use alternative routes which are not congested at peak hours. The theory behind road pricing suggests that, in order to reach social optimum, a toll needs to be charged which is equal to the difference between social marginal costs (which include external costs that users impose on each other on a congested road) and private average costs of users(travel delays, fuel, maintenance etc*.)" (Arnott, R, and Small, K.A., (1994) Morrison (1986) explained the theory of optimal tolls used in congestion pricing by making use of the speed-flow curve. According to his economical explanation, commuters do not consider how much delay they impose on other travelers and they only pay attention to how long it takes them to travel. As seen in Figure 2-1, the demand equilibrium where personal costs are considered is at Q_0 , whereas when the social optimum conditions are considered equilibrium occurs at Q*. The difference means that each vehicle joining the system causes a delay on every other vehicle which is not taken into account in private costs and therefore more vehicles are present in the system as it should be at the social optimal conditions. The idea of charging the corresponding cost difference from every vehicle enables shifting the demand from Q_0 to Q and operating the system at its best.

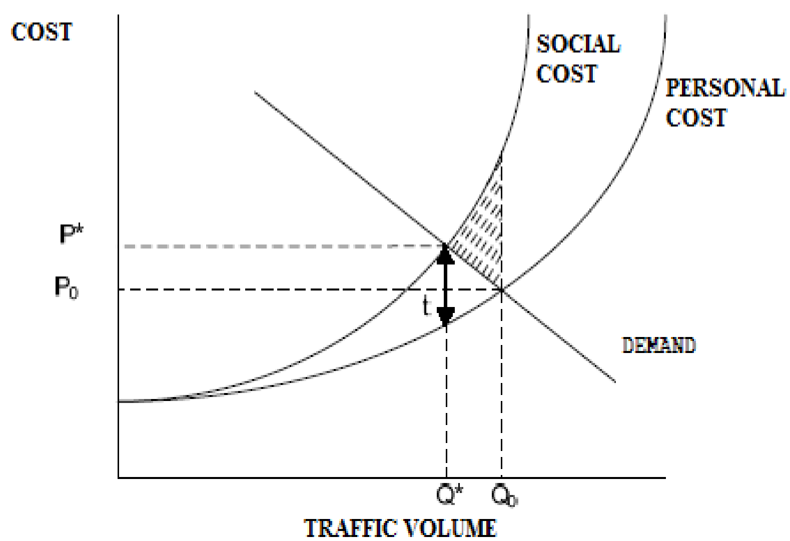

Figure 2-1: Economics of Congestion Pricing (Morrison, 1986)

Congestion pricing can be categorized into two as static and dynamic congestion pricing and the following two sections explains the two types in detail.

2.2.1 Static Congestion Pricing

Static congestion pricing refers to a tolling system where toll rates are only changed depending on time of day. The system is static, because the toll rate schedule is not affected by the real-time traffic conditions and usually do not change for a long period of time. The first studies for congestion pricing always considered this “static” type of tolling, mostly focusing on the optimization of toll rates, toll plaza locations or which links to be tolled in a large network.

The idea of tolling on roads has been an important topic of study for many decades. Pigou (1920) argued the idea of charging motorists for the first time in his book “Economics of Welfare”. Following Pigou’s argument, Walters (1961) gave the first comprehensive explanation of congestion pricing in his study about measuring private and social costs of highway congestion. Within the following years, Vickrey (1963) published a paper about road pricing in urban and suburban transport, Beckman (1965) studied the optimal tolls for highways, bridges and tunnels and Vickrey (1969) conducted another study about congestion theory. These studies constituted the fundamentals of modern congestion pricing theory.

The concept of congestion pricing further expanded with different perspectives by both economists and traffic engineers in the following years. Table 2-1 gives a brief list of various studies that have been conducted in the last two decades on various different aspects of congestion pricing.

Table 2-1: Major Congestion Pricing Studies

Author	**Date**	**Study**
Braid	1989	Comparison of flat and peak tolls for bottleneck congestion
Arnott et al.	1990	Bottleneck model with departure times
Hau	1992	Economic fundamentals of road pricing
Smith et al.	1994	Optimal tolls under stochastic user-equilibria
Ferrari	1995	Road pricing in a network equilibrium
Yang and Lam	1996	Optimal toll formulation
Verhoef et al.	1996	Developed a second-best congestion pricing model
Yang and Bell	1997	Road pricing in a network equilibrium with traffic restraints
Hearn and Ramana	1998	Developed models for solving congestion toll
Yang and Haung	1998	Developed a model for application on a general network
Wie and Tobin	1998	Developed a model for dynamic network equilibrium
Arnott et al.	1998	Developed a bottleneck model with elastic demand
Mun	1999	Peak period pricing for bottleneck traffic jam
Eliasson	2001	First-best pricing with heterogeneous users
Verhoef	2002	Second-best pricing algorithm for a static network
De Palma et al.	2004	Congestion pricing with heterogeneous travelers
Verhoef et al.	2004	Congestion pricing with heterogeneous users
Levinson	2005	Pricing analysis using game theory with two players
Mun	2005	Optimal cordon pricing in a non-monocentric city
De Palma et al.	2005	Congestion pricing application with dynamic user equilibrium

Ozbay et al.	2006	Evaluation study for NJTPK time-of-day pricing
Arnott	2007	Congestion tolling with agglomeration externalities
Holguin-Veras et al.	2009	Optimal toll formulations for multi-class traffic conditions

Although successful implementations proved that congestion pricing can reduce the peak hour congestion (Sullivan, 2000), the question of equity and fairness was also brought out by researchers (Giuliano, 1994; Litman, 1996). Several studies were conducted to solve the problem of adverse equity perception in public, focusing on different distribution methods for toll revenues (DeCarlo-Souza, 1994; Adler et al., 2001), income tax-reductions (Parry et al., 2001) and credit-based congestion pricing (Kockelman et al., 2004).

2.2.2 Dynamic Congestion Pricing

Dynamic congestion pricing is the tolling system in which real-time traffic conditions are also considered. It is a quite new area of study in traffic engineering and the number of real world applications is limited. Several traffic parameters can be considered to determine the toll rate including travel speed, occupancy and traffic delays. These parameters are measured real-time and the toll rates are updated within short time intervals. Users are informed about the current toll rate with the help of variable message signs and they are allowed to make their route choice either using the tolled road to save time, or using an alternative road without a fee.

Although dynamic congestion pricing studies are more recent than static congestion pricing studies, there are several theoretical studies available in literature. Several authors conducted network optimization based theoretical studies for dynamic pricing considering both fixed and variable demands and even including different mode choices. Wie and Tobin (1998) provided two theoretical models for dynamic congestion pricing for general networks. First model considered day-to-day learning of users with stable demands every day and second model was the case where users make independent decisions each day under fluctuating travel demand conditions. Joksimovic et al. (2005) presented a dynamic road pricing model with heterogeneous users for optimizing the network performance. Wie (2007) considered dynamic congestion pricing and the optimal time-varying tolls with Stackelberg game model. Simulation-based models for dynamic pricing were also developed by some researchers. Mahmassani et al. (2005) conducted a study about variable toll pricing with heterogeneous users with different value of time preferences. Teodorovic and Edara (2007) proposed a real-time road pricing model on a simple two-link parallel network. Their system made use of dynamic programming and neural networks.

Yin and Lou (2007) proposed and simulated two models for dynamic tolling. The first one is a feedback-control based method which is similar to ALINEA concept in ramp-metering. The control logic for determining the toll rates is stated as;

$$r(t+1) = r(t) + K(o(t) - o^*) \qquad (2.1)$$

where, $r(t)$ and $r(t+1)$ are the toll rates at time intervals t and $t+1$, respectively, $o(t)$ is the measured occupancy, K is the regulator parameter and o^* is the desired occupancy for the tolled lane. The second method is a reactive-self learning approach in which motorists' willingness to pay can be learned gradually and this data can be used to determine the toll rates.

Lu et al. (2008) conducted a study for dynamic user equilibrium traffic assignment and provided a solution algorithm for dynamic road pricing. Their model considers traffic dynamics and heterogeneous user types with their responses to toll charges. Friesz et al. (2007) considered dynamic optimal toll problem with user equilibrium constraints and presented two algorithms with numerical examples. Karoonsoontawong et al. (2008) provided a simulation-based dynamic marginal cost pricing algorithm. They compared the dynamic and static scenarios in the simulation and obtained minor system benefits in dynamic case.

Feedback-based algorithms for dynamic pricing were also developed for practical applications. Zhang et al. (2008) developed a feedback-based dynamic tolling algorithm for HOT (High Occupancy Toll) lane applications. In their model they used travel speed and toll changing patterns as parameters to calculate optimal flow ratio for the HOT lanes using feedback-based piecewise linear function. Then using the discrete route choice model they calculate the required toll rate by backward calculation.

2.3 REAL WORLD IMPLEMENTATIONS

This section summarizes different types of road pricing implementations in real world which are categorized as “static” and “dynamic” pricing applications.

2.3.1 Static Congestion Pricing Applications

Several different implementation approaches exist for static congestion pricing. Time-of-day pricing method provides lower toll rates during off-peak hours to reduce peak-hour traffic congestion. The idea is to discourage users to travel during peak periods and make them switch their travel schedules to off-peak periods. Toll rates are pre-determined and basically do not rely on traffic conditions.

Distance-based pricing is simply the case when users pay tolls according to the miles they traveled in the facility. This is a very common type of application and there are many domestic and international examples.

Cordon pricing, is charging motorists, usually within a city center, as part of a demand management strategy to relieve traffic congestion within that area. There are a number of applications in Europe and Asia, including major cities such as London, Rome and Stockholm.

HOT lane (High Occupancy Toll Lane) conversion is allowing lower-occupancy vehicles to use HOV (High Occupancy Vehicle) lanes for a fee. HOT lanes allow users to travel at higher speeds either by meeting minimum occupancy requirements or by paying a toll. HOT lanes generally use variable pricing to reduce congestion in peak hours and to achieve an acceptable LOS for both HOT lane users and free lane users (FHWA).

As a new concept, there have been studies for truck only lanes in the US. The first truck corridor project was considered for Interstate 10 (I-10).In the scope of this project they conducted a trucker survey. Two important findings were; the users need information within the next four hour traffic conditions to schedule their deliveries and meet customer satisfaction and only half of them want to pay for this information and do not want to pay for anything else. (I-10 National Freight Corridor Study, 2003). Another study was conducted for Atlanta, GA TOT (Truck only toll) lanes which is proposed to be operating in 2014. The final report of the study (Parsons, Brinckerhoff, Quade & Douglas, Inc. 2005) focused on two key issues; 1) these lanes would be open for voluntary usage and a possible mandatory usage will cause over-congestion in TOT lanes and this will conflict with the idea of always free flowing reserved lanes, 2) the level of fee is a critical factor for the overall success of the system. Wyoming Department of Transportation (WYDOT) plans to toll Interstate-80 in a truck-only manner. The main drawback is trucking industry opposition to tolled roads and the suggested way to convince them is to allow them to increase hauling capacity through either heavier loads or longer vehicle lengths (I-80 Tolling Feasibility Study, 2008). Killough (2008) conducted a value analysis of truck toll lanes in Southern California and she stated that although improvements obtained in travel time and reliability, toll revenue alone cannot cover the investment costs and additional funding will be required. Indiana Department of Transportation (INDOT), in partnership of Missouri, Illinois and Ohio Departments of Transportation (DOTs) is designing a dedicated truck only lane project on Interstate 70 (I-70) called "Corridor of the Future". It is proposed to develop an 800 mile long tolled truck lanes separated from passenger cars to manage truck related congestion. The project is in the phase of feasibility studies for dedicated truck lane concept, freight market analysis to quantify the demand and environmental impacts (INDOT, 2009).

In Europe, there are specific truck toll applications based on vehicle emission category, distance traveled and maximum laden weight of the vehicle. "Distance-Based Heavy Vehicle Tolls" in which charges are levied on all heavy trucks above 12 tons that use highways in participating countries. In August 2003, Germany introduced its own distance-based heavy vehicle tax called "Toll Collect". The system, which was implemented in 2005, is based on a high-tech electronic tolling scheme developed specifically for Germany and replaces the motor fuel taxes formerly paid by trucks operating on the Autobahn in Germany (FHWA, 2006). The innovative toll charging system in Germany is based on a combination of mobile communications (GSM) and the satellite-based global positioning system (GPS). An on-board unit is installed in trucks and using satellite signals, trucks are continuously monitored. The software in on-board unit is capable of recognizing 5200 road charge segments and it can add up the toll-route segments travelled and calculate the charge then transfers this data to the computing centre via mobile radio communications (GSM). This innovative system operates without toll booths meaning trucks do not have to stop or slow down therefore the free-flow conditions are not interrupted for toll collection (Satellic Traffic Management Report). Other international applications for distance-based truck tolling are depicted in Table 2-2.

Table 2-2: International Distance-Based Heavy Vehicle Toll Initiatives

Project	**Status**
Swiss "HVF" Truck Toll	Operational since 2001
Austrian "GO" Truck Toll	Operational since 2004
German "Toll Collect" (LKW Maut)	Operational since 2005
U.K. Truck Toll	Planned 2007-deferred
Czech Republic Truck Toll	Trial
Australian "Austroads" Monitoring	In planning phase

2.3.2 Dynamic Congestion Pricing Applications

Dynamic congestion pricing is a quite new concept in road pricing applications. Although, the number of present facilities using this system is low compared to facilities with static toll pricing, dynamic pricing is becoming more popular with the recent advances in traffic technologies. Toll collection is done via Electronic Toll Collection (ETC) system for the sake of the uninterrupted flow in tolled lanes. California SR-91 Express lanes were planned to be the first dynamic pricing application in the U.S. and in the World before it opened in 1995. Although they had the software written and technically ready for dynamic pricing, they decided to use pre-determined toll rate schedules which are adjusted yearly depending on the congestion after user surveys (Sullivan, 2000). The first truly dynamic road pricing operation was implemented in San Diego I-15 FasTrak HOT lanes in 1998. Single-occupant vehicle users pay tolls when they use the HOV lanes. Toll schedule varies dynamically every 6 minutes depending on the congestion level in express lanes which are always maintaining a LOS “C” for the HOT facility. Users are informed by variable message signs which are located at entry points of the HOT lanes. Total length is 16 miles after the extension completed in March 2009 and there are ongoing lane addition projects due 2012.

Figure 2-2: I-15 FasTrak Map (Sandag, 2010)

Figure 2-3: San Diego I-15 FasTrak HOT Lanes (Sandag, 2010)

Toll rate differentiation within a day and within a week are shown in Figure 2-4 and Figure 2-5 respectively. Toll rates are the highest in peak hours and lower in the peak shoulders as expected.

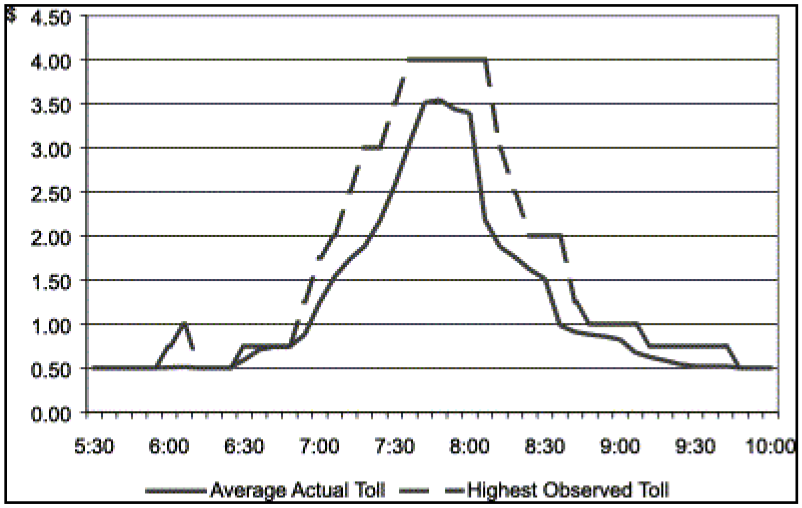

Figure 2-4: FasTrak Tolls by Time-of-day for October and November,1998 (Brownstone, 2003)

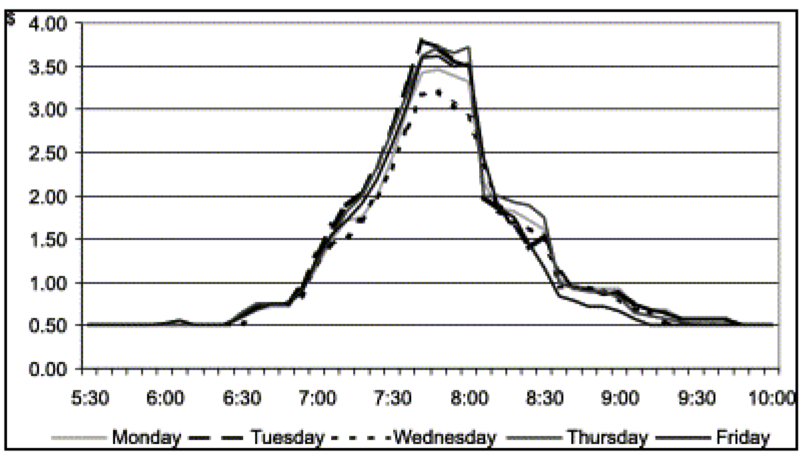

Figure 2-5: FasTrak Tolls By Day-of-week for October and November, 1998. (Brownstone, 2003)

The performance of the facility has been a topic of study for some researchers in the following years of the implementation. Brownstone et al. (2003), analyzed the time savings associated with the usage of Express Lanes, and they found median time savings peak at about 7 minutes (Figure 2-6).

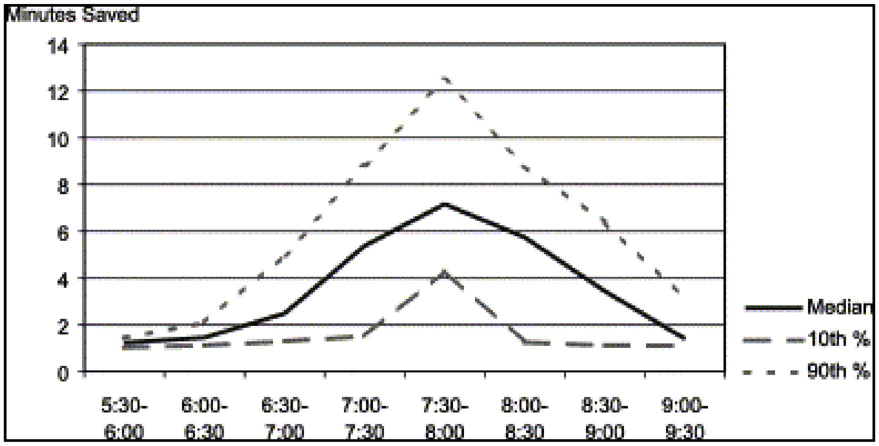

Figure 2-6: Time Savings Associated with Express Lane Use for October-November 2008 (Brownstone, 2003)

Supernak et al. (2002) conducted a study for behavioral issues related to San Diego I-15 congestion pricing study. Their findings indicated that compared to a fixed monthly pricing, dynamic per-trip pricing offers a customized use of the facility which means motorists use the express lanes when most needed or when it is most beneficial for them. They also stated that *"Fixed monthly pricing can create strong reactions to fee levels. This finding does not appear to be applicable to the dynamic pricing."* In a similar study, Supernak et al. (2003) analyzed the impacts of dynamic pricing on travel time and its reliability. Their study showed that variability of travel times on I-15 Express Lanes was very low since free flow conditions were met by real-time toll rate changes and as a second finding they stated that *"Ramp and freeway delay data revealed a significant advantage of using FasTrak (Electronic Toll Collection Unit) or carpooling in situations when reliability of on-time arrival is important."*

The second application which is also one of the World's most dynamic systems is Minnesota's I-394 HOT lanes. This facility is more complex compared to the San Diego I-15 HOT lanes, since there exists multiple entry and exit points and toll rates are changed as frequently as every three minutes. Dynamically priced section is 11-mile long. Pricing is based on the level of service in the express lanes. Similar to I-15, the minimum level of service that the system has to maintain is level "C" which means maximum 29 vehicles are expected to pass a given point in 30 seconds and traffic flows at a speed range between 50-55 mph. Sensors are located every half mile to determine the service level.

Halvarson et al. (2006) describes the HOT lane innovations that were firstly used in Minnesota I-394 facility. Two of the significant characteristics are; tolling is performed on lanes which are not seperated with barriers from general purpose lanes in 8-mile section of total 11-mile long facility and dynamic pricing is applied on multiple sections with multiple entry and exit points.

Figure 2-8 shows the toll rate changes by hours in I-394 HOT lane facility. Compared to the San Diego I-15, toll rates tend to change more frequently and sharp increases and decreases can be observed in price. The main reason is the different algorithm for tolling, in particular I-394 updates the toll for every three minutes whereas in I-15 it is updated within 6 minutes intervals.

Figure 2-7: Minnesota I-394 HOT Lanes (MNDOT, 2010)

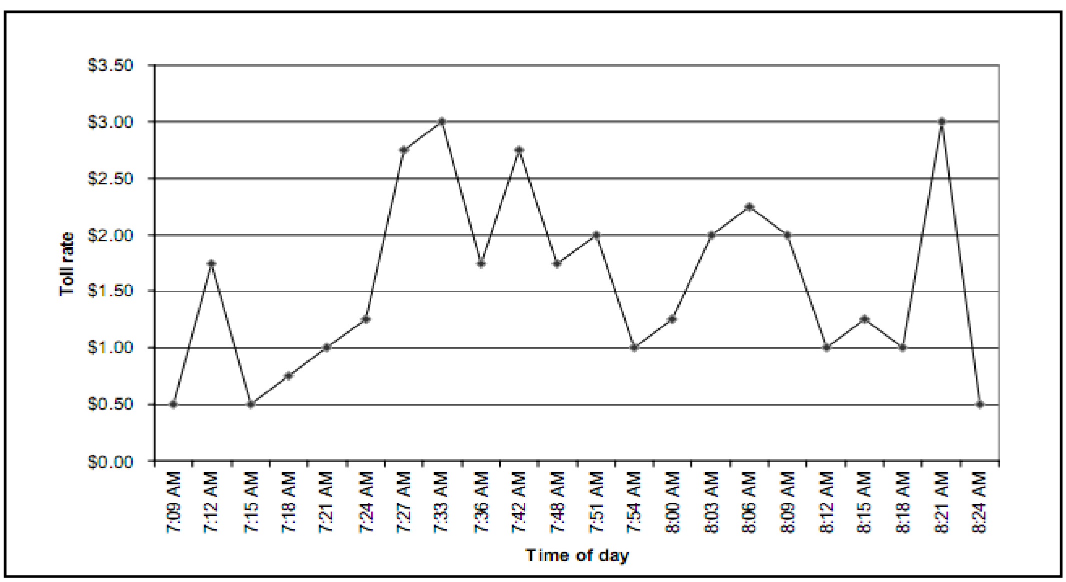

Figure 2-8: Minnesota I-394 Toll Rates, 2005 (Yin and Lou, 2007)

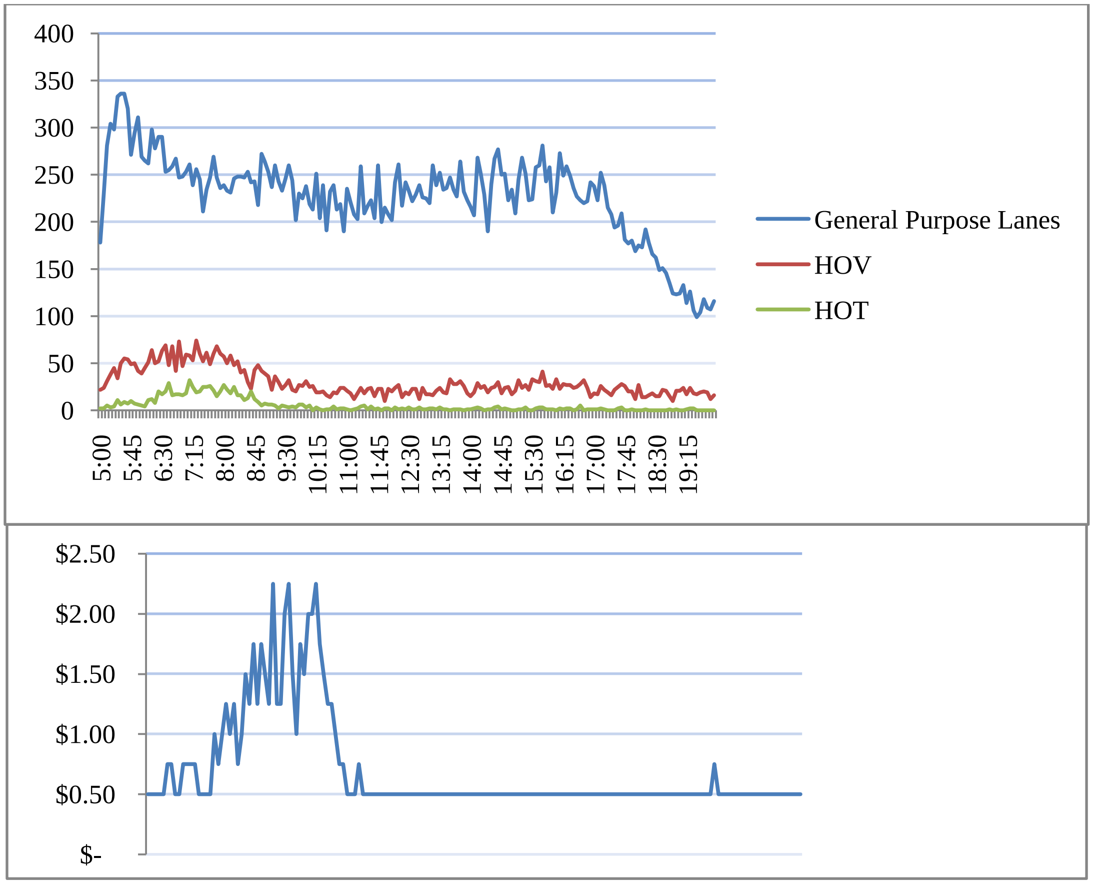

Figure 2-9: Washington SR-167 Traffic Volumes and Toll Rates (WSDOT, 2009)

The third dynamic pricing application in the US was opened on SR167 HOT lanes in Washington in 2008. Morning peak-hour direction is northbound which is 13 miles with six different toll zones is and southbound is 9 miles with four toll zones. Toll rates are variable between $0.5 and $9. The tolling algorithm which depends on speed, rate of change of the number of cars entering the system and absolute traffic counts in a lane enables system to keep an average speed of at least 45 mph in the HOT lanes. Operation hours of the system are between 5 a.m. and 7 p.m. One year performance report of the facility stated that, general purpose lane speeds increased by 10% while volumes increased 3%-4% (WSDOT).

Figure 2-9 shows the traffic volume changes on general purpose lanes and HOT lanes and corresponding dynamic toll rate changes for a typical daily operation. HOT lanes are used by both single occupancy vehicles who are paying tolls for the service and HOV users which do not pay toll and have more than three people traveling. Toll rates are calculated every 5 minutes and the figure shows that during morning peak hours, there are fluctuations in toll rate within short time intervals which creates inconvenience for making decisions for the users. Another significant observation can be the low number of users which pay toll to use the HOT lanes throughout the day. Although during peak periods the number of HOT lane users who are paying toll are also at its peak, throughout the day most of the time there are very few or no users paying for the HOT lanes. The reason might be the lower difference in traffic conditions between the two alternatives which is also supported by the fact that the toll rates remain unchanged at its lowest level from morning peak to the end of the HOT lane operation.

Another dynamic pricing implementation was started to operate in summer 2008 on I-95 Express Toll lanes in South Florida. Lanes previously used as HOV lanes were converted to HOT lanes. Florida Department of Transportation District 6 Traffic Management Center (TMC) developed software called “Express Lane Watcher” (ELW) to be used in the daily operation of the HOT lanes. This software is capable of collecting real-time data, analyzing the information, generating the dynamic toll rate in every 15 minutes to maximize the throughput while maintaining the free-flow conditions.

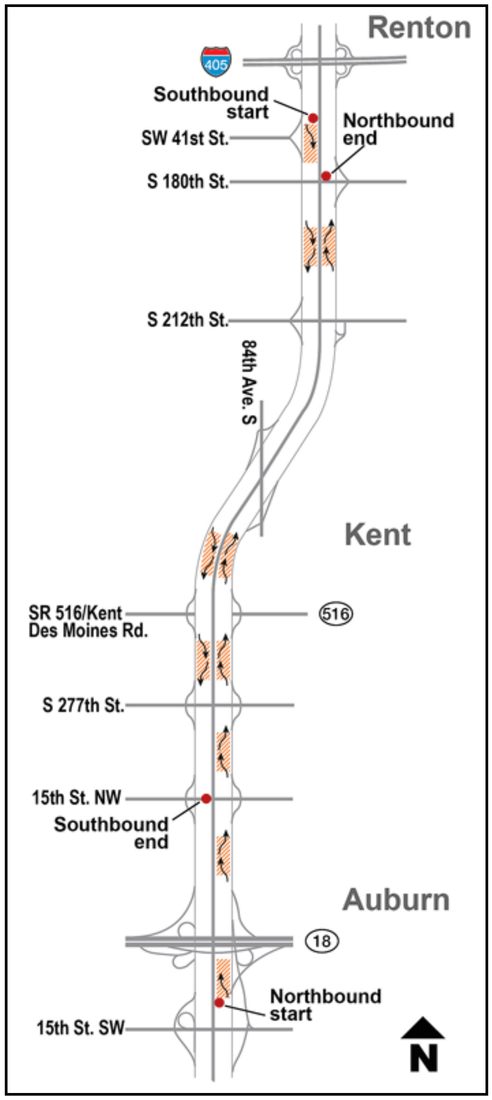

Figure 2-10: Washington SR 167 HOT Lane Facility Map (WSDOT, 2010)

Although the toll rates are determined automatically by the ELW software, an operator also monitors the real-time traffic conditions and the toll rate is shown in the variable message sign after the approval of the operator. Performance analysis of the project showed that travel speeds in Express Lanes increased 35mph in average after the HOT lane conversion. Another significant finding was the increase in bus ridership; an average of 30 percent increase was observed within the first six months of the implementation. In six months period the facility generated $2.8 million toll revenue which is the 89 percent of the projected value.

Figure 2-11: Dynamically Priced SR 167 HOT Lanes in Washington (WSDOT, 2010)

A survey conducted on daily users in May 2009 showed that: *"76% of those who have used 95 Express believe it is a more reliable trip than the general purpose lanes and 58% of commuters familiar with the express lanes would like to see express lanes developed on other roadways in southeast Florida"* (FLDOT, 2009).

Figure 2-12: I-95 Express Lanes in South Florida (WSDOT, 2010)

There are also several HOT lane conversion projects which are proposed and some of them are planning to utilize dynamic pricing in their operations. One of the prospected dynamic pricing projects is for the HOT lane conversion in I-85 in Atlanta which is planned to be opened in January 2011. Dynamic tolls will be used for charging HOT lane users to provide them with peak hour speeds averaging 45+ mph. The tolled section is planned to be 15 miles long (GADOT, 2010). I-495 Beltway HOT lane project in Northern Virginia is one of the other prospected dynamic pricing projects. HOT lanes will be two directional and approximately 14 miles long. Toll rates will be dynamic and the rate will be locked in upon a driver’s entrance (Virginia

HOT lanes, 2010). Another HOT lane conversion project is on I-10 and I-110 in Los Angeles County, California (METRO, 2010).

Another dynamic pricing application is planned to be operated in Florida I-595 Express Lanes, in which tolls will be variable to optimize the traffic flow. Construction of the road was started in February 2010 (I-595 website, 2010).

Although the continuously time-varying optimal tolls suggest a fair system for the users, it is also debatable whether smoothly-varying toll rate will be appreciated by drivers (Lindsey, C.R., Verhoef, E.T., 2000). Sullivan (2000) stated the reason for not applying dynamic pricing in SR-91 as "some potential customers' being uncomfortable with the unpredictability of dynamic tolls". However, successful implementations may diminish the public opposition as in the case of San Diego I-15. Collier and Godin (2002) stated that, *"Research in I-15 corridor showed that eighty-eight per cent of the dynamically tolled road users and sixty-six per cent of the non-users approve of the program and a majority of both groups agree that the FasTrak program reduces congestion on I-15."* A recent survey for Minnesota I-394 users showed more promising results, such as 91% of users expressed satisfaction and 84% agreed that the lanes provided them with *"a fast, safe, reliable commute every time."* (MNDOT, 2010).

Major road pricing applications and their tolling methods are depicted in Table 2-3.

Table 2-3: Major Value Pricing Applications in the US

Facilities with Static Pricing	**Initiation Date**	**Pricing Method**
Orange County SR-91, CA	December 1995	Pre-determined toll schedule
Houston I-10, TX	January 1998	HOT lanes
Lee County, FL	August 1998	Time-of-day pricing on bridges
New Jersey Turnpike, NJ	Fall 2000	Time-of-day pricing
Houston US 290, TX	November 2000	HOT lanes
Port Authority of NY&NJ Interstate Crossings	March 2001	Time-of-day pricing
San Joaquin Hills Toll Road, Orange County,CA	February 2002	Time-of-day pricing
Illinois Tollway, IL	Winter 2005	Time-of-day pricing
Facilities with Dynamic Pricing Lanes		
San Diego I-15, CA	April 1998	Dynamic pricing in HOT lanes
Minnesota I-394, MN	Spring 2005	Dynamic pricing in HOT lanes
WA167, WA	May 2008	Dynamic Pricing in HOT lanes
I-95, FL	Summer 2008	Dynamic pricing in HOT lanes

2.4 VALUE OF TIME

Value of time, in other words, the change in amount of the user's willingness to pay for a unit change in travel time, is also one of the topics that have to be taken into account in determining toll rates. Value of travel time is one of the important factors for determining user's route and time departure choices. Depending on the value that commuters set for their travel time, they make the decision to use a tolled road and reduce their travel time or to use a free alternative road and spend more time in traffic because of delays and travelling longer distances.

It is also important to distinguish user groups in traffic when considering value of travel times. Commuter value of time basically depends on travel time savings, therefore their income, route choice and departure time choice are basically the three determining factors. Ozbay et al. (2008) presented an analytical model for value of travel time investigating the relationship between departure/arrival time, travel time and income.

For commercial vehicles, on the other hand, value of travel time is not solely dependent on the same parameters identified to be important for commuters. Since commercial are also a part of a business activity, they have several other criteria to consider for their departure time and route choices. Most of the commercial vehicles are working as carriers, meaning they have receivers and suppliers, therefore costumer needs come into play in their travel choices. They have to make profit therefore any kind of costs related to their trips (e.g. fuel, toll, delay penalties) not only affect their time savings (which is the case for commuters) but also affects their overall budget.

2.4.1 Commuter Value of Time

Several "value of travel time" studies were conducted for passenger trips in different regions of the world. Discrete choice models (e.g., binary logit, mixed logit, multinomial logit, and nested logit) based on traveler survey data are commonly used in estimating commuters' value of times (Small and Rosen, 1981: Leurent, 1998; Hensher, 1996; Algers et al., 1998; Calfee and Winston, 1998; Ghosh, 2000; Sullivan, 2000; Small and Sullivan, 2001; Hultkrantz and Mortazavi, 2001; Brownstone et al., 2003; Cirillo and Axhausen, 2006). In these models, utility models include variables which were selected via trial-and-error method. It is important to determine user's willingness to pay to figure out their behavior, such as route or mode choice, in a network where tolled roads take place. Blayac et. al. (2001) proposed the idea of relaxing the constancy of marginal utilities and derived analytical functions to relate VOTT, time, price, income level and departure/arrival time restrictions. Following the same idea, Ozbay et. al. (2008) improved the functions by adding departure time choices and used nested logit model to estimate value of travel time of New Jersey Turnpike users under the presence of a time-of-day pricing.

Table 2-4 gives a summary of the major commuter value of time studies for different facilities, the models they use and the value of time they obtain for the commuters.

2.4.2 Commercial Value of Time

Although there are many studies done for commuter value of time for commercial vehicles there is a limited amount of research available. One of the first

Table 2-4: Commuter Value of Times in Literature (Ozbay et al., 2008)

Study	Region	Model	VOT
Leurent (1995)	Marseilles,France	RP,Binary Logit	$12 /hr
Hensher (1996)	Australia	SP,Heteroscedastic Logit	$6.34-$10.2 / hr
Algers et.al. (1998)	Sweden	SP, Mixed Logit	$7.96/hr
Calfee et al. (1998)	Michigan	SP, Multinomial Logit	$4/hr
Ghosh (2000)	I-15 San Diego	RP, Conditional Logit	$22 /hr
Sullivan (2000)	SR 91, California	RP, Multinomial Logit	$8-$16 /hr
Small et al. (2001)	SR 91, California	RP, Multinomial Logit	$13-$16 /hr
Hultkrantz et al. (2001)	Sweden	SP,Probit	$6.43 /hr
Browstone et.al. (2003)	I-15, San Diego	RP,Conditional Logit	$30 /hr
Steimetz et. al. (2005)	I-15, San Diego	RP,Conditional Logit	$45-$30 /hr
Ozbay et al. (2008)	NJTPK,New Jersey	SP,Nested Logit	$15-$20 /hr

studies for the evaluation of the value of travel time for commercial vehicles was published by Haning and McFarland (1963). Their analysis showed that commercial vehicle value of time should be greater than passenger car value of time even if no cargo is being carried. Kawamura (1999) defined a commercial vehicle value of travel time with using two different methods; first switching point analysis and second a random coefficient logit model. In his study, he analyzed the stated preference by conducting a survey on 77 trucking companies. Switching point analysis is a straightforward method in which the estimation of value of time based on the level of trade-off where the user chooses to switch from the cost option to free option. For example a traveler states that he/she would pay a toll for a given amount of time savings up to $10, then for all tolls above $10 he/she chooses the alternative road without a toll then the switching point for this individual is $10 and this would be the estimate of his/her value of time. In the second method, he fitted seven models by dividing the data into groups, by company ownership status and distance traveled. He first tried to estimate a logit model but the results are not suitable to generalize for every company therefore he fitted a random coefficient logit model that allows him to define different value of times for different types of companies. His findings showed that value of time of commercial vehicles has a mean of 23.4/hr and a standard deviation of $32/hr. At conclusion, he noted that the limited sample size bounds the study at a level that for further analysis a larger sample size is needed. Smalkoski and Levinson (2003) conducted a study for value of time determination for commercial vehicle operators in Minnesota. They fit a tobit model to the data they obtained from the adapted stated preference survey. 50 companies were interviewed and they found a VOT of $49.42/hr.

Bergkvist (2001) summarizes the work done in this field along with the methods they use. The values are given in Table 2-5. Value of time differs significantly from region to region, and truckers make their travel time and route decisions according to their value of time. Therefore it is important to set a toll rate by considering their value of time to make them use the facility even if it is not mandatory.

Table 2-5: Commercial Vehicle Value of Times in Literature (Bergkvist, 2001)

Country	Year	Method	Value of Time ($)*
Sweden	1995	Logit	8.6
The Netherlands 1	1986	Factor Cost	30
The Netherlands 2	1991	Factor Cost	32.05
The Netherlands 3	1992	Logit	53.6
The Netherlands 4	1995	Logit	49.4 – 57.7
Great Britain	1995	Logit	45.02 – 57.95
Norway	1994	Box-Cox Logit	0-85.8
Norway	1995	Box-Cox Logit	0-56.1
Denmark	1996	Logit	38.6-87.9
Sweden	1998	Logit	120.8
Denmark	1998	Logit	2.81-9.1

***: In 2009 $ values using Bureau of Labor Statistics Inflation Calculator (BLS website, 2010)**

Most of the value of time estimation studies are done based on stated preference user surveys. In these surveys, there are questions to get an idea about the traveler choice behavior under different circumstances. Vilain and Wolfram (2001), conducted a survey for truckers in New York region and their study indicate that the response of truckers to congestion charges would be relatively modest. Holguin-Veras et al. (2005) state that as a result of their trucker survey 61.6% of commercial vehicles travel at the time they do because of customer requirements. This is an important finding showing that most of the truckers do not have schedule flexibility. In addition to stated preference, revealed preference analysis also gives an idea about possible trucker behavior. Ozbay et al.(2006) conducted an analysis of the impacts of time-of-day pricing application that is initiated at 2001 by Port Authority of New York and New Jersey (PANYNJ). Authors conclude that there is a decrease in truck traffic on peak shoulders but they also note that there may be other factors affecting this decline such as economic recession that began in the New Jersey-New York region in 2001.

CHAPTER III

ESTIMATION OF THE COMMERCIAL VEHICLE VALUE OF TIME

3.1 INTRODUCTION

In this chapter commercial vehicles' values of time are estimated using a logit model from the stated preference data obtained from Port Authority New York New Jersey (PANYNJ) trucker survey.

3.2 MODEL SPECIFICATION

Value of time estimation is critical in modeling the behavior of users in response to the factors affecting their travel time and route choices. In a network that includes tolled links, value of time defines the individual's willingness to pay the specified toll rate to obtain the perceived travel time benefits. A simple and efficient method for the estimation of value of time is through the use of a *logit* model. Previously several studies were conducted to estimate passenger and commercial vehicle value of times using a logit model which was discussed in detail in the literature review part. There are basically two methods used in value of time estimation to derive the choice from data; stated preference and revealed preference. Stated preference estimations make use of travel surveys in which users of a specific road are asked for their possible behavior in one or more hypothetical scenarios. Revealed preference, on the other hand, refers to the observed behavior after a condition change in the roadway. Both methods have their advantages and shortcomings. Although, in general revealed preference data generates more reliable results for economical analysis, Smalkoski and Levinson (2003) state the advantages of stated preference methods in their commercial vehicle value of time study:

> "*Stated preference (SP) methods have several benefits over revealed preference methods. Louviere, et.al. (2000) state how SP surveys can be designed to control for outside influences whereas data from revealed preference (RP) methods sometimes cannot satisfy model assumptions, thus observed relationships cannot provide reliable and valid inferences. SP data are often less expensive to collect. SP methods are used widely in marketing studies to explain preference for items that are not in the actual marketplace. SP can introduce variability in explanatory variables to estimate preference where little variation exists in the marketplace.*"

In the scope of this study, for the simulation work performed for testing a novel dynamic pricing scenario in New York- New Jersey region, values of travel time of the travelers are needed in building the simulation model. There are basically two different types of users defined in the simulation study; commuters which refer to the individual passenger cars and commercial vehicles which refer to the trucks and commercial vans. The values of travel time for these two different types of users have to be defined separately because of the different characteristics they have. Commuter cars generally make their route decisions depending only on the travel time whereas commercial vehicles also consider the relationship between travel time and their marginal profit. Since commercial vehicles are a part of a running business every trip related cost such as tolls, late delivery penalties, parking costs or depreciation of vehicles and tires in congested traffic should be considered as parameters that are affecting their willingness to pay. In addition to these, different business types are also supposed to have different value of times. For example a commercial vehicle carrying industrial goods may be more reluctant to pay a toll for a faster trip compared to a commercial vehicle carrying daily products since the delivery window is larger and it may not be worth to pay toll for an early delivery. Therefore commercial vehicle value of time estimation is not as straightforward as the value of time estimation for commuter vehicles.

A study about commuter value of time for New Jersey Turnpike users was previously conducted by Ozbay, et.al. (2008). They used DeSerpa's time allocation theory as the basis for their methodology to fit a nested logit model using the data obtained from the 2004 travel survey for the New Jersey Turnpike Facility. Different from the previous studies they also considered departure time and deviation from the desired arrival time as new variables. The calculated mean value of time values for EZ-Pass users were ranging between \$15 and \$20 depending on trip type and selected period. Important conclusions they draw include; the highest mean value of time was observed for work related trips in peak periods, lowest mean value of time was observed for leisure trips in post peak period, value of times for work related trips are higher than leisure related trips for peak and post-peak travel.

For commercial vehicle value of time there have been several studies for different regions around the world as discussed in the literature review. However there is no value of travel time study specific for New York-New Jersey region found in the literature. Therefore in this section, an estimation of commercial vehicle value of time using a logit model is presented. This model is then used in dynamic pricing simulations.

A methodology similar to the Kawamura (1999)'s work for commercial vehicle value of time estimation using logit model was developed. A utility function for an individual or a firm n choosing an alternative *i* was assumed as

$$U_{in} = \alpha C_{in} + \gamma T_{in} + \varepsilon_{in} \tag{3.1}$$

where C_{in} is the monetary cost of travel and T_{in} is the monetary cost of travel time for using alternative *i* for an individual or firm n. The coefficients α and γ are parameters and the random variable ε_{in} is the unobserved portion of the utility which is assumed identically and independently distributed (IID) with extreme value distribution. Unobserved portion of the utility include unobserved attributes, taste variations, measurement errors and imperfect information (Kawamura, 1999).

Standard logit formula is then used to calculate the probability P_{in} of choosing alternative *i* among *j* alternatives:

$$P_{in} = \frac{\exp(V_{in})}{\sum_{i=1}^{j} \exp(V_{in})} \tag{3.2}$$

where V_{in} is the observable part of the utility (i.e. $\alpha C_{in} + \gamma T_{in}$)

Coefficients α and γ can be obtained by the maximum likelihood method and the

$$\frac{\partial V_{in}}{\partial C_{in}} = \alpha \tag{3.3}$$

$$\frac{\partial V_{in}}{\partial T_{in}} = \gamma \tag{3.4}$$

These ratios give the marginal effects of each parameter on utility function and value of time is simply calculated by the ratio of the two coefficients as

$$\text{Value of Time} = \frac{\gamma}{\alpha} \tag{3.5}$$

The ratio in equation (3.5) means how much an individual or a firm n is willing to pay to reduce travel time by one unit. In a more simple way, this equation is the equal to

$$\text{Value of Time} = \frac{\Delta p}{\Delta t} \tag{3.6}$$

where Δp is the unit change in price and Δt is the unit change in travel time. Unit change in price can be either a change in toll rate or any other savings or extra costs that are proposed when the user changes his/her behavior.

3.3 MODEL APPLICATION

After defining the utility function and deriving the method for calculation of value of time, an the parameters α and γ are estimated using the stated preference data obtained from the survey conducted as part of a study conducted by Holguin-Veras, (2006). The target population of the survey is defined as, all carriers that have used any of the PANYNJ toll facilities on a regular basis (at least once per week) since the time of day pricing implementation took place in March 2001.

There are 200 respondents to the survey. This sample size is acceptable when compared with the similar studies that were conducted before. From the previous studies which estimated value of time for commercial vehicles, Kawamura (1999) had a sample size of 77 and Smalkoski and Levinson (2003) had a sample size of 50. Since each of these respondents are operating trucking companies, they are both limited in amount and some of them may not be reachable most of the time.

Table 3-1: Sample Breakdown (Holguin-Veras, et al., 2006)

Carriers	Raw Sample (200 observations)			
	Current regular users		Former regular users	
	Responses	%	Responses	%
Private Carriers	92	50.5	11	61.1
New Jersey	75	41.2	10	55.6
New York	17	9.3	1	5.6
For-hire carriers	90	49.5	7	38.9
New Jersey	75	41.2	5	27.8
New York	15	8.2	2	11.1
Total	182	100.0	18	100.0

The survey data was evaluated in detail by Holguin-Veras et al. (2006). Sample breakdown is given in Table 3-1. The target companies were separated into two as; private carriers which refers to the companies that provide transportation service to a parent or related company and for-hire carriers which are operating independently for open market. From the 200 companies interviewed, 182 (91%) of them were regularly using the facilities when the survey was conducted and 18(9%)

of them were the former regular users. There were 103 private carriers (52%) and 97 for-hire carriers (48%) in the sample which was stated to be consistent with the national statistics by Holguin-Veras, et al. (2006).

Surveys were conducted via telephone interview with the participating companies and had 6 different sections to collect data about:

(1) Information on current regular users' operations, time of travel flexibility, including commodities types transported frequency and number of stops made on a typical roundtrip for deliveries between New York City and New Jersey, among others.

(2) Respondents' level of awareness of EZ-Pass features and the available toll discounts.

(3) The impacts of the 2001 PANYNJ time of day pricing on carriers, changes in operations, trip frequency, number of stops, time of travel, duration of tour, shipment size, shipment charge, load factor, type of vehicles used, fleet size and routes for deliveries.

(4) Assessment the impact of different hypothetical combinations of toll rates and travel time savings (stated preference scenarios) on respondents' decisions about EZ-Pass usage and travel schedules.

(5) Respondents' input regarding the fairness of tolls, and other related issues.

(6) The profile of the carriers in terms of company type, business type, fleet size and composition, the number of interstate drivers employed, and origins and destinations of deliveries.

The section which was used for the estimation of value of time was based on the data gathered from section 4. However, it should be noted that the main objective of this survey was to analyze the impacts of time of day pricing on the behavior of commercial vehicles in New York New Jersey area. Therefore stated preference questions do not exactly focus on learning the value of travel time of the users. For example switching point analysis which was a simple method used in the literature cannot be conducted using this data. Nevertheless the resulting data shows the willingness to pay of the interviewed carriers under hypothetical toll rate and off-peak combinations. Thus the data can be modified to use as an input for the estimation of the parameters of the discrete choice model presented in the previous section.

3.4 MODEL ESTIMATION

3.4.1 Model Fit

In this section, detailed independent variable analysis using the raw data without making any modification on it is presented. The objective of this section is to understand the behavioral change of different carrier groups under the condition selected as dependent variable and to observe the effects of different independent variables on their decisions. In addition to these, statistical tests were performed to obtain an idea about the quality of the data and model fit.

The dependent variable which defines the decision of changing travel behavior in response to the toll increase is selected as the responds of the users for the question:

> *"Would your company switch many of your deliveries to off-peak or overnight travel if it saved your vehicles $4 per axle in tolls if they traveled during off-peak hours and $5 if they traveled during overnight hours?"*

Three different response options were presented with the question as: *"Yes", "No", "Don't know/Refused"*. The methodology for the logit model explained in the previous sections can only be used for binary decisions. To take into account all three answers, multinomial logit model which is an extension of binary logit model can be used. The equations for this model are:

$$P(y_i = j) = \frac{\exp(X_i \beta_j)}{1 + \sum_j^J \exp(X_i \beta_j)} \qquad (3.7)$$

and

$$P(y_i = 0) = \frac{1}{1 + \sum_j^J \exp(X_i \beta_j)} \qquad (3.8)$$

where for the *i*th individual, y_i is the observed outcome and X_i is a vector of explanatory variables. The unknown parameters β_j are typically estimated by maximum likelihood.

Multinomial logit model assumes that each single case has individual values for each independent variable. Using multinomial logit model enables to see the differences in each category individually. Similar to the other regression methods, in the multinomial logit model collinearity is assumed to be low.

Nine independent variables which were assumed to be related to the decision of changing behavior were selected from the survey data.

(1) Shipment size; size of the shipment in terms of pounds, continuous variable.

(2) EZ-Pass usage; whether the responder is using EZ-Pass or not, binary variable (i.e. 1 if the carrier uses EZ-Pass, 0 if it does not).

(3) Trip duration; how many hours a typical round trip takes when making delivery, continuous variable.

(4) Trip distance; distance in miles traveled for a typical delivery, continuous variable.

(5) Company type; company's ownership conditions (i.e. private or for-hire), binary variable (i.e. 1 if the company is private, 0 if it is not).

(6) Large truck numbers; how many large trucks the company owns, continuous variable.

(7) Peak-hour trips; what percentages of trips are during peak hours, continuous variable.

(8) Commodity type; what type of commodities are carried, binary variable (i.e. 1 if goods are daily, 0 if they are not).

(9) Number of drivers, how many licensed drivers are employed, continuous variable.

Multinomial logit model coefficient estimate results are given for the case of “switching” taking base cases as the two alternative options. Table 3-2 and Table 3-3 give the coefficient estimates and their standard errors using the two cases of multinomial logit model, first taking “not switching” as the base case and second taking “undecided” as the base case. Analysis of the variables with t-test individually shows that only one variable is significant in the 95% confidence interval for the first case. For the second case, on the other hand, having an EZ-Pass transponder or not is the only significant variable.

Table 3-2 Coefficients and Standard Errors for the Case of Accepting Switch

Independent Variable	Coefficient	Standard Error
Shipment Size	-0.074	0.102
EZ-Pass	-0.413	0.592
Trip Duration	-0.003	0.002
Trip Distance	0.685	0.382
Private	-1.733	0.692
Large Trucks	0.009	0.013
Drivers Employed	-0.009	0.01
Peak Hour Usage	-0.002	0.002
Commodity Type	-0.589	0.914
Constant	-0.64	0.52

Table 3-3 Coefficients and Standard Errors for Case of Unsure Users

Independent Variable	Coefficient	Standard Error
Shipment Size	-0.006	0.057
EZ-Pass	-2.15	0.542
Trip Duration	-0.0004	0.001
Trip Distance	0.456	0.361
Private	-0.462	0.423
Large Trucks	-0.011	0.012
Drivers Employed	-0.012	0.006
Peak Hour Usage	--0.0007	0.001
Commodity Type	0.4168	0.489
Constant	2.5	0.822

General model fit shows that the likelihood ratio chi^2 value is 46.48 with 18 degrees of freedom. Pseudo R-squared term is 0.1524. Both values are slightly better than the critical values therefore it shows that the model fit can be accepted as reasonable at 90% level of significance.

Hypothesis testing is performed by the Combine Test results at 95% level of significance are presented in Table 3-4. The results show that “Yes-Unsure” and “Yes-No” responses can be combined or all the independent variables for each of the categories have zero effect.

Table 3-4 Combine Test Results at 95% Level of Significance

Alternatives Tested	Chi^2	df	$P > Chi^2$
Yes – Unsure	14.306	9	0.112
Yes – No	11.157	9	0.265
Trip Distance	21.867	9	0.009

Likelihood ratio test results for each variable are given in Table 3-5. The null hypothesis is stated as all coefficients associated with given variables are 0. Similar to the t-test results at 95% level of significance, all independent variables except company's being private or not and E-ZPass usage are not significant. One of the interesting conclusions from this test is that shipment size and peak hour trips are strongly insignificant variables.

Table 3-5 Likelihood Ratio Test Results

Independent Variable	Chi^2	df	$P > Chi^2$
Shipment Size	0.577	2	0.749
EZ-Pass	23.683	2	0.00
Trip Duration	2.535	2	0.281
Trip Distance	3.901	2	0.142
Private	6.916	2	0.031
Large Trucks	2.094	2	0.351
Drivers Employed	3.508	2	0.173
Peak Hour Usage	0.865	2	0.649
Commodity Type	1.741	2	0.419

The first conclusion of this analysis is that most of the independent variables selected here are not statistically significant to be included in the model to define a reliable value of travel time. The only significant variable for switching to off peak hours if certain savings are obtained is company's operating status. Although general model fit suggests that the model is slightly better than the critical values, two different test results showed that independent variables are not statistically significant and including the insignificant ones in our model might lead to wrong results. Therefore in the next section data is modified to obtain more acceptable time and cost coefficients and a new analysis is conducted with binary logit model.

3.4.2 Estimation of Value of Time

In this section, value of time estimation results for commercial vehicles using proposed logit model methodology with the data obtained from Holguin-Veras et al. (2006). Statistical data analysis software STATA was used for the logit model construction and evaluation.

Based on results obtained in the previous section, the data from the survey needed to be modified for using in the value of time estimation method described in Section 3.2.

In this section analysis was conducted by categorizing responses as *change* or *not change*, therefore "undecided" and "refused to change" answers were assumed to be in the same category as "not change". Therefore all 200 data points were used in the analysis as valid answers who declared whether to change or not change their behavior in response to the prospected savings. This enabled to work with a larger sample space.

Independent variables which were used to define the cost related parameter α and time related parameter γ are type of business and trip distance, respectively.

Levinson, et al. (2004) provided a detailed study for per kilometer costs for different industries depending on their trucker survey. The values they provided is for 2004 which is the same year of the PANYNJ survey. Only difference is the regional difference since their survey was done for Minnesota and PANYNJ study is concerned about New York New Jersey region. Therefore regional consumer price indexes obtained from the Bureau of Labor Statistics (BLS) are used for adjustment factors and for all data points per-mile operation costs are calculated. Results are given in Table 3-6. Then this value was used as the cost parameter.

Table 3-6 Commercial Vehicle Operating Costs

Bussiness Type	Per-mile Cost
Rubbish	$3.45
Dairy	$2.31
Food Products	$2.02
Paper	$1.90
Petroleum	$1.81
Timber	$1.70
Aggregate	$1.57
Industrial Supplies	$1.52
Construction	$1.50
Chemical	$1.39
Agricultural	$1.37
General Products	$1.34
Beverages	$1.12

There exists a time parameter which can be directly obtained from the survey data as response to the “trip duration” question, however it was shown in the previous section that this parameter becomes strongly insignificant when we use the trip decision variable as dependent. Since time spent in traffic and the distance traveled is linearly related in a non-congested environment we can use the distance parameter to have a realistic representative for the time parameter. There is also a “trip distance” question which is again insignificant when used in a logit model as shown in the previous analysis. The main reason for these two parameters’ failing to be usable is the missing points in data which means a lot of respondents did not reply at least one of the two questions. Therefore a manual way of calculating trip distance is developed. Each respondent was asked for the origin and destination states of their regular trips. Time parameter was calculated for every data point by determining the average distance they travel. To be consistent in dimensions both time and cost parameters were used in for 100 mile values. In other words the cost is calculated for per 10 mile travel and the time is calculated by multiplies of 100 miles (i.e. how many 10 miles the respondent travels for a regular trip).

Binary logit model was used for the same dependent variable as in the previous section with using the two new modified variables. Analysis was conducted for different combination of carrier types and different origins (e.g. county or state) where the respondents stated that their trips generally originate. However due to the limited sample size for some of the regions it was not possible to obtain meaningful results therefore they are not stated in here.

The results show that commercial vehicles that generate their trips from New York have a higher value of time compared to the commercial vehicles that generate trips from New Jersey. In addition when the shipment sizes are considered, Less-than-truckload (LTL) type of carriers have higher value of time compared to the Truckload (TL) type of carriers. When the data is not categorized and considered at all a value of time of $33.62 is obtained for commercial vehicles. Table 3-7 shows the estimation results obtained.

Table 3-7: VOT Estimation Results

Sample Group	**Sample Size**	**Time coefficient,** γ	**Cost coefficient,** α	Chi^2	**VOT ($)**
Origin: New York	32	137.4	4.16	5.14	$32.99
Origin: New Jersey	152	79.48	4.01	4.21	$19.82
Origin: Middlesex County, Union County	65	48.03	0.84	3.49	$56.72
Size: LTL	93	17.4	0.44	3.64	$38.9
Size: TL	52	29.8	2.2	3.74	$13.5
All sample	198	35.1	1.04	4.45	$33.62

Table 3-8 shows the estimated values of travel time by different authors in previous studies. The numbers are adjusted to the 2004 numbers for comparison with the numbers obtained in this section.

Table 3-8: VOT Estimation Results from Literature

Author	Year	VOT ($)
Haning & McFarland	1963	$20.33-$26.46
Kawamura	1999	$31.37
Smalkoski & Levinson	2003	$25.08-$51.43

3.5 CONCLUSION

The purpose of this study is to estimate the value of time for commercial vehicles in New York-New Jersey region that will be used as input in the dynamic pricing simulation work. Literature review showed that a number of studies have been conducted for commuter value of time estimation including for New Jersey region (Ozbay et al., 2008). However, commercial vehicle value of time studies are both limited in quantity and there was no specific study considering the region that will be used in the simulation work.

Estimation process started with the derivation of the utility function for period/route choice behavior under different circumstances including toll rate change, incentives for off-peak shifts or any other change that affects the cost of the trip. The utility function given in (3.1) basically defines the major two concerns of a traveler when making route decisions which are trip costs and travel times. The coefficients α and γ are cost and time related parameters, respectively. Regarding the studies conducted so far it was seen that logit model was the mostly used method for estimating commercial vehicle value of times, therefore parameter estimations are given after utilizing a logit model in equations and (3.4).

Stated preference data was obtained from PANYNJ trucker survey in 2004 was one of the most comprehensive and detailed data for commercial vehicles in New York-New Jersey region which was previously used to define behavioral analysis of truckers. One section of the survey consists of hypothetical toll schedule scenario questions and asking whether or not the respondent is willing to change his/her behavior under the stated conditions. The data points obtained for this question can be regarded as indicators of value of time of the respondent, thus these data points are selected as the dependent variable. Independent variables that will be included in cost and time parameters were first tried to be selected directly from the survey data however due to the several missing data points the selected variables turned out to be insignificant in the logit model. Therefore using the selected cost and time related variables would lead to biased results in the value of time estimation. As a second method data is modified manually to generate the cost and time related variables to be used in the utility function. Data is divided into categories depending on the origin and the size of shipment. For each category, values of time are estimated separately.

Results showed that values of time of the commercial vehicles in New York-New Jersey region are ranging from $13.5-$56.72. The estimated numbers are similar to the estimates of the previous studies. The results showed that the values of time for commercial vehicle trips generated from New York are higher than the values of time for trips generated from New Jersey. Considering complete sample for the value of time estimation gives an estimate of $33.62 and this value assumed to be the most representative estimate since the sample size is the highest in this case. Finally, for the case study which is presented in the next chapter, commuter vehicle value of time is taken from the paper published by Ozbay et al. (2008) as $18 since this paper estimated value of time using the data collected specifically in the greater NY/NJ area.

CHAPTER IV

CASE STUDY: DYNAMIC PRICING APPLICATION FOR NEW YORK CITY CROSSINGS

4.1 INTRODUCTION

In this section, the simulation based evaluation of TransModeler's default dynamic pricing strategy for New York City crossings is explained.

4.2 SOFTWARE

4.2.1 Implementation of Dynamic Pricing Scenario in TransModeler

TransModeler is a traffic simulation software which allows running large scale simulations with several fidelity options (e.g. microscopic, mesoscopic, macroscopic). It easily integrates with TransCad which is one of the most commonly used travel demand forecasting software (Caliper, 2009). TransModeler offers both static and dynamic pricing capabilities for a given network under the High Occupancy Toll (HOT) lane editor. Although the in-built module is designed for HOT lanes, it can be applied to any transportation network.

Static pricing can be performed in two ways:

1. Fixed pricing which is the case that toll rate remains unchanged,
2. Time-dependent pricing in which the toll rates change for different time periods according to a pre-determined tolling schedule.

In both cases different toll rates can be assigned to different types of vehicles or different user groups.

Dynamic pricing, on the other hand, can be performed under the "traffic responsive" type of tolling capability provided by TransModeler's HOT lane editor (TransModeler) .In this case toll rates vary over time, but rather than following a pre-determined schedule, they change in response to real-time traffic conditions. One or more sensors measure the occupancy and travel speed on specified lanes or links that are subjected to tolling. The data received from the sensors are used to update the toll rates within a previously determined time cycle. When the threshold values for minimum occupancy and/or maximum speed are reached, the rates are automatically changed.

Figure 4-1 shows a screen capture for the toll rate schedule assignment editor. An example traffic responsive dynamic tolling algorithm can be as shown in Equation (4.1):

$$TOLL = \begin{cases} if\ \ t_{occ} \geq 40\%\ or\ u_{\max} \leq 40\ mph\ then\ SOV: 2.25, HOV2: 1.5, HOV3+: 1.1 \\ if\ \ t_{occ} \geq 30\%\ or\ u_{\max} \leq 45\ mph\ then\ SOV: 2.0, HOV2: 1.2, HOV3+: 0.8 \\ if\ \ t_{occ} \geq 20\%\ or\ u_{\max} \leq 50\ mph\ then\ SOV: 1.75, HOV2: 0.8, HOV3+: 0.5 \\ if\ \ t_{occ} \geq 10\%\ or\ u_{\max} \leq 55\ mph\ then\ SOV: 1.5, HOV2: 0.5 \\ else\ SOV: 1.0 \end{cases} \quad (4.1)$$

where,

t_{occ} is the measured occupancy of the lane or the link depending on the sensor type, u_{max} is the maximum speed on the link and SOV, HOV2 and HOV3 represent different type of users which are subjected to different toll rates

To run the simulation, a network, has to be either created from scratch or extracted from an existing TransCad network. An OD Matrix then must be determined for this network. If necessary, different OD demand matrices for different time periods and for different modes can be selected. TransModeler offers several modification choices for trip matrices. Trip rate percentages can be controlled within a time period or can be assigned randomly.

To see the effects of a road pricing application on traffic, alternative routes must exist for the tolled roads. The network should offer different road choices to the users in case of a toll increase. For different types of user classes, such as trucks or passenger cars, different toll rates, values of travel time, and level of response to traffic conditions can be defined. All of these parameters contribute to the dynamic structure of the system. In addition, special lanes can be reserved for one type of user class to see the effects of separated traffic. TransModeler allows for assignment of several route choice options using the mostly preferred methods. An example is shown in Figure 4-2.

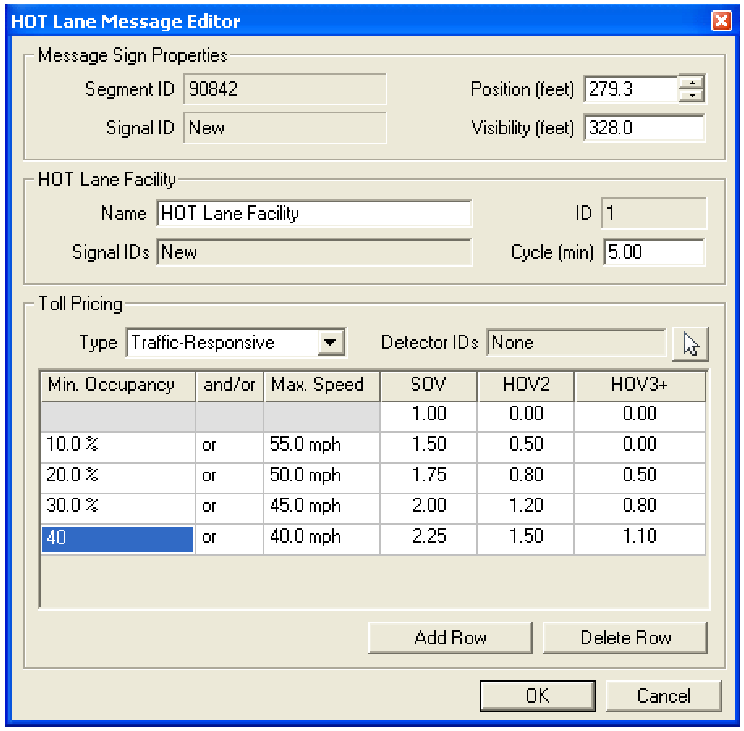

Figure 4-1: Dynamic Road Pricing Module in TransModeler (TransModeler, 2009)

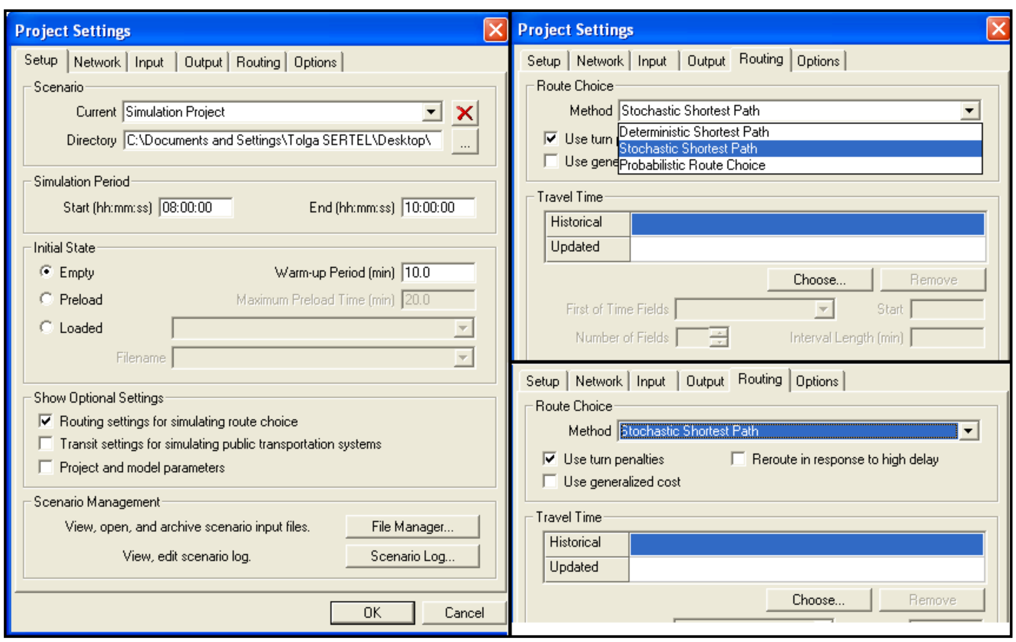

Figure 4-2: “Routing” Tab in “Project Settings” in TransModeler

(TransModeler, 2009)

The output obtained from a simulation includes travel times, average delays, toll revenues, and several trip statistics. Therefore, user response can be observed in accordance to toll changes. Route choice, one of the most complex driver behaviors in traffic simulations, can also be adjusted. In real conditions people do not make their route decisions only depending on the time or cost criteria. There are several parameters to take into account such as familiarity with the road, value of travel time and being informed about the traffic conditions. TransModeler offers the following methods to determine how to assign paths to each driver (TransModeler, 2009).

> ***Deterministic Shortest Path*** *The simplest method that assumes users follow the absolute shortest path. It is not recommended to use in large scale networks where cost structures are more complex.*
>
> ***Stochastic Shortest Path*** *Similar to the previous method, users select the shortest path but additionally path costs are randomized for each vehicle to consider variations in perception and behavior. Therefore shortest paths are not the same for everyone in the system.*
>
> ***Probabilistic Route Choice*** *This method uses Multinomial Logit Model (MNL) to simulate driver's choice among alternative paths. Every route has a utility that describes its relative attractiveness.*

In addition to these methods, TransModeler also has an option to use historical travel times for route choice. It is an optional feature that can use a previous simulation's travel time information to affect user's route decisions. Another optional feature in TransModeler is "Reroute in response to High Delay". This option can be used to update the paths in case of unexpected high delays. This feature is recommended to be used with

"Historical Travel Times", because when there is no previous data on hand, normal delays will be considered as excessive when compared to the free flow travel times.

The last option is to use "Generalized Cost". This is an important feature while working with tolls because it allows users to include toll costs to their travel costs in addition to travel times and other costs. The value of travel times of users is then also taken into account in route choice. It is also noted that generalized costs should be used with one of the shortest path methods stated above, since probabilistic route choice has an internal logic considering tolls and travel times.

4.2.2 Initial Tests

Six different test runs were performed with different combinations of the route choice options stated above. These test runs used an extracted portion of the New York metropolitan highway network found in the New York Best Practice Model (NYBPM), shown in Figure 4-3. This network represents the highway crossings over/under the Hudson River between New Jersey and Manhattan. Demand was held the same during all runs with its distribution throughout the period given in Figure 4-4.

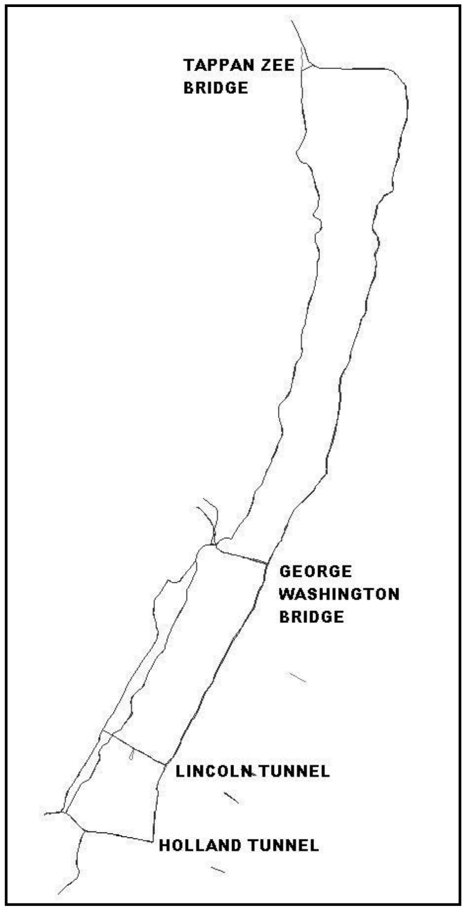

Figure 4-3: Test Network Created for Dynamic Pricing Simulation in TransModeler

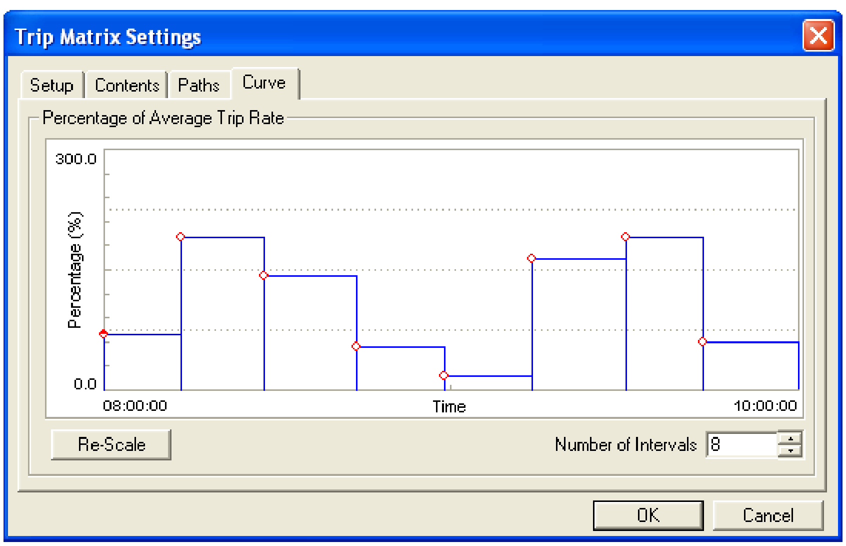

Figure 4-4: Demand Distribution Throughout a Period (TransModeler, 2009)

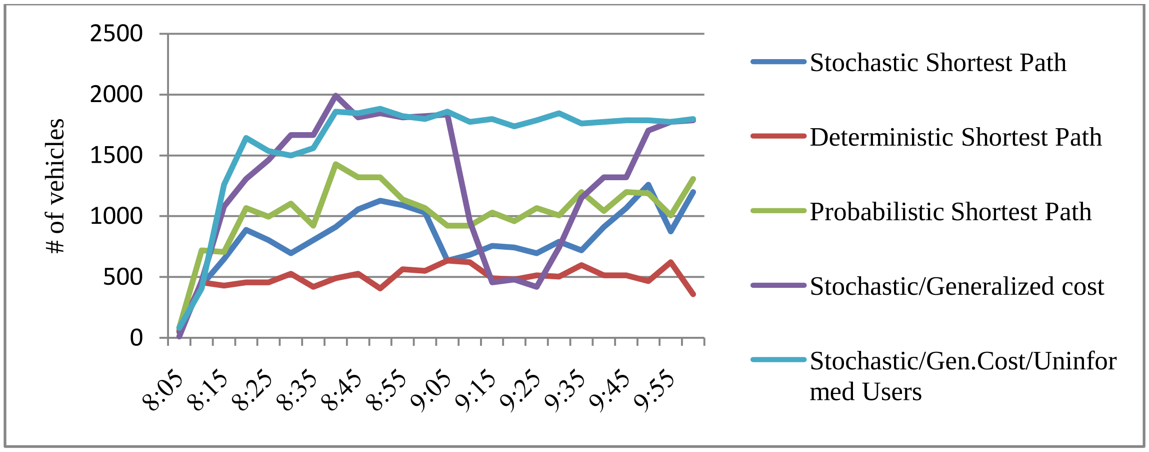

Figure 4-5: Time Dependent Change of Flow in Holland Tunnel

Figure 4-5 shows the traffic volume differences in the same route between different route choice methods. Each method, when combined with different options (e.g. users being uninformed), gives significantly different route choice behaviors for the same users. Value of time (VOT), or how much a user is willing to pay for a certain amount of time saving, must be defined in the simulation. If a user, for example, has a VOT of $20 per hour, it means he/she can pay $20 to save one hour from his/her travel time. As shown in Figure 4-6.

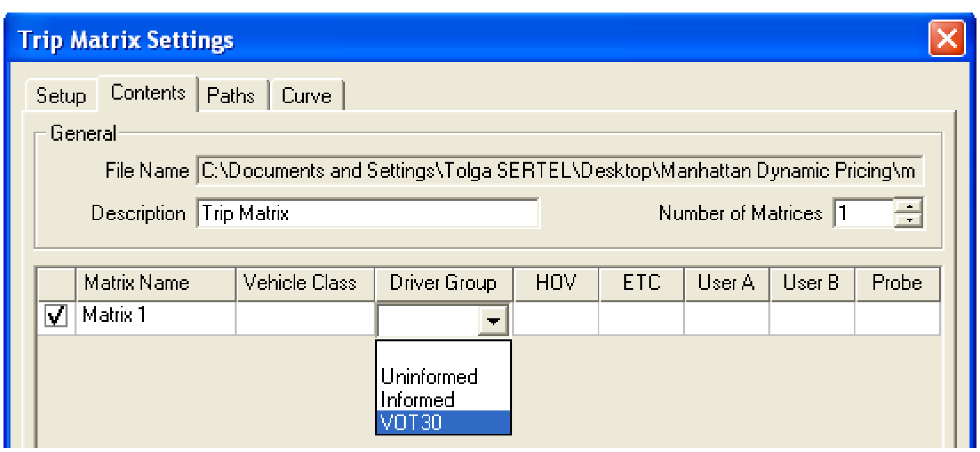

Figure 4-6: Assigning Different Values of Time for OD Matrices (TransModeler, 2010)

TransModeler allows to define different value of travel times for each Origin-Destination (OD) matrix, therefore different classes can have different route choice preferences according to their value of time (VOT).

Three different runs in the test network with different value of times showed that the module works properly. The sample OD matrix included one type of user all having the same value of travel time. Figure 4-7 shows the flow comparisons in one of the crossings (Holland Tunnel) for the three different cases; value of time equal to $10/hr, $20/hr, and $30/hr. It can be seen that with a lower value of travel times users may consider alternative routes, whereas when the value of time increases users prefer the shortest path to save time.

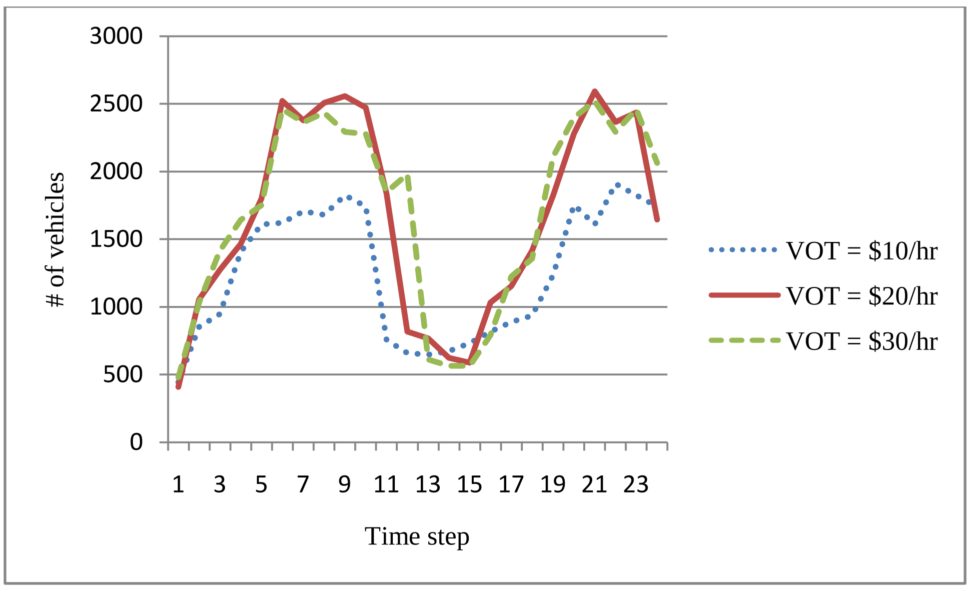

Figure 4-7: Flow vs Time for Different Values of Time

4.3 SIMULATION NETWORK FOR DYNAMIC PRICING

Initial testing of dynamic pricing established its suitability for this study. Both dynamic and static congestion pricing scenarios are studied with a primary focus on charging tolls to enter Manhattan Island. Static pricing, which is currently applied at the crossings, is the case when toll rates are fixed throughout the day. Traffic conditions do not affect the toll rates as they do in the dynamic pricing case.

TransModeler, which allows for microscopic, mesoscopic, and macroscopic level simulations, is used for simulating the described pricing schemes. Mesoscopic level is chosen for conducting dynamic tolling simulation scenarios considering the relatively large size of the study network.

4.3.1 Dynamic Pricing Implementation in Manhattan Sub-Network

The extracted sub-network of the New York Best Practice Model (NYBPM) focusing on Manhattan used for pricing simulations is shown in Figure 4-8. Since pricing is expected to affect users' route decisions, Manhattan network was extended to include alternative links connecting the crossings into Manhattan from New Jersey for entering Manhattan from the west side and crossings from Bronx and Brooklyn for entering from the east side. This enables simulated drivers to select a different path to enter Manhattan to either save money due to different toll costs or travel times as a result of congestion in the paths that they regularly use.

Crossings included in pricing simulations were selected based on several criteria for a feasible dynamic pricing application. One of the major requirements in real world dynamic pricing implementations is the availability of an alternative route for travelers to select in case they are not willing to pay the toll. Dynamic pricing is performed only in High Occupancy Toll (HOT) lanes in the US where only one or two lanes alongside a free highway is tolled and users who prefer to avoid congestion in regular lanes use HOT lanes by paying a dynamically priced toll. Travel speeds in HOT lanes are guaranteed to be higher than a previously set level of service by adjusting toll rates in accordance to congestion level. Therefore users know that the maximum time they will spend when they use HOT lanes.

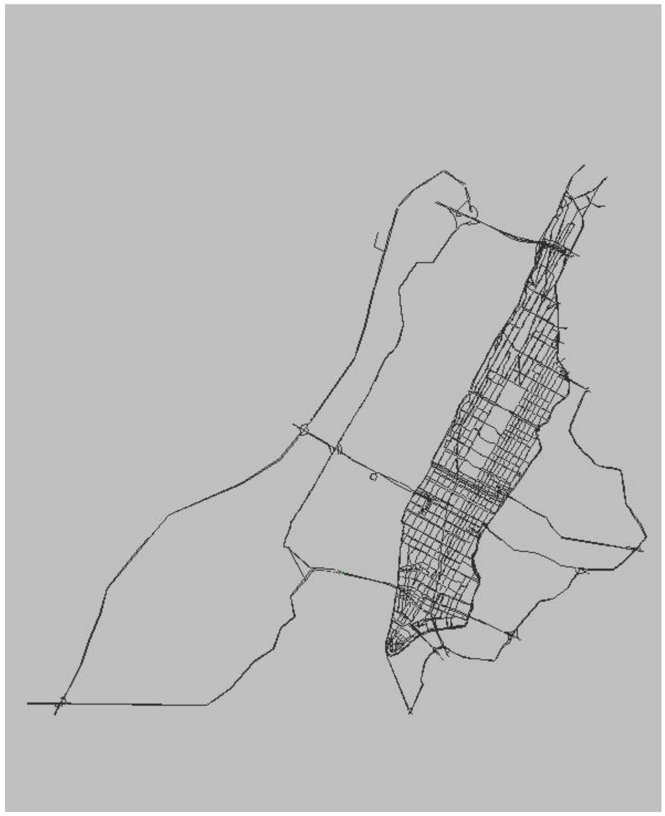

Figure 4-8: Network Created for Mesoscopic Simulation

Dynamic pricing application on crossings to Manhattan cannot be handled in the same way, with the most obvious obstacle being the limited number of lanes in crossings. Reserving one or more lanes for dynamic pricing and using other lanes as an alternative is impossible due to this limitation. Additionally for the crossings that are already tolled, the alternative lanes cannot offer free trips. Instead each crossing is dynamically priced depending on the congestion level and other crossings serve as the alternatives. This system allows users to know the cheapest or the fastest possible route by comparing the toll rates and select the best possible alternative to enter Manhattan.

Guaranteeing a minimum level of speed, which is presented as the second goal of real world dynamic pricing implementations in HOT lanes, also cannot be applied to the Manhattan crossings. In the peak hours, due to factors such as the limited number of lanes, bottleneck propagation in the entry or exit points is commonly seen in these crossings. Additionally, the crossings have previously set speed limits which were decided according to structural design of the crossings and cannot be exceeded. Therefore instead of defining a minimum speed goal a reasonable commitment can be diminishing – or at least shortening – the duration of the jam (e.g. stopped or very slowly flowing) conditions at the entry and exit points of the crossings. The meaning of this in the simulation work is decreasing the average occupancy values which are measured by the sensors in the bottleneck points.

4.3.2 Crossings Used in Dynamic Pricing

The crossings used in the simulation network (shown in Figure 4-9) are:

<u>Manhattan-Brooklyn/Queens Crossings</u>

- Triborough Bridge (Tolled)
- Queensboro Bridge (Free)
- Queens Midtown Tunnel (Tolled)
- Williamsburg Bridge (Free)
- Manhattan Bridge (Free)
- Brooklyn Bridge (Free)

- Brooklyn Battery Tunnel (Tolled)

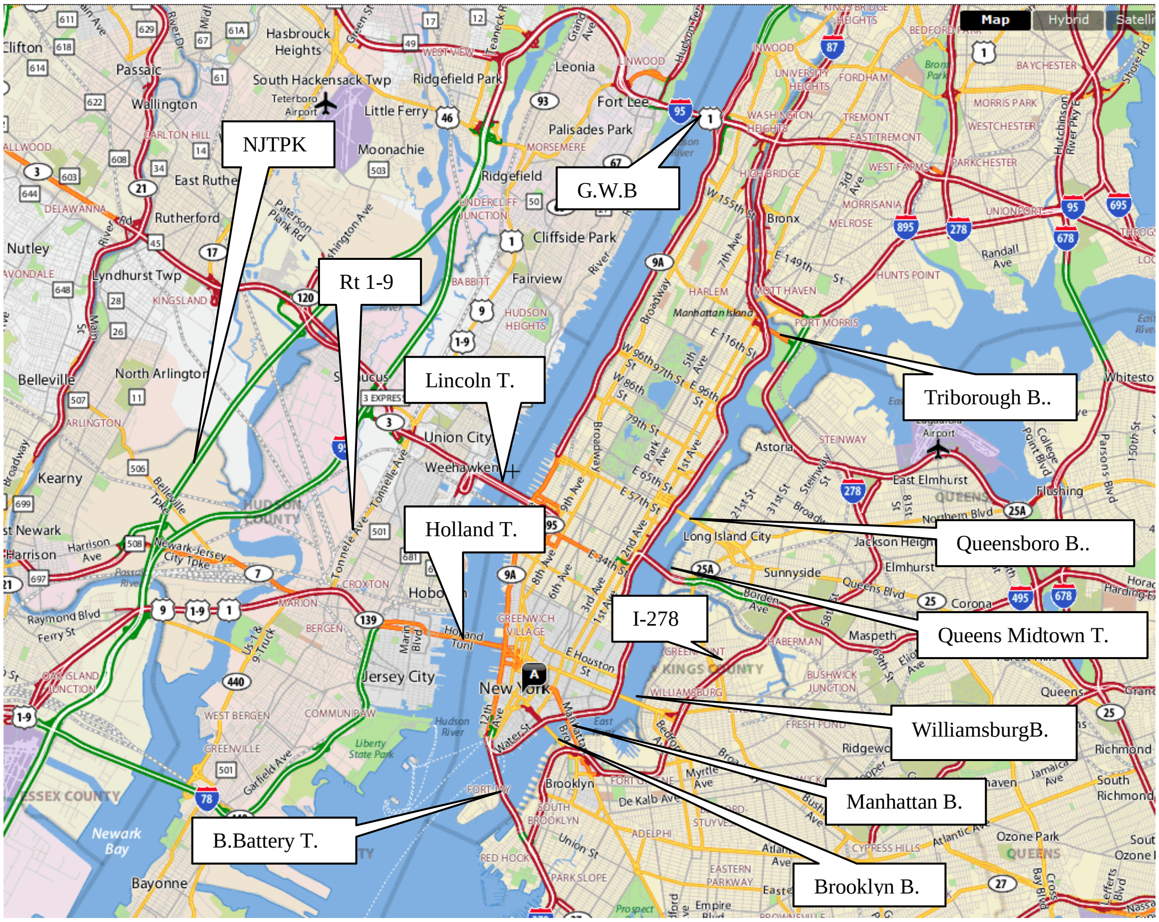

Figure 4-9: Crossings and Routes Used in the Simulation Network (Yahoo Maps, 2010)

<u>Manhattan-New Jersey crossings</u>

- George Washington Bridge (Tolled)
- Lincoln Tunnel (Tolled)
- Holland Tunnel (Tolled)

Manhattan-New Jersey crossings (George Washington Bridge, Lincoln Tunnel and Holland Tunnel), which allow entering Manhattan from the west side, are ideally positioned for a dynamic pricing simulation. In the simulation, two connecting roads are included between the crossings for users who want to use an alternative route to cross to Manhattan. These two routes are New Jersey Turnpike (NJTPK) and Route 1-9 which carry the complexity of the network one step further since one of these connecting roads (NJTPK) is tolled and the other one (Route 1-9) is free. NJTPK is a major highway with speed limits of 55mph while Route 1-9 is an arterial with traffic lights and much lower speeds. In addition traffic is disturbed more compared to the NJTPK. It should be noted that all of the traffic carried by these three crossings are assumed to be using or have an option to use one of the two routes before using crossings.

To enter from the east side of Manhattan, there are seven different alternatives in the simulation (Triborough Bridge, Queensboro Bridge, Queens Midtown Tunnel, Williamsburg Bridge, Manhattan Bridge, Brooklyn Bridge, Brooklyn Battery Tunnel). All the bridges and tunnels are located close enough to constitute alternatives for each other. However, different from the west side crossings of Manhattan, among these seven alternatives only three are tolled. Free crossings remained un-tolled in the simulations and tolled ones are dynamically priced. I-278 (Brooklyn-Queens Expressway) is provided to link the alternative crossings.

4.3.3 Simulation Study Area Selection

The simulation study area was focused on Manhattan crossings therefore some possible alternative routes were not considered in the network. Including New Jersey-Staten Island crossings (Goethals Bridge, Outer Crossing) and Verrazano-Narrows Bridge to connect NJTPK and Interstate 278 would offer a system that enables users to enter Manhattan even from a different side (e.g. from the west side instead of the east side). Although this may not be the case for most of the users whose destinations are inside Manhattan, it may be a possible alternative for through trips. But the limited traffic data for network calibration forces to make assumptions for the traffic distributions in the connection points of the roads and this may result in more unrealistic or unreliable results. For example, in such a configuration aggregated traffic in the connecting roads must be realistically distributed to all crossings (e.g. similar traffic volumes as in real traffic counts) for the base case where the tolls are remained static. TransModeler has specific features for route choice depending on the value of time of users but the distributions do not match the real counts most of the time in meso-scale simulations. Therefore it needs to be recalibrated to get realistic traffic volumes in each crossing.

Calibration for the dynamic extended sub-network model is done by either modifying route characteristics (e.g. free flow speed, number of lanes) to adjust the total cost of travel time or putting a fake toll to match the real costs of travel in the selected route. Both ways are useful in terms of simulation purposes for obtaining real traffic counts in the crossings but the network dynamics are also changed by these modifications and reality of the network is lost for some links. Therefore instead of using these methods to simulate a larger network, network construction was finalized with including the previously stated crossings only.

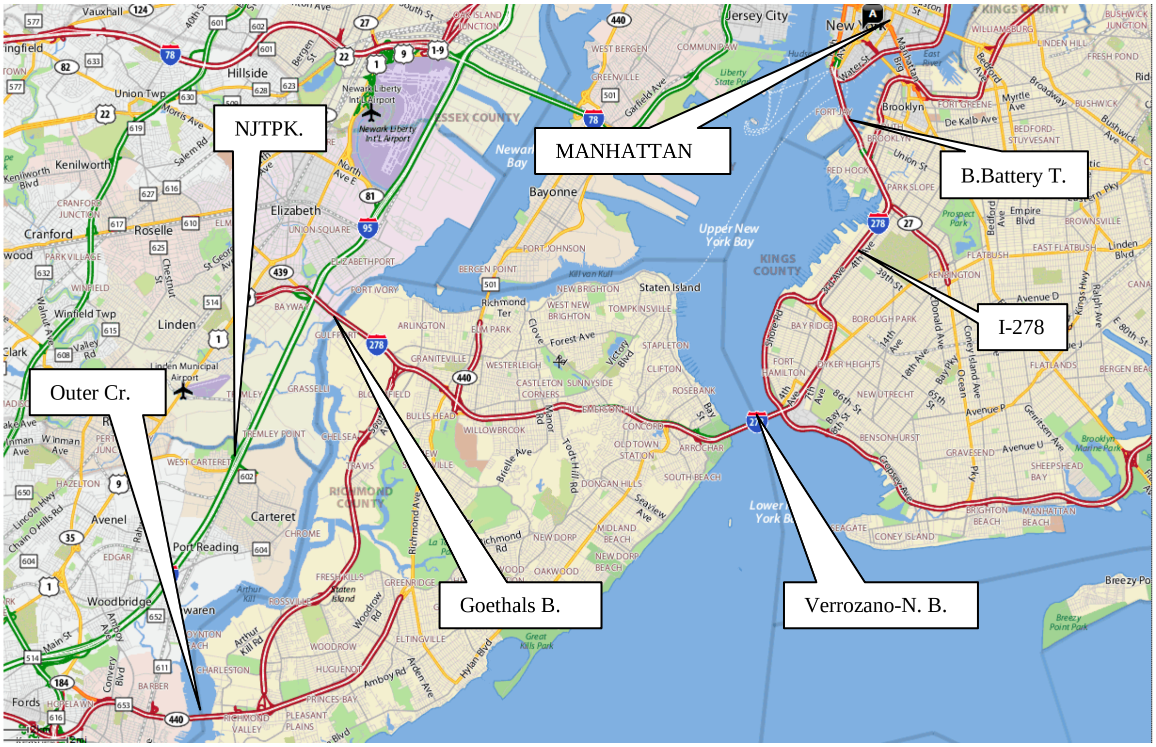

Figure 4-10: Possible Additional Alternative Routes (Yahoo Maps, 2010)

Another reason to keep the network limited to Manhattan crossings is to meet the basic requirements for dynamic pricing. Dynamic pricing needs users to be kept informed continuously and earlier enough for them to be able to make their route decisions. Variable message signs in HOT lanes may be located a few miles prior to the separation point of the tolled lanes but in the crossings this distance must be longer. For example in case of the West side crossings of Manhattan, the distance between Lincoln Tunnel and Holland Tunnel is approximately 3 miles and the distance from Lincoln Tunnel to George Washington Bridge is approximately 7.5 miles. In a larger network (Figure 4-10), the distance from Outerbridge Crossing and George Washington Bridge, for example, is approximately 30 miles. Infrastructure requirements of the dynamic pricing strategy presented in this simulation work are beyond the scope of this study but it may be assumed that the possibility of a user to make a healthy decision for his/her route choice

30 miles before the alternative decision point is quite low. Another possible way to inform travelers about dynamic prices is through the use of GPS technology. However, to ensure that all the vehicles have access to the time-dependent prices, at least in the near future, variable message signs are the best alternative. On the other hand, vehicles traveling on this network can be give an option of using a GPS based in-vehicle system to access the dynamic pricing information and make their routing decisions accordingly. A similar implementation has been operated in Germany in which the toll charging system is based on the distance traveled that is measured by the GPS unit on-board (Satellic). Another important feature of this network, is the limited number of decision points drivers have. Thus, there is no real difference between providing the pricing information via VMS or in-vehicle devices. In the short run, VMS is a more practical alternative since it does not require the in-vehicle GPD devices that might prove to be an impractical approach given the institutional and other implementation issues.

As stated in detail in the previous section, route choice of drivers can be simulated by three different methods in TransModeler, namely, stochastic shortest path, probabilistic shortest path, and deterministic shortest path. Among the three, the stochastic shortest path method was used during the pricing simulations. Compared to the deterministic shortest path, this method takes more parameters into account and is more reliable to use in large-scale networks. Probabilistic shortest path method has an in-built algorithm which also includes tolls in route choice of users, but this model generates random results which are difficult to control by adjusting parameters. In the stochastic shortest path method, path costs are randomized for each vehicle to consider variations in perception and behavior, which results in shortest paths not being the same for everyone in the system. Using this option, driver behavior can be defined for different driver groups using different generalized costs. This feature allows users in the system to change their route decision by considering toll levels on the alternative routes to their destination based on defined values of travel time for user groups.

4.3.4 Network Calibration

For dynamic pricing simulations that allow users to select their route to enter Manhattan among different crossings, traffic volumes for all crossings are aggregated at several demand generating points. These points have connections to all possible crossings in one side via the connecting roads (NJTPK and Route 1-9 on New Jersey side, I-278 on Brooklyn/Queens side). For the static case network calibration is performed to make sure the traffic volumes are realistically distributed to the crossings. A schematic flow chart for the calibration procedure is given in Figure 4-11.

Simply adding connecting roads on both sides of the Manhattan simulation network created unrealistic traffic volume distributions in some of the crossings. However, for the static case the main objective is to simulate the real highway network as accurately as possible to use as a base for comparison of the results with dynamic pricing simulation. Several sensors are set up in the network including all connecting roads and crossings to measure what portion of the traffic change their route in the static case due to the additional links between crossings (e.g. NJTPK, Route 1-9 and I-278). Traffic volumes from the simulation were compared with the real volume counts (NYCDOT) and the network was calibrated by modification of the link characteristics (e.g. free flow speed, speed limit, lane width etc.) for the sections where significant disparities in traffic volumes were observed. After several calibration trials all the crossings were set to have at most a 10% error in traffic volume compared with the expected counts. Table 4-1 shows the values obtained after the final calibration.

For dynamic pricing simulations the behavior of users in response to the dynamically priced tolls necessitated its own calibration. Calibration was needed for both driver behavior and the network cost structure since most users try to select the cheapest possible option according to the simulation settings. The costs for some of the roads connecting the crossings outside of Manhattan were adjusted by increasing or decreasing the toll rates on the road (if there is a toll). The driver values of time are adjusted to successfully implement the dynamic toll rate schedule. There are also error factors defined in TransModeler which affect the perception of the shortest path of the user, such as how many links in advance users consider before doing a change in their route choice or gap acceptance models which one can adjust in several ways for calibration.

Table 4-1: Error Between Expected and Simulated Volumes after Final Calibration

Facility	ERROR
Holland Tunnel	4.1%
Lincoln Tunnel	-4.7%
George Washington Bridge	-0.1%
Triborough Bridge	0.0%
Queensboro Bridge	0.8%
Queens-Midtown Bridge	4.4%
Williamsburg Bridge	-6.7%
Manhattan Bridge	-0.8%
Brooklyn Bridge	4.8%
Brooklyn Battery Tunnel	-0.3%
TOTAL	**0.2%**

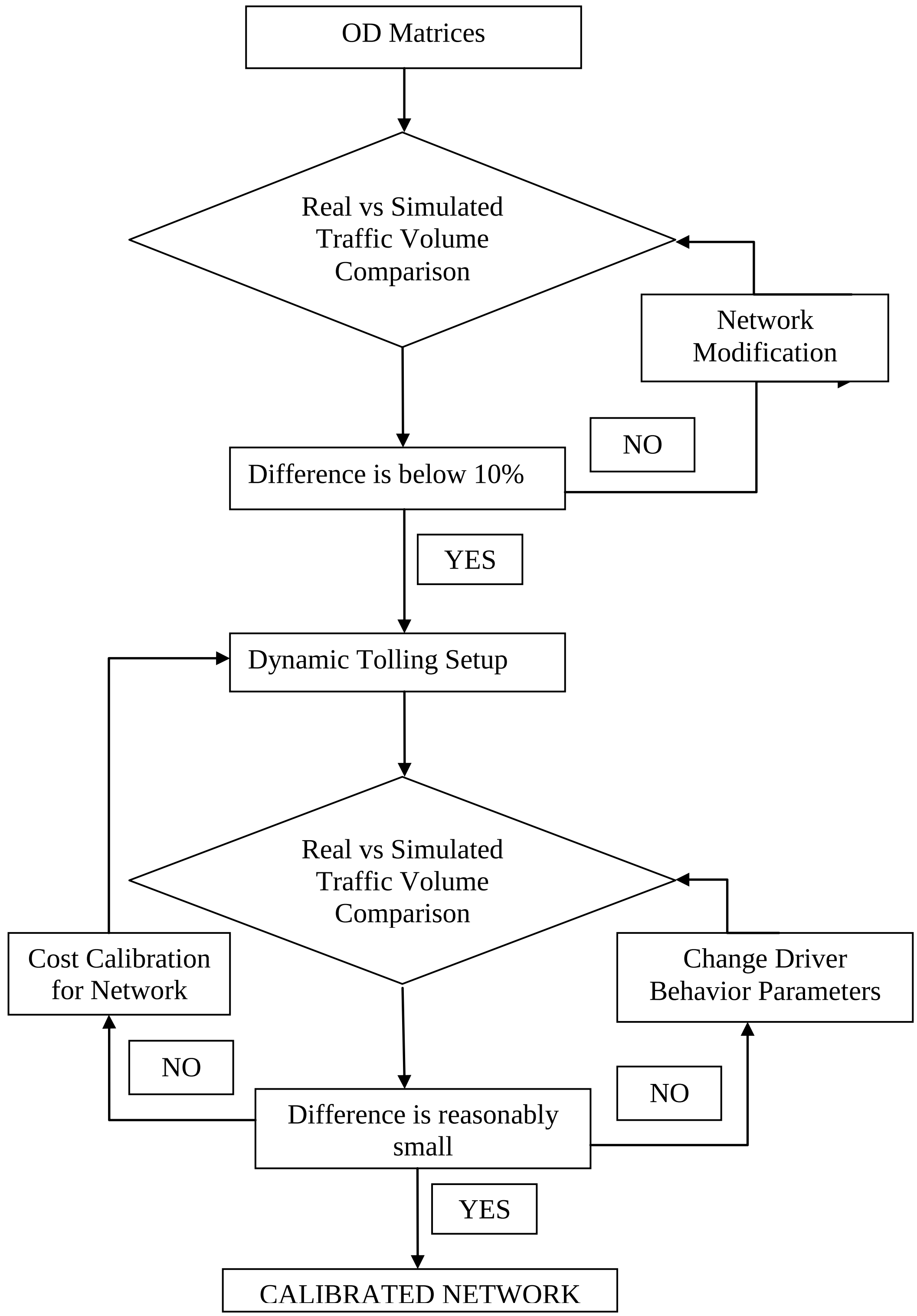

Figure 4-11: Calibration Procedure

4.3.5 Simulation Scenarios

Two different scenarios were run for all hours separately for a typical day. One is with static pricing in the crossings to Manhattan with the toll rates given in Table 4-2, held constant throughout the day, and the other is with dynamic pricing. Static pricing refers to the case when the toll rates are either fixed throughout the day or previously determined and separated as peak and off-peak tolls (this is the system currently in place in the real highway network). The current tolling application in all of the tolled crossings included in the simulation network is static pricing. Toll rates in static pricing are defined differently by vehicle class. Since not all vehicle classes were defined in the simulation, average values for each class are used for toll rates. Truck tolls are calculated by taking the traffic volume percentages of truck classes by axle. Toll rates for cash users is assumed to be the same for all hours, however users of the electronic toll collection system E-ZPass have off-peak discounts (PANYNJ). The data used for traffic demand was not split into E-ZPass users and others, therefore off-peak discounts were ignored in this version of the simulation scenarios. Static pricing simulations were taken as the base case for the dynamic pricing simulation study since it represents the real world conditions in traffic volumes and toll revenues. The data obtained from static pricing simulations was used for comparison with dynamic pricing output data. The same demands were used in both simulations to compare the different volume distributions to the crossings and different toll revenues gained.

Table 4-2: Static Pricing Simulation Toll Rates

MANHATTAN-NEW JERSEYCROSSINGS (George W. Bridge, Lincoln Tunnel, Holland Tunnel)	
Vehicle Class	Toll Rate
Passenger Car	$8.00
Trucks	$27.00
Small Commercial Vehicles	$13.00
MANHATTAN-BROOKLYN/QUEENS TOLLED CROSSINGS (Triborough Bridge, Queens-Midtown Tunnel, Brooklyn Battery Tunnel)	
Vehicle Class	Toll Rate
Passenger Car	$5.50
Trucks	$24.00
Small Commercial Vehicles	$11.00

In static pricing, driver behavior is not influenced by the toll rate since they are the same for all hours and for all alternative routes. In this case travel times are the decisive factor for the route choice of users. The main purpose of running this scenario was to use it as a base case and analyze the differences from the results obtained from the dynamic pricing scenario.

In the dynamic pricing scenario a robust tolling model is needed to meet driver satisfaction, by offering them acceptable toll rates to travel and to meet the minimum requirements for a previously set level of service for traffic. As stated, TransModeler offers dynamic pricing with using two parameters, “minimum occupancy” and “maximum speed”. However the data obtained after running the static pricing scenario for different time periods showed that there was no statistically significant correlation between speed and occupancy levels that would allow for robust formulation of a meaningful algorithm for dynamic pricing using the two parameters together. This is mainly due to the internal modeling assumptions of TransModeler as well as the network specific characteristics. Therefore only occupancy level was considered in determining the real-time toll rates.

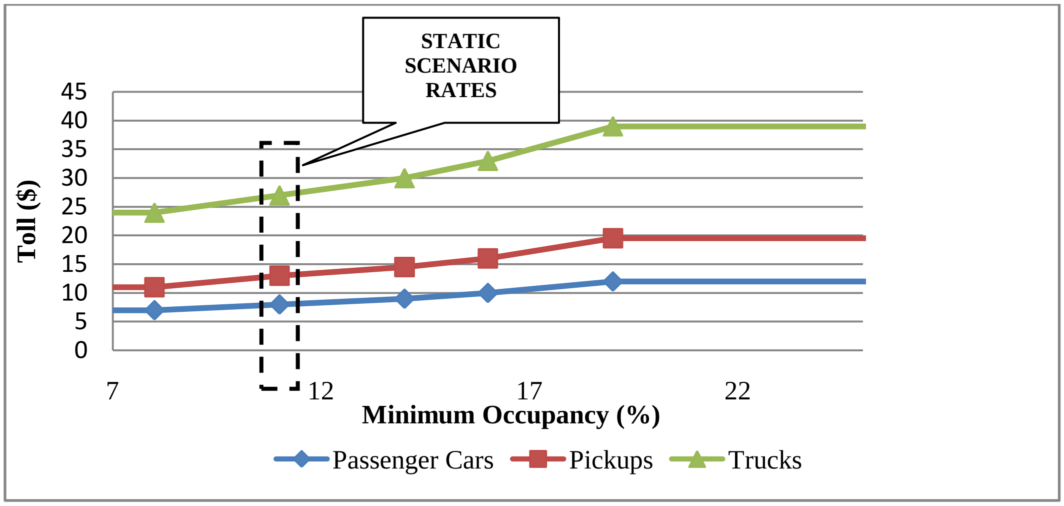

Figure 4-12: Toll Rate Change by Occupancy (NJ-Manhattan Crossings)

Figure 4-12 shows the toll rate change in New Jersey-Manhattan crossings in accordance with occupancy values, which are obtained in real-time with the help of sensors located on the crossings in the simulation network. In the static pricing scenario an average occupancy rate of 11.6% was observed for all crossings, therefore the static pricing rates were set at 11% occupancy for the dynamic case. The same toll schedule was applied to all crossings, and this toll schedule suggests lower toll rates compared to the static case if free flow conditions are met. In the simulation, toll rates were updated every five minutes.

Similarly Figure 4-13 shows the toll schedule in the static pricing simulation for the Manhattan-Queens/Brooklyn Crossings which have an average occupancy of 12%

throughout the day. Therefore static toll rates were set to the minimum 12% occupancy interval in the dynamic pricing toll schedule. It can be seen that when the occupancy is lower than the daily average, toll rates are lower than the static case.

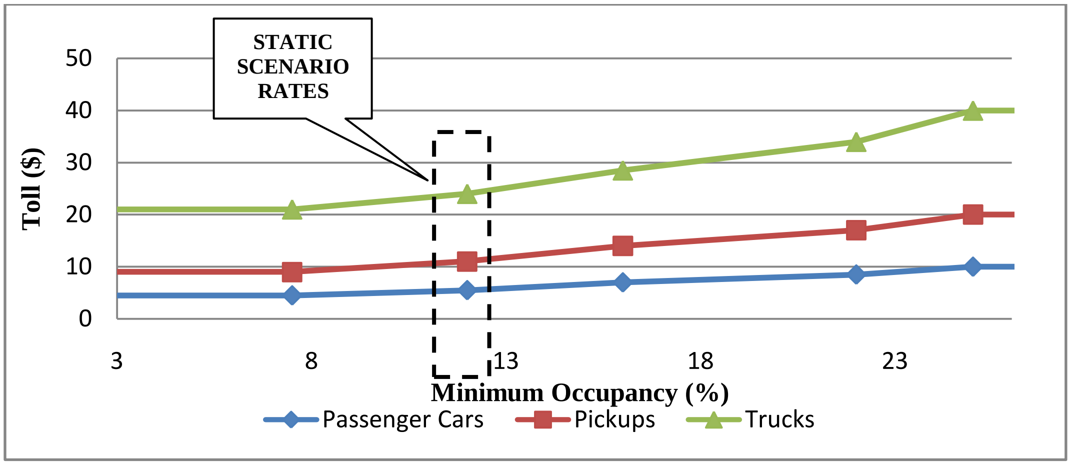

Figure 4-13: Toll Rate Change by Occupancy (Brooklyn/Queens-Manhattan Crossings)

4.4 DYNAMIC PRICING RESULTS

Both static pricing and dynamic pricing simulations were run for 24 hours as four separate periods (AM: 6am-10am, MD: 10am-3pm, PM: 3pm-7pm, NT: 7pm-6am). Table 4-3, Table 4-4, Table 4-5, and Table 4-6 show the simulation data obtained from the point sensors located in each crossing for AM, MD, PM and NT periods respectively. Sensors measure the traffic count within the simulation period and the average occupancies. Lower occupancy values mean better flow conditions and higher speeds.

The results show that hourly average occupancy levels in the Holland Tunnel decreased for all periods with the dynamic pricing scenario. Occupancy levels in the Lincoln Tunnel were slightly lower in the dynamic pricing scenarios compared to the static pricing scenario. For the George Washington Bridge, occupancy values increased in the dynamic pricing case for all periods except the AM period. The differences are mainly caused by different route choice of drivers with the different pricing schedules. In the dynamic pricing case, when occupancy levels increase in one crossing, toll rates also increase accordingly; thus some of the users decide to use a different crossing with a lower toll and create a new path for their destination.

4.4.1 Time-of-day Results

Table 4-3: AM Period Comparison by Traffic Volumes and Occupancies

AM	VOLUMES	OCCUPANCIES
Facility	% Difference	% Difference
Holland Tunnel	-4.5%	-1.1%
Lincoln Tunnel	-1.0%	7.3%
George Washington Bridge	0.4%	0.4%
Triborough Bridge	0.0%	-0.6%
Queensboro Bridge	12.7%	0.8%
Queens-Midtown Tunnel	-26.1%	-4.9%
Williamsburg Bridge	17.3%	3.4%
Manhattan Bridge	4.3%	0.7%
Brooklyn Bridge	0.5%	0.0%
Brooklyn Battery Tunnel	-3.6%	0.9%

For the crossings on the Brooklyn/Queens side, tolled crossings (Triborough Bridge, Queens-Midtown Tunnel and Brooklyn Battery Tunnel) generally carried less traffic in dynamic pricing simulations than the free bridges. This is due to users avoiding higher tolls and using alternative routes in the peak periods. As a supporting result, free crossings' (Queensboro, Williamsburg, Manhattan and Brooklyn Bridges) traffic volumes increased.

AM period results showed that average occupancies of Holland Tunnel decreased as opposed to Lincoln Tunnel and George Washington Bridge average occupancies increased. As expected, on the Brooklyn/Queens side all of the free crossings' average occupancies increased with the traffic shifted from tolled crossings. Similarly, traffic volumes increased for the free crossings and decreased or did not change for the tolled crossings. For Triborough Bridge there was no significant change in both traffic volumes and average occupancies. The reason is the location of the bridge which makes using an alternative crossing more time consuming since the distance to the nearest alternative is approximately 9 miles while the average distance between other crossings is approximately 2.5 miles.

Table 4-4: MD Period Comparison by Traffic Volumes and Occupancies

MD	VOLUMES	OCCUPANCIES
Facility	% Difference	% Difference
Holland Tunnel	-11.0%	-2.0%
Lincoln Tunnel	8.6%	-0.8%
George Washington Bridge	-0.2%	0.0%
Triborough Bridge	0.0%	-0.7%
Queensboro Bridge	6.7%	-0.1%
Queens-Midtown Tunnel	-23.9%	-2.4%
Williamsburg Bridge	14.3%	0.9%
Manhattan Bridge	1.9%	-0.2%
Brooklyn Bridge	-0.3%	2.9%
Brooklyn Battery Tunnel	-2.3%	-0.1%

Midday (MD) period simulation results show that all of the tolled bridges in Queens/Brooklyn-Manhattan crossings show reduced occupancy values. Average occupancies show that Brooklyn-Battery Tunnel and Queens-Midtown Tunnel had higher average toll rates compared to the static pricing and this fact encouraged users to select one of the free alternative crossings. For example Williamsburg Bridge, which is toll-free, carried 14.3% more traffic in the dynamic pricing scenario. Remaining volumes were distributed to the other free crossings that lead to increased traffic volumes.

Table 4-5: PM Period Comparison by Traffic Volumes and Occupancies

PM	VOLUMES	OCCUPANCIES
Facility	% Difference	% Difference
Holland Tunnel	-0.5%	-2.0%
Lincoln Tunnel	-2.9%	-1.3%
George Washington Bridge	2.7%	1.3%
Triborough Bridge	-0.8%	-1.1%
Queensboro Bridge	8.2%	0.4%
Queens-Midtown Tunnel	-22.6%	-2.2%
Williamsburg Bridge	16.8%	0.7%
Manhattan Bridge	3.4%	0.1%
Brooklyn Bridge	4.3%	2.1%
Brooklyn Battery Tunnel	-9.5%	-0.7%

For the PM period significant changes were observed in traffic volumes for Queens-Midtown Tunnel, Williamsburg Bridge and Brooklyn Battery Tunnel. Compared to the static case, Queens-Midtown Tunnel carried 22.6% less traffic and Williamsburg Bridge carried 16.8% more traffic. Since these two crossings are neighbors the reason of the changes can be the shifted traffic volume to avoid the tolls. On Queens/Brooklyn-Manhattan crossings side all of the tolled crossing traffic volumes decreased while all free crossing volumes increased. For average occupancies, higher changes were observed in Queens-Midtown Tunnel by 2.2% and in Holland Tunnel by 2% due to the decrease in traffic volumes, and an increase by 2.1% observed in Brooklyn Bridge due to the shifted traffic from tolled crossings.

In the NT period a significant amount of traffic was switched from Queens-Midtown Tunnel to the free crossings such as Williamsburg and Queensboro Bridges. Occupancy values reveal that most users did not prefer to pay toll for almost similar traffic conditions. Another route shift can be also observed between Lincoln and Holland Tunnels. Traffic using George Washington Bridge was almost the same therefore it can be concluded that approximately 8% traffic was switched from Holland Tunnel to Lincoln Tunnel. The reason was the higher toll rates in Holland Tunnel due to high occupancy values.

Table 4-6: NT Period Comparison by Traffic Volumes and Occupancies

NT	VOLUMES	OCCUPANCIES
Facility	% Difference	% Difference
Holland Tunnel	-8.2%	-1.1%
Lincoln Tunnel	8.4%	0.4%
George Washington Bridge	-0.1%	0.0%
Triborough Bridge	0.0%	0.4%
Queensboro Bridge	1.3%	0.5%
Queens-Midtown Tunnel	-12.3%	-0.5%
Williamsburg Bridge	5.3%	0.2%
Manhattan Bridge	0.3%	0.0%
Brooklyn Bridge	0.3%	1.0%
Brooklyn Battery Tunnel	-0.4%	0.0%

4.4.2 Full Network Results

Figure 4-14 shows the total number of vehicles in the system that changed their paths due to dynamic congestion pricing. As expected, with the higher toll rates in the peak hours more vehicles decided to change their routes and used a different crossing with a lower toll rate.

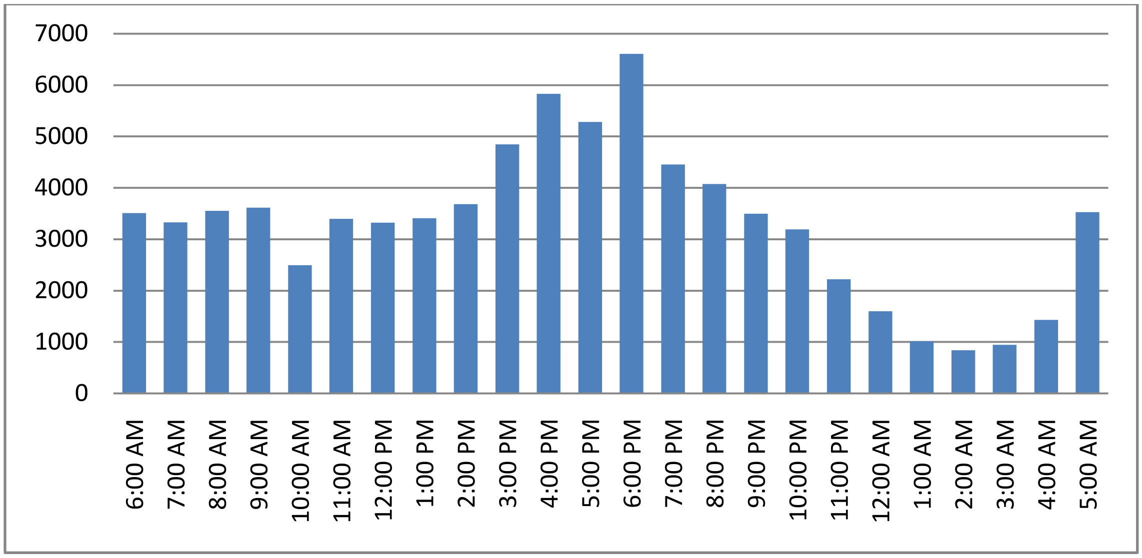

Figure 4-14: Number of Vehicles Changing Paths Due to Dynamic Pricing

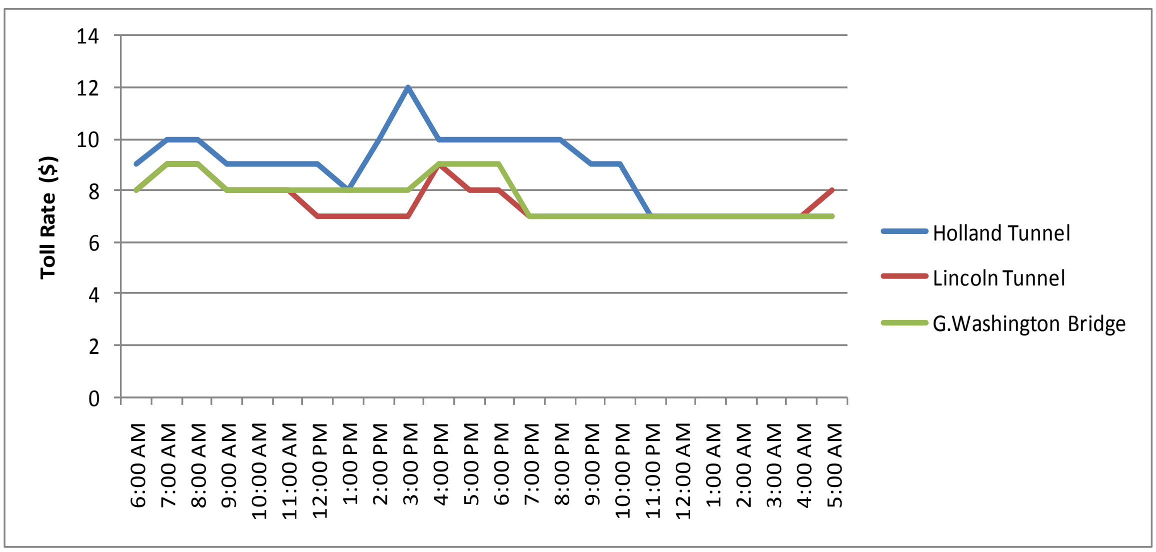

Figure 4-15: Average Hourly Dynamic Toll Rates in Hudson River Crossings

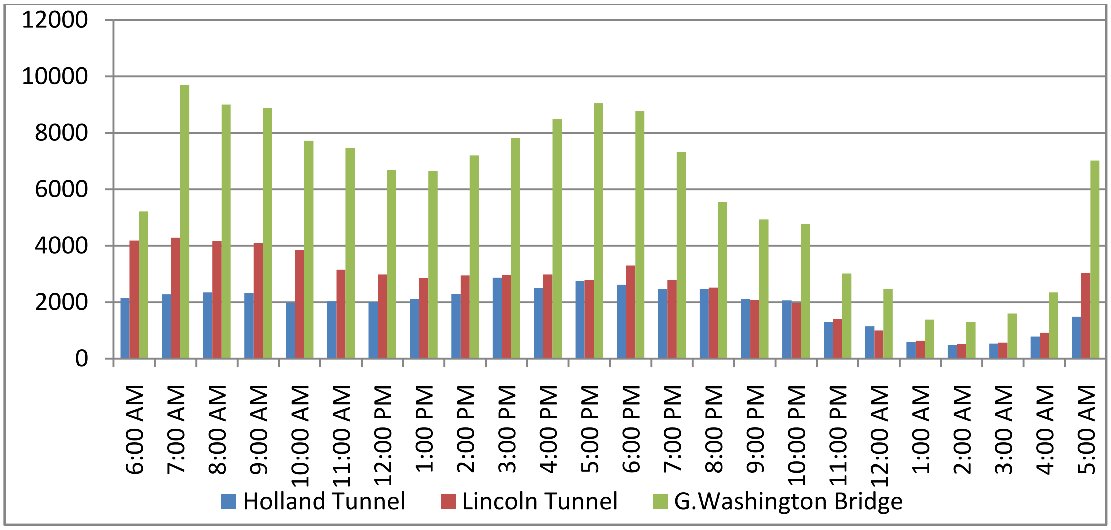

Figure 4-16: Total Vehicle Counts in Dynamic Pricing Scenario

Average hourly toll rates for the whole simulation period in the dynamic pricing scenario are given in Figure 4-15. Since the rates are determined with respect to real-time occupancy values, toll rate changes are directly related with the total number of vehicles using the crossings within a time period. Figure 4-16 shows the hourly traffic counts for the same three crossings.

Total daily toll revenues observed in both scenarios are given in Table 4-7. Results show that with the assumed toll schedules all Hudson River crossings made higher revenues in the dynamic pricing scenario compared with the static pricing scenario. However on the Queens/Brooklyn to Manhattan side, only Queens-Midtown Tunnel generated lower revenues. The reasons for the increase on New Jersey-Manhattan crossings are charging higher toll rates during peak hours and increase in throughput as a result of dynamic pricing. Since there is no free alternative crossing on the west side, users have to pay a toll in any route decision, therefore in the peak hours it is inevitable to pay higher tolls compared to the static pricing case. On the other hand, entering

Manhattan from the east side is possible without paying a toll, therefore users changed their routes to cross from free bridges in response to high toll rates, and the total revenue was decreased.

Table 4-7: Total Daily Toll Revenues by Scenario

Facility	Toll Revenues		*Increase*
	Static Pricing	Dynamic Pricing	
Holland Tunnel	$482,520	$563,830	17%
Lincoln Tunnel	$594,110	$686,587	16%
George Washington Bridge	$1,437,000	$1,841,780	28%
Triborough Bridge	$358,717	$361,225	1%
Queens-Midtown Tunnel	$317,030	$228,048	-28%
Brooklyn Battery Tunnel	$187,005	$222,435	19%
TOTAL	$3,376,382	$3,903,905	16%

4.5 DYNAMIC PRICING WITH DEMAND SHIFTS

The main drawback of the simulation study presented in this section was keeping the demands constant in one time period and does not allowing users to change their departure times from one period to the other. This problem is rising from the lack of sufficient data in case of a change in traffic conditions, such as shift factors in case of a real-time toll application. However, the work done by Ozbay et al. (2006) showed that departure time can be incorporated into the utility function of the users when they are deciding on their route choices.

A way of plugging departure time changes into the case study we conducted in this part is to use the demand shift factors used by Iyer (2010). The factors only consider truck traffic shifts from daytime periods to the night period via implementing tax incentive scenarios. This may be regarded as a manual way of doing the shifts and since trucks are one of the big factors in traffic congestion in daytime, changes in traffic conditions in such a case may give an idea for future studies with demand shifts due to other factors such as real-time toll rate changes.

The modeling of this part focused the goal of observing the changes in toll revenues and traffic conditions for each crossing into Manhattan in the highway network in a case of demand shifts among different time periods. The developed scenarios were tested within the mesoscopic simulation network to study the effects of the program with both static and dynamic pricing. The results are then compared with static pricing and dynamic pricing outputs obtained in the previous part of this chapter for the purpose of evaluating each of the scenarios modeled.

4.5.1 Scenarios Modeled

The shift factors change according to the business type and destination zone of the trip, thus an average percentage shift is used to describe each scenario, shown in Table 4-8. The Origin-Destination (OD) matrices of commercial traffic were updated to accurately represent the shifted traffic volumes of vehicles entering Manhattan. However in this study three types of vehicle classes are defined and the business type factors cannot be incorporated into the simulation, because the data used for OD matrix construction gave the aggregate traffic volumes for trucks in which the business types were not specified. Region factors were also combined and average shift factors were used. Figure 4-17 describes the research procedure followed for the simulation in this task.

Table 4-8: Average Shift Factor by Scenario (Iyer, 2010)

Scenario	Average Shift Factor
-	0.00%
1	2.93%
2	6.90%
3	10.42%

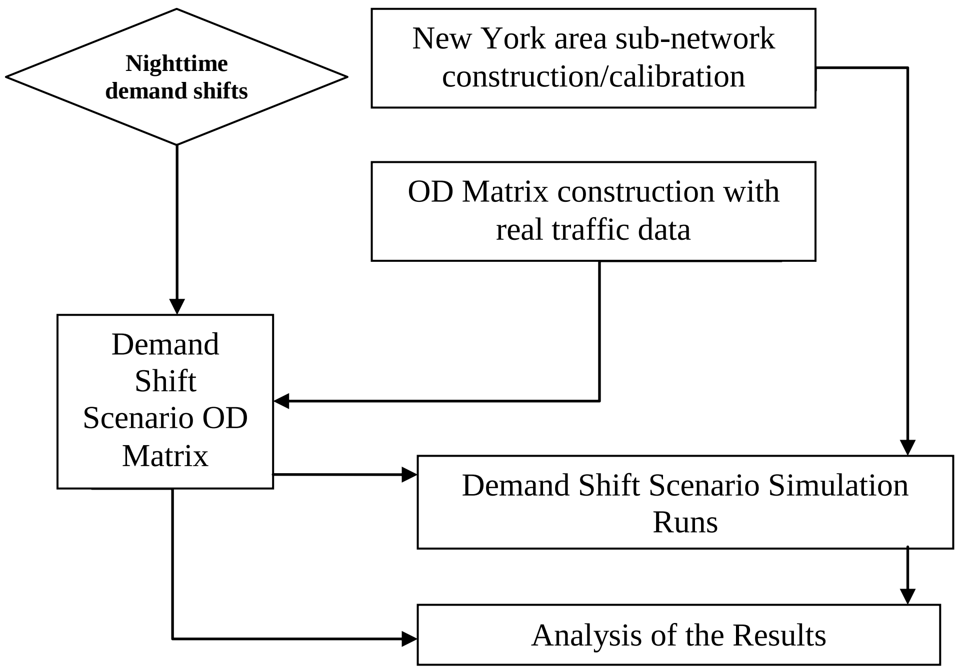

Figure 4-17: Simulation Procedure for Demand Shift Scenarios

After studying changes the demand shift scenarios we have in the static model, three demand shift scenarios were simulated in the Manhattan network. For comparison, the scenarios were simulated in the mesoscopic network when tolls to enter Manhattan are statically priced, which is the case when tolls are fixed throughout the day, and dynamically priced, which is the case when toll rates change according to the real-time occupancy levels on the crossing. The traffic simulation software TransModeler was used to run the mesoscopic simulations. The following sections describe the procedure and results of the simulations for each of the three scenarios.

4.5.2 Dynamic pricing simulation results

Table 4-9 shows the weighted average of percentage differences in average occupancy and traffic volumes in the demand shift scenarios compared to the base static scenario (Scenario A) and dynamic pricing scenario (Scenario B). The numbers indicated in red show a decrease in the stated quantity in the demand shift scenario when compared to the two other scenarios, Scenario A and Scenario B. Seven crossings are combined into three categories as Hudson River Crossings (e.g. Holland Tunnel, Lincoln Tunnel and George Washington Bridge), East River Free Crossings (e.g. Queensboro Bridge, Williamsburg Bridge, Manhattan Bridge, Brooklyn Bridge) and East River Tolled Crossings (e.g. Triborough Bridge, Queens Midtown Tunnel, Brooklyn Battery Tunnel) and the average percentage changes are presented. East River Crossings are analyzed in two categories since the behavior in tolled and free crossings differs significantly when the demand shifts are applied with dynamically priced tolls.

Table 4-9: Percent Occupancy and Percent Volume Changes

VOLUMES		vs SCENARIO A			vs SCENARIO B		
		Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
AM	Hudson River Crossings	-6.1%	-3.6%	-3.8%	-4.2%	-1.8%	-1.9%
	East River Free Crossings	8.9%	8.8%	8.3%	0.2%	0.1%	-0.4%
	East River Tolled Crossings	-10.4%	-10.2%	-10.6%	-0.9%	-0.6%	-1.1%
MD	Hudson River Crossings	-1.4%	-1.6%	-2.0%	-0.5%	-0.7%	-1.1%
	East River Free Crossings	5.5%	4.2%	5.1%	-0.1%	-1.5%	-0.5%
	East River Tolled Crossings	-7.9%	-8.0%	-9.0%	1.0%	0.8%	-0.2%
PM	Hudson River Crossings	0.0%	0.0%	-0.3%	-0.2%	-0.3%	-0.1%
	East River Free Crossings	8.0%	8.6%	8.6%	-0.2%	0.4%	0.3%
	East River Tolled Crossings	-0.9%	-2.1%	-0.5%	-0.9%	-2.1%	-0.5%
NT	Hudson River Crossings	4.6%	5.3%	5.5%	0.6%	1.2%	1.4%
	East River Free Crossings	0.5%	1.8%	3.5%	0.5%	1.8%	3.5%
	East River Tolled Crossings	-9.7%	-8.4%	-7.2%	-5.6%	-4.2%	-2.9%
OCCUPANCIES		vs SCENARIO A			vs SCENARIO B		
		Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
AM	Hudson River Crossings	-1.2%	-0.8%	-0.8%	-0.9%	-0.5%	-0.5%
	East River Free Crossings	1.3%	0.9%	0.7%	0.1%	-0.3%	-0.5%
	East River Tolled Crossings	-2.8%	-3.1%	-2.8%	-0.7%	-1.0%	-0.7%
MD	Hudson River Crossings	-0.4%	-0.5%	-0.5%	0.0%	-0.1%	-0.2%
	East River Free Crossings	0.8%	0.6%	0.1%	-0.2%	-0.4%	-0.9%
	East River Tolled Crossings	-1.0%	-0.9%	-1.1%	0.1%	0.1%	0.0%
PM	Hudson River Crossings	0.4%	0.5%	0.5%	-0.2%	-0.3%	-0.3%
	East River Free Crossings	0.4%	0.6%	0.5%	-0.2%	0.0%	-0.1%
	East River Tolled Crossings	-1.3%	-1.4%	-1.4%	0.0%	-0.1%	0.0%
NT	Hudson River Crossings	-0.3%	-0.2%	-0.2%	-0.1%	0.0%	0.0%
	East River Free Crossings	-0.3%	0.2%	0.7%	0.1%	0.5%	1.0%
	East River Tolled Crossings	-0.4%	-0.4%	-0.2%	-0.1%	-0.1%	0.1%

The results show that the average occupancies in tolled crossings in daytime periods (e.g. AM Peak, Midday and PM Peak) decreased for most of the crossings with shifted commercial vehicle traffic. The impact of dynamic pricing can be observed with the comparison of average percentage changes within the same demand shift scenario with different pricing practices. For the AM Peak period the results show that there was a significant difference in the demand shift scenario traffic volumes when compared with the static pricing base case scenario. However the average values in the same demand shift scenarios do not differ significantly when compared to the dynamic pricing-only scenario. This is an indication that the main factor decreasing the traffic volumes was dynamically priced tolls for AM Peak period.

When the demand shifts were applied in the AM Peak period, average occupancies increased in free crossings when compared with the base case. The reason can again be stated as the different pricing strategies. This is also shown by the fact that in scenarios with dynamic pricing, average occupancies decrease in most of the crossings when demand shifts to the off-hours. For Midday period average occupancies increased in free East River crossings when compared to the base case as a result of the traffic shifting from tolled crossings. Similar to the AM Peak period, percent traffic volumes using the crossings decreased for most of the tolled crossings in MD Period. In PM Peak period average occupancies decreased for both tolled and free crossings of the East River for all demand shift scenarios. Similarly, in Hudson River crossings, average occupancies and the number of vehicles using the crossings decreased for all demand shift scenarios. In Night period, as a result of the shifted commercial van and truck traffic volumes, average occupancies increased in most of the crossing except the tolled crossings of the East River. The main reason of the decrease in traffic volumes and average occupancies on those crossings is most of the users' shift to the free alternatives to avoid tolls.

4.5.3 Facility analysis

According to the simulation results improvements in traffic conditions in the crossings to Manhattan are not solely due to the number of vehicles shifting to the off-hours. Percentage differences in traffic volumes in each crossing were different depending on the real time toll rates and the number of vehicles shifted to the nighttime period. Observed differences between dynamic pricing-only simulations and dynamic pricing with demand-shift simulations are depicted in the following figures for the three Hudson River crossings into Manhattan from New Jersey. The results are shown for each of the scenarios run: Scenario 1 (2.93% average shift), Scenario 2 (6.90% average shift) and Scenario 3 (10.42% average shift).

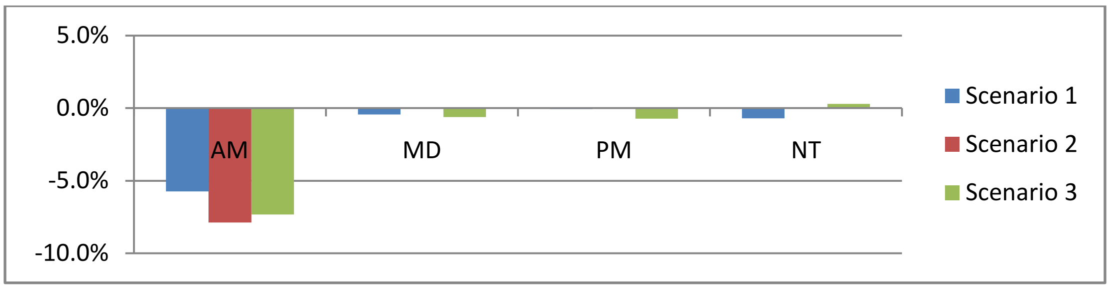

Figure 4-18: Holland Tunnel Percent Volume Change by Scenario

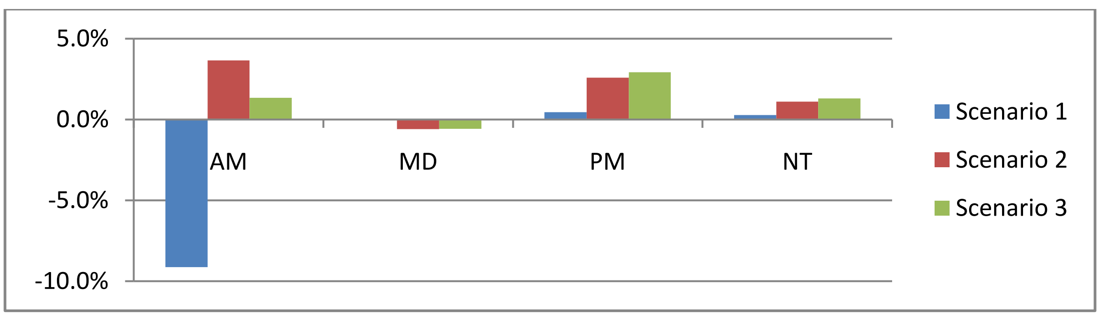

Figure 4-19: Lincoln Tunnel Percent Volume Change by Scenario

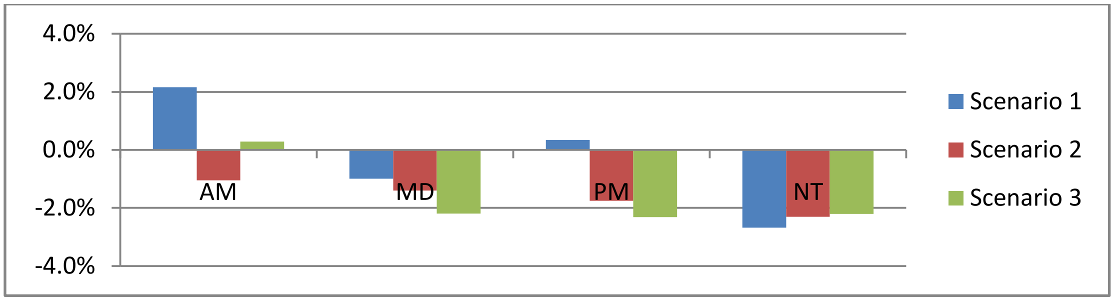

Figure 4-20: George Washington Bridge Percent Volume Change by Scenario

Figure 4-18 shows the percent changes in traffic volume in the Holland Tunnel. The results show that traffic volumes decreased significantly in the AM Peak period for all scenarios modeled. Scenario 2 and Scenario 3 gave similar results when daytime traffic decreased and the overnight traffic increased. However in Scenario 1 traffic volumes in all time periods decreased, meaning that there were shifts to the other crossings as a result of dynamic pricing. Figure 4-19 shows the percent changes in traffic volume in Lincoln Tunnel. All scenarios gave similar results except the AM Peak period of Scenario 1 when the decrease in traffic volume was excessively high due to the dynamic tolling. Changes in traffic volumes were observed in similar ways in all other periods for different scenarios. Percent differences in traffic volumes for the George Washington Bridge are given in Figure 4-20. For all tested scenarios traffic volumes in the selected crossings are very heavy and thus the effect of relatively low demand shift due to tax incentives is not too high. However, pricing affects all the users, thus its effects appear to be more significant. This is the reason for the increase in traffic volume in the PM Peak period in Scenario 1. It should be also noted that all three Hudson River crossings to Manhattan are tolled and there is no free alternative. Since they are all dynamically priced, some irregular changes in traffic volumes can be observed because of the different time-dependent toll rates. Therefore drawing a conclusion about the effectiveness of each scenario is not attempted.

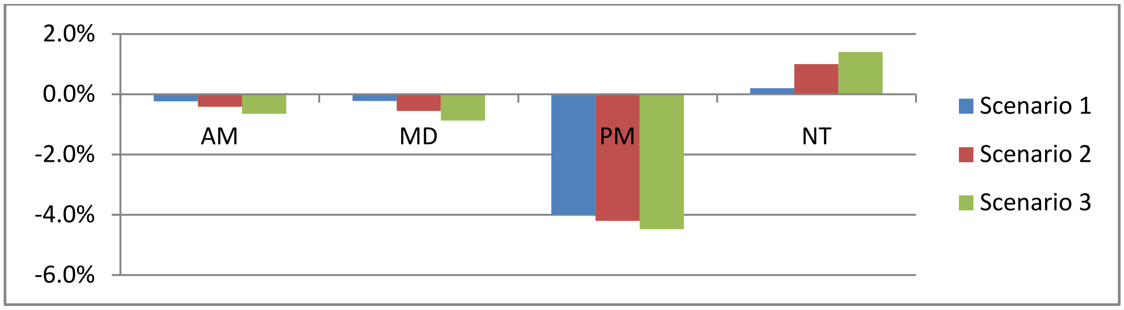

Figure 4-21: Triborough Bridge Percent Volume Change by Scenario

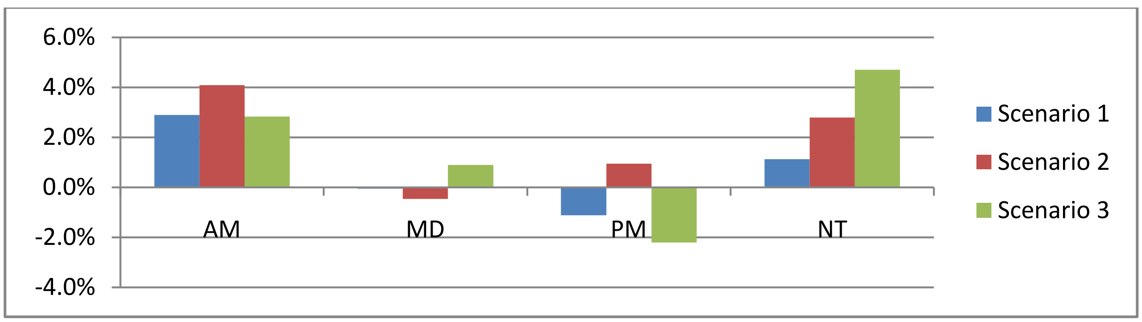

Figure 4-22: Queensboro Bridge Percent Volume Change by Scenario

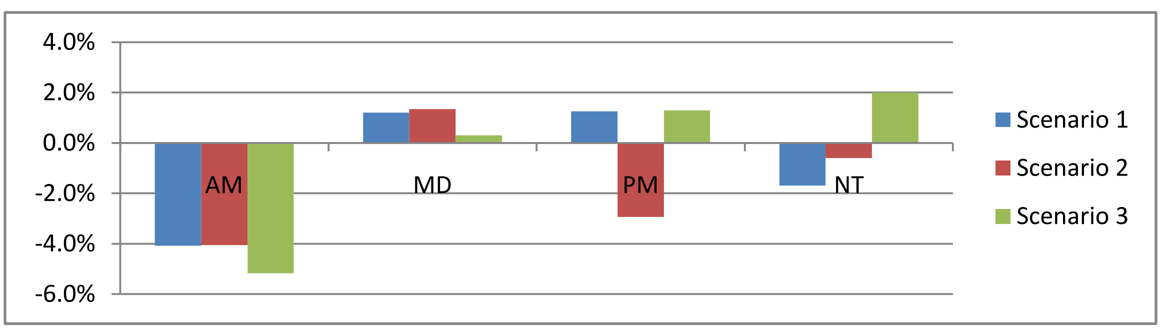

Figure 4-23: Queens-Midtown Tunnel Percent Volume Change by Scenario

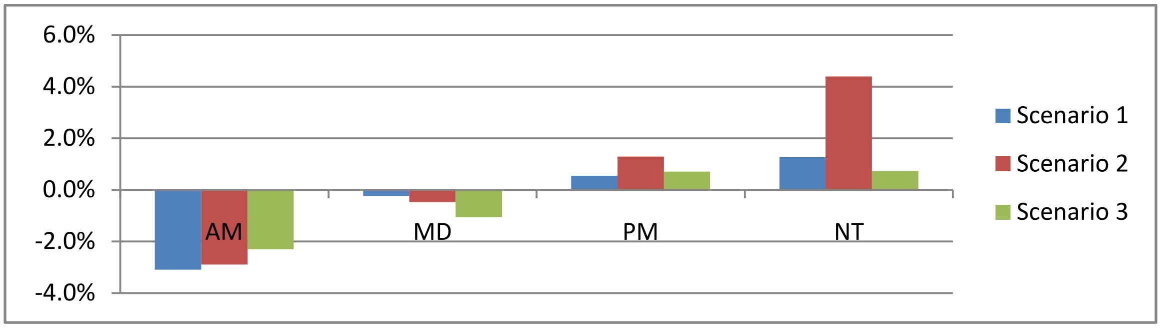

Figure 4-24: Williamsburg Bridge Percent Volume Change by Scenario

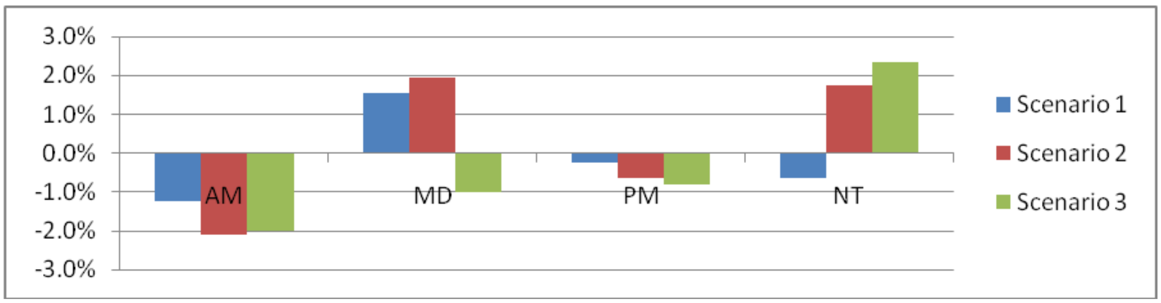

Figure 4-25: Manhattan Bridge Percent Volume Change by Scenario

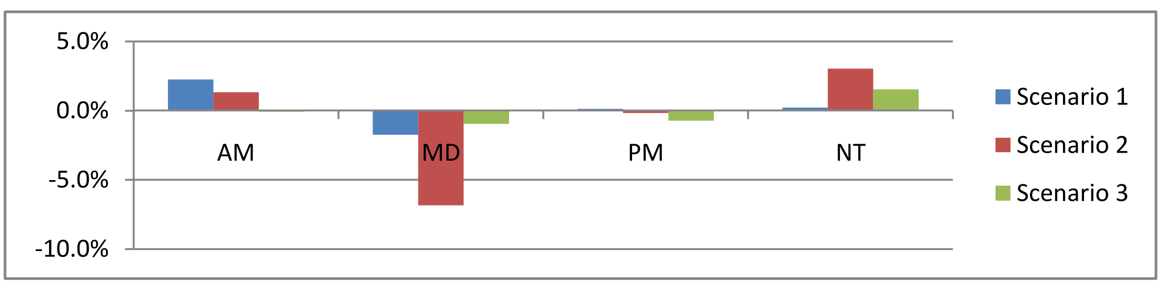

Figure 4-26: Brooklyn Bridge Percent Volume Change by Scenario

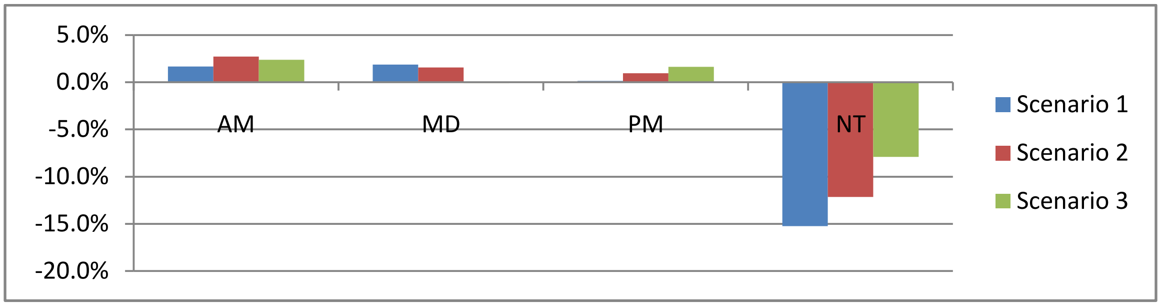

Figure 4-27: Brooklyn Battery Tunnel Percent Volume Change by Scenario

Figure 4-21 shows percent changes in traffic volumes for the Triborough Bridge (entering Manhattan) for different demand shift scenarios. Triborough Bridge is a tolled bridge and the distance between the closest free alternative, Queensboro Bridge, is approximately 5 miles. It was observed throughout the simulation that very few users changed their path to save travel time. As a result the effect of dynamic pricing is minimal and the change in traffic volumes were mainly controlled by changes due to the demand shifts. It can be seen that the change in traffic volumes is directly proportional to the magnitude of the demand shift for this crossing; as the percentage gets higher more vehicles shift to the Night period. Traffic volume changes in the Queensboro Bridge are depicted in Figure 4-22. Queensboro Bridge is a free crossing between Queens and Manhattan which attracts traffic from tolled bridges when the toll rates are high. Thus the increase in traffic volumes in daytime periods can be explained by the users who tried to avoid high tolls and changed their paths. Among the three scenarios tested Scenario 2 showed the highest differences in traffic volumes.

Figure 4-23 shows the percent changes in traffic volumes for the Queens-Midtown tunnel. For all demand shifts scenarios AM Peak traffic volumes decreased and the only scenario where traffic volumes for Night period increased is Scenario 3. Although a portion of vehicles in Midday and PM Peak periods shifted to the nighttime period, for Scenario 1 and Scenario 3 there were increases in traffic volumes. Queens-Midtown Tunnel is a tolled crossings and one of the reasons for the increase is the decrease in average occupancy levels in several time intervals, and accordingly the time-dependent decrease in toll levels. For Williamsburg Bridge the difference in traffic volumes does not change in a regular way related to the demand shifts, as seen in Figure 4-24. Therefore the route decisions were mainly controlled by dynamically priced toll rates of the alternative crossings. The best performance was observed in Scenario 3 where the AM Peak, Midday, and PM Peak period traffic volumes decreased and the Night period increased.

Figure 4-25 depicts the change in traffic volume percentages in the Manhattan Bridge with different demand shift scenarios. It can be seen that the traffic volume is not directly related to the shifted demands only. Midday period traffic volumes using the bridge increased in Scenario 1 and Scenario 2. For Scenario 3 in all daytime periods there were fewer users and the increase in traffic volume in Night period is the highest. Percent change in Brooklyn Bridge traffic volumes are shown in Figure 4-26. For all tested scenarios Night period traffic volumes increased. Scenario 2 was the scenario where the highest percent changes were observed in Midday and Night periods. In other periods different behavior observed with different off-peak shift values. The difference in daytime periods also results from the traffic shifting from the closely located tolled alternatives. Figure 4-27 shows the Brooklyn Battery Tunnel traffic volume differences by percent change. Some of the users changed their path to avoid tolls. The differences in volumes mainly resulted from different toll rates depending on average occupancy levels measured in real-time.

4.5.4 Dynamic pricing with demand shifts scenario assessment

Simulation results show that Scenario 1 (2.93% average shift) did not change the traffic conditions significantly, due to the minimal demand shift. However the percentage differences in traffic volumes show irregularities compared to other scenarios for some crossings. The results show that dynamic pricing was the main reason for the differences in most of the crossings in this scenario. Although collected toll revenue is higher than the base static scenario, there were no major improvements observed in traffic conditions.

For some of the crossings, Scenarios 2 and 3 ran as expected (i.e. decreasing traffic volumes in daytime, increasing traffic volume in nighttime) and gave higher differences in traffic volumes compared to Scenario 1. However there were again irregularities in changing patterns. They did not follow a smooth pattern, e.g. the percentage of traffic volume decrease is not always increasing with higher shift factors. For some crossings such as Triborough Bridge and Williamsburg Bridge, increased shift factors for trucks and other commercials created better traffic conditions in the daytime periods for all vehicles. It was observed from the simulation results that the estimated toll revenues collected in Scenario 3 are slightly higher than the other two scenarios tested.

4.5.5 Toll revenues

Toll revenues collected from the simulation of the seven tolled crossings are given in Table 4-10. The first three columns compare the dynamically priced demand shift scenarios with the statically priced base-case (existing conditions). The next three columns compare the demand shift scenarios with a dynamically-priced base-case. It can be seen that while dynamically priced tolls are projected to increase toll revenues overall, the increase is slightly tempered by shifting commercial vehicles to the off-hours. The reasons are the higher toll rates in peak periods and the different throughputs in different periods. Trucks and commercial vans pay high toll rates compared to passenger cars and during peak periods dynamically-priced tolls are at their highest values. Therefore shifting a portion of trucks and commercial vans to the nighttime period, where the average occupancies are lower (e.g. lower toll rates), decreases total daily revenue.

Table 4-10: Total Daily Toll Revenues for Different Demand Shift Scenarios

Facility	vs BASE STATIC			vs BASE DYNAMIC		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
Holland Tunnel	14.2%	14.1%	14.0%	-2.3%	-2.3%	-2.4%
Lincoln Tunnel	12.3%	17.8%	16.9%	-2.8%	1.9%	1.2%
George Washington Bridge	27.5%	25.9%	25.8%	-0.5%	-1.8%	-1.9%
Triborough Bridge	0.0%	-4.2%	-0.7%	-0.7%	-4.9%	-1.4%
Queens-Midtown Tunnel	-18.1%	-18.7%	-15.1%	-1.4%	-2.1%	2.2%
Brooklyn Battery Tunnel	18.6%	20.1%	19.2%	-0.3%	1.0%	0.3%
TOTAL	**15.6%**	**15.5%**	**15.9%**	**-1.2%**	**-1.4%**	**-1.0%**

4.6 CONCLUSION

This chapter has discussed the implementation of different tolling strategies to the Manhattan network. A methodology to perform mesoscopic simulations using the traffic simulation software TransModeler was developed. The mesoscopic simulation network was selected to include the crossings between Manhattan and New Jersey, Brooklyn, and Queens, and their connector roads. Static and dynamic pricing applications have been described in two different simulation scenarios and the results have been compared in terms of traffic conditions and toll revenues.

The second part of this chapter has discussed the implementation of pricing strategies in conjunction with the proposed demand shift scenarios to analyze the effect of pricing on traffic conditions.

OD Matrices were created for each demand shift scenario to shift the truck and commercial vans from daytime periods (AM Peak, Midday, and PM Peak) to the nighttime period. Mesoscopic simulations using the traffic simulation software TransModeler were then performed to study dynamic pricing. The results of each demand shift scenario were compared to the results obtained in previous tasks for static pricing and dynamic pricing simulations. Comparison of the results showed that increasing the demand shift to the night period enhances the traffic conditions under the application of dynamic pricing on the crossings. Total toll revenues, on the other hand, decreases when more trucks and commercial vans are shifted to the night period. Among the three scenarios considered in this task, better performances were observed in Scenario 2 and Scenario 3 in terms of the effects on traffic conditions compared to Scenario 1. Toll revenues generated in each scenario was quite close to each other and all of them were higher than the base static scenario.

CHAPTER V

DYNAMIC PRICING ALGORITHM

5.1 INTRODUCTION

Dynamic pricing algorithm for New York – New Jersey crossings is provided in this section. Depending on the travel time and toll rates on the alternative routes, two different utilities are calculated. Developed algorithm uses logit model for driver route choice behavior including value of time for different users.

5.2 PRICING ALGORITHM

Currently, dynamic pricing is only applied for HOT lanes in the US. As mentioned in detail in the literature review section, these applications generally measure real time traffic flow speeds and adjust the toll rates to obtain a Level of Service (LOS) of “C” which refers to minimum speed of 45 mph. Although in practical applications this system works as to define the toll rates considering real time traffic conditions, lack of theoretical background of the tolling algorithms may raise the question of whether this system is achieving the best possible performance.

Starting from a similar question, Zhang, et al. (2008) provided a feedback based step-wise tolling model for HOT lane operations. The model they presented is easy to implement when the necessary infrastructure is present. It uses traffic flow speeds as the threshold parameter for the toll rate changes. In their model they have two alternative lane options on one road; HOT and general purpose lanes. HOT lanes are tolled and supposed to be flowing at least 45 mph as, on the other hand general purpose lanes are free alternatives and do not have any congestion control mechanism. Therefore the decision of the drivers is simply the selection of paying a toll to save travel time or save toll cost by using free lanes with lower travel speeds under congested conditions.

A similar model is developed for crossings. There are two main differences in the proposed model. First instead of HOT lanes where there is a free alternative, the model is developed for two tolled crossings which are each others alternatives. Therefore the decision of the users will be selecting one of the crossings for either faster trips or lower toll rates. Second, instead of using traffic flow speed as the threshold parameter, average occupancies on the crossings are used in the step functions. The reason for using occupancy is that it is found to be a better representative of congestion conditions for New York – New Jersey crossings since the speed limits are lower than normal freeways.

The simple network considered in this model is given in Figure 5-1. The users have to use one of the crossings which are both dynamically priced. The crossings are assumed to be close enough that the travel time spent when switching the alternative crossing can be assumed to be zero.

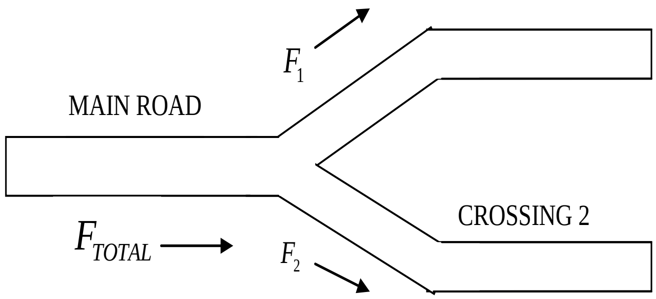

Figure 5-1: Test Network for the Tolling Algorithm

Total cost for choosing one of the crossings is computed as

$$TC_i = \alpha \times TT_i + TR_i \tag{5.1}$$

where TT_i is the average travel time for the i th alternative, TR_i is the toll rate for the i th alternative and α is the coefficient to convert TT_i into cash value.

The utility function for selecting crossing 1 and crossing 2 are:

$$U_1 = \frac{1}{TC_1} = \frac{1}{\alpha_1 \times TT_1 + \beta_1 \times TR_1} \tag{5.2}$$

$$U_2 = \frac{1}{TC_2} = \frac{1}{\alpha_2 \times TT_2 + \beta_2 \times TR_2} \tag{5.3}$$

Logit model is used to define the traffic assignment,

$$\begin{aligned} F_1 &= F_{TOTAL} \times P_1 = F_{TOTAL} \times \frac{\exp(U_1)}{\exp(U_1) + \exp(U_2)} \\ &= F_{TOTAL} \times f(TR_1, TT_1, TR_2, TT_2) \end{aligned} \tag{5.4}$$

where F_{TOTAL} is the total approaching flow from the main road, P_1 is the probability of choosing Crossing 1. The function $f()$ uses the independent variables TR_1, TT_1, TR_2, TT_2 and the dependent variable P_1. The toll rate can be calculated inversely from using the function $f^{-1}()$ as a result of one-to-one transformation between TR_1 and P_1.

$$TR_1 = f^{-1}(F_1 / F_{TOTAL}, TT_1, TT_2, TR_2) \tag{5.5}$$

$$TR_1 = f^{-1}(P_1, TT_1, TT_2, TR_2) \tag{5.6}$$

It is assumed that TT_1, TT_2 and F_{TOTAL} are measurable with the necessary detector infrastructure. Therefore if F_1 is known, toll rate in Crossing 1 can be obtained by backward calculation.

The flow ratio for Crossing 1, P_1, is supposed to be changing depending on the congestion levels. For example if the average occupancy difference is too high between the two crossings the ratio of vehicles using the less congested alternative should be higher. Therefore a step-wise linear algorithm is defined to calculate P_1 for different congestion conditions. As stated before congestion level in the crossings is defined with the average occupancy in this model. $\Delta P_1(t)$, change in the rate of Crossing 1 users at time increment *t* depending on the congestion level can be defined in a step function. Desired occupancy levels are previously determined by the agencies operating the crossings and the value changes depending on the number of lanes and the lane widths. If we assume the desired occupancy in Crossing 1 as 10% a step-wise control mechanism can be formulated as follows:

$$P_1(t+1) = P_1(t) + \Delta P_1(t)$$

$$\Delta P_1(t) = \begin{cases} b_1 + k_1(O_1(t) - O_2(t)) & O_1 > 15 \\ sign \times [b_2 + k_2(O_1(t) - O_2(t))] & 15 \geq O_1 > 10 \\ k_3(O_1(t) - 10) & O_1 < 10 \end{cases} \qquad (5.7)$$

where $P_1(t+1)$ and $P_1(t)$ are the flow ratios for the traffic using Crossing 1 at time interval between *t* and *t+1*, $\Delta P_1(t)$ is the change increment, b_1, b_2, k_1, k_2, k_3 are the parameters used for controlling the intensity of the feedback increment, sign is a variable which is defined as follows:

$$sign = \begin{cases} 1 & P_1(t-1) > P_1(t) \\ 0 & P_1(t-1) = P_1(t) \\ -1 & P_1(t-1) < P_1(t) \end{cases} \qquad (5.8)$$

Finally derivation of the inverse function for TR_1 gives;

$$TR_1 = \frac{1}{\dfrac{1}{\beta \times TR_2 + \alpha \times TT_2} - \ln(\dfrac{1-P_1}{P_1})} - \alpha \times TT_1 \qquad (5:9)$$

Toll rate for the second crossing can be calculated using the same calculations. Travel time parameters are measured by the traffic detectors therefore the only variable that has to be determined is the parameter α .Regarding equation (5.1), this parameter refers to the value of time of the drivers which can be determined by surveys or past traffic data. The methodology to determine the toll rates with a step-wise algorithm is shown in Figure 5-2.

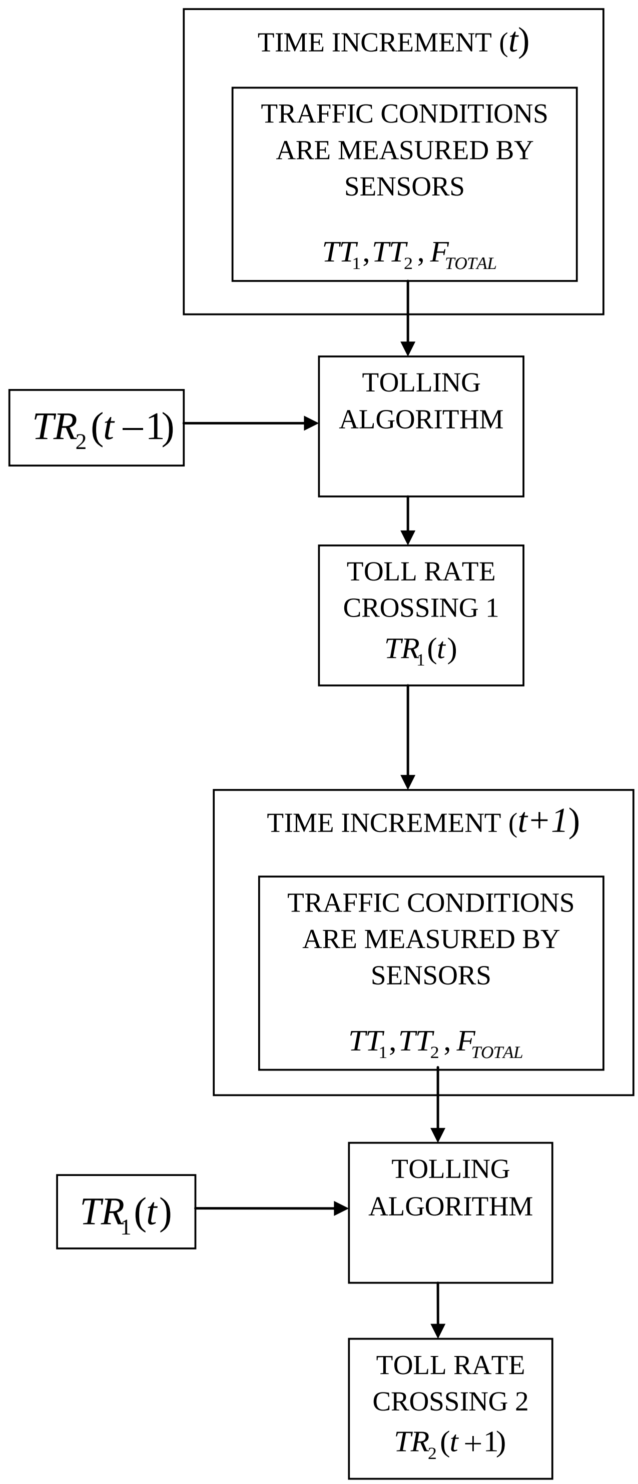

Figure 5-2: Dynamic Pricing Algorithm

CHAPTER VI

TRAFFIC SIMULATION

6.1 INTRODUCTION

In this section a microscopic traffic simulation model for dynamic pricing application to Holland and Lincoln Tunnels is presented. Paramics software tool is used for the simulation study.

Paramics is one of the most popular software packages that is widely used by transportation engineers. Complex networks can be easily built by a simple node-link system. Application Programmer Interface (API) feature of the software allows the users to override almost all of the in-built functionalities. API coding is done through programming in C++ and this gives enough flexibility to apply a new tolling algorithm specific to the selected network.

6.2 MODEL DEVELOPMENT

6.2.1 Network

The applicability of the dynamic tolling algorithm presented in the previous section requires two crossings which can be regarded as alternative routes to each other. Holland and Lincoln Tunnels are selected for the case study since the location of the two crossings allows users to select one of the tunnels in case of a dynamic tolling implementation. In addition to their proximity, connecting roads between the two tunnel entrance points from New Jersey side makes it easier for the drivers to switch from one alternative to the other. New Jersey Turnpike is the major connector which provides the exit to Holland and Lincoln Tunnels. The distance between the two tunnels is approximately 5.5 miles which can be driven in 6 minutes under free flow conditions. The other alternative connecting road is Route 1-9 which runs through urbanized areas of New Jersey and the traffic is generally slowed down by signalized intersections. On the other side of the two tunnels, the distance between the two exit points inside Manhattan is approximately 3 miles. The map of the network is shown in Figure 6-1.

The section of New Jersey Turnpike which is included in the simulation network includes the Exits 14A, 14B, 14C, 15E, 15X and 16E. There are two alternative exits for Holland Tunnel considered in the simulation which are; first through the New Jersey Turnpike Extension Road and using Exit 14C and second using Exit14A which leads to Pulaski Skyway (which is a part of Route 1-9) through Holland Tunnel. At the end of the Pulaski Skyway users have two decisions, either to exit for Holland Tunnel or to continue to drive on Route 1-9 to north to cross from Lincoln Tunnel. Lincoln Tunnel exit from the New Jersey Turnpike is 16E which is one of the major demand transfer point to the Lincoln Tunnel. The other major traffic demand is coming from Route 3 which is also included in the simulation model.

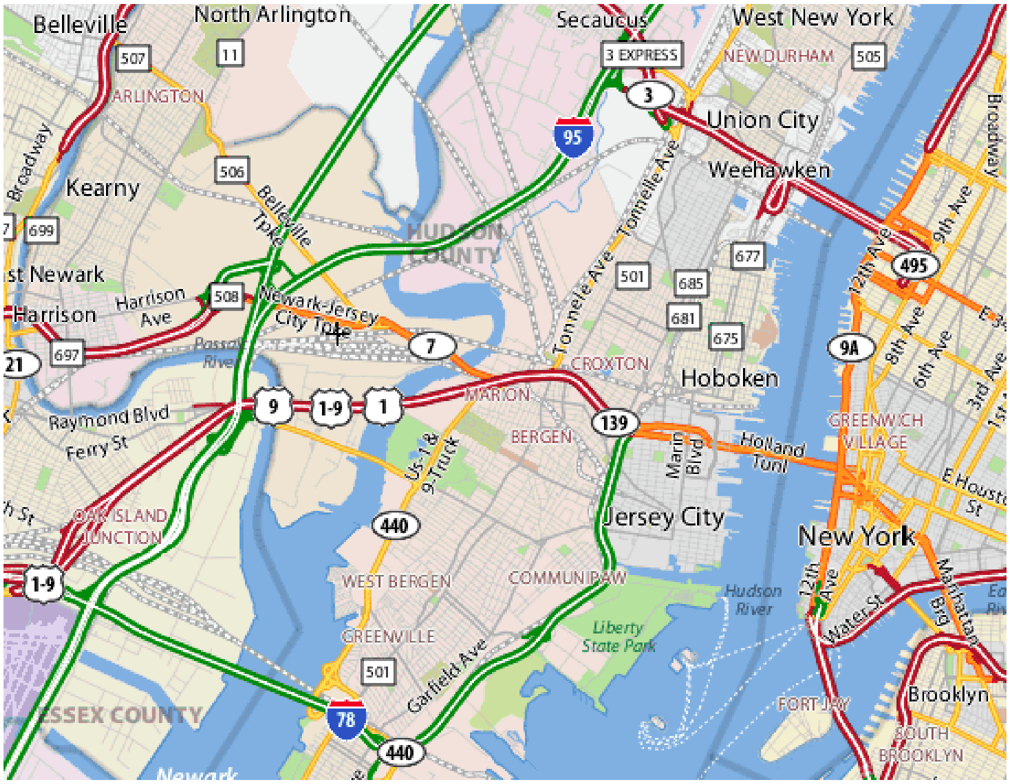

Figure 6-1: Map of the Simulated Network (Yahoo Maps, 2010)

Route 1-9 is considered as the second alternative connector road between the two tunnels. Compared to the New Jersey Turnpike, which has a speed limit of 65 mph in the simulated section, Route 1-9 has slower travels with a speed limit of 40mph on the Tonnele Avenue and 45mph on the Pulaski Skyway. In addition to these three signalized sections are also included in the Tonnele Avenue and the signal cycles are assumed to be fixed throughout the simulation. The network built in Paramics is shown in Figure 6-2.

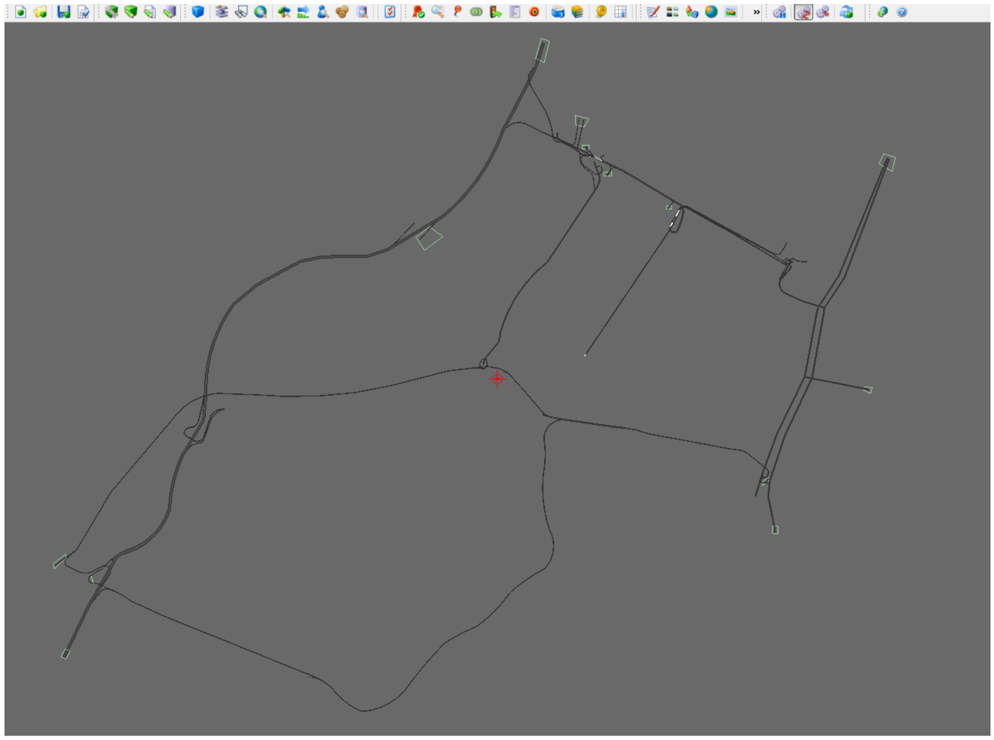

Figure 6-2: Paramics Network

6.2.2 Simulation

Microsimulation model developed for testing a dynamic pricing application for New Jersey - New York City crossings was run in Paramics. In-built features of Paramics allow the simulation of dynamic pricing scenarios. However this feature is only available for HOT lane implementations. In addition to this, drivers' route decisions cannot be controlled effectively for each vehicle with regular trip cost formulations provided by the software. Therefore the tolling algorithms discussed in the previous section were implemented by developing an API code which utilizes dynamic toll formulations and the driver behavior in response to toll rates.

API code is written in C programming language and the released (.bin) file of the code is plugged into the Paramics program files.

The developed API code incorporates two main functions with the simulation. The first function is for the real time toll rate calculation which utilizes the equation (5.9) presented in the Tolling Algorithm section of this thesis. This function takes the travel time needed to cross the tunnel, the travel time required to cross the alternative tunnel and the toll rate calculated for the alternative tunnel in the previous time step. Using these parameters as inputs it calculates a toll rate which is used to determine the route decision in the second stage of the API code.

The second major function that the API code is the route choice depending toll rates calculated in real-time. According to this function, when a vehicle arrives to one of the decision points which are basically junctions which are then forked into two alternative roads, two utility functions are defined for the two alternatives. Utility functions are defined in the previous section have coefficients for the two parameters namely, travel time and toll rate. Since we are mainly simulating the route choice decision of New Jersey Turnpike users, the coefficients used in the simulation are obtained from a study conducted by Ozbay et al. (2006) for New Jersey Turnpike users. In this study, authors defined a utility function for work related trips in peak hours as:

$$\begin{aligned} V_i = {} & 0.05R_i - 0.14R_i\overline{t_i} - 0.2\overline{t_i}\,p_i - 0.24\,p_i - 0.48\overline{t_i} - 0.18t_{oi} - 0.11\Delta_i^{early} \\ & - 0.16\,p_i^2 - 0.44\overline{t_i^2} - 0.11d_i - 0.3\overline{t_i}t_{oi} \end{aligned} \tag{6.1}$$

In which the terms are defined as follows:

i = travel choice index
V = utility
R = income level ($ thousands)
t = time spent in activities other than travel time (h)
t_i = travel time for selected travel choice
t_{oi} = (desired arrival time) - (departure time to travel on travel choice i) (h)
p_i = cost of travel choice i ($)

This utility formula includes two parameters we use in our dynamic pricing algorithm, which are travel time and the cost of travel choice (simply toll). The remaining terms are not considered in the scope of this study. When we take all other terms as zero we can observe that the coefficient of travel time (0.48) is double the coefficient of toll rate (0.24). This means one unit increase (one hour in this case) in travel time decreases the utility function twice as many as in the case of one unit increase (one dollar) in the toll rate. Following this conclusion for the peak period work trips of New Jersey Turnpike users, the coefficient of travel time is set as double the coefficient of travel time in our utility function formulation in the API code,.

After defining the utilities for the alternatives, probability of a user to select one alternative is calculated by equation (5.4). To avoid unrealistically high probabilities of selecting one alternative, maximum probabilities were defined for some of the decision points.

In the simulation work, only inbound traffic to Manhattan is considered. Decision points are selected at the points where users are likely to decide to use an alternative route. Three of the decision points (Decision Points A, B and C) are the in the New Jersey Turnpike exits for the two tunnels, namely exits 14, 14A and 16E respectively. Decision point D is at the junction where Pulaski Skyway has an exit to Route 1 north (Tonnele Avenue), for the users to switch to the Lincoln Tunnel if they had a lower utility for the Holland Tunnel. Finally, Decision point E is located at the point where the Lincoln Tunnel users can use Route 1 south to switch to the Holland Tunnel. At all of the decision points two alternatives are defined and the travel times are calculated for these two alternatives. According to the utility function users also consider the current toll rates on the crossings and subsequently make their decision to use one of them.

There were also three destination points defined to obtain different travel times for users which might end up in different parts of Manhattan Island. Travel times directly affect the route choice of the users and the results are presented as the average travel time of all trips.

Simulation was run for morning peak hours where the inbound traffic to Manhattan in the two tunnels is the highest throughout the day according to the bridge traffic volumes collected in 2007 (NYCDOT, 2008).Start time was selected as 6.15 AM and end time was set as 11.45 AM. The warm-up period was considered as the first 30 minutes. Simulation results were collected collect after the warm-up period was over.

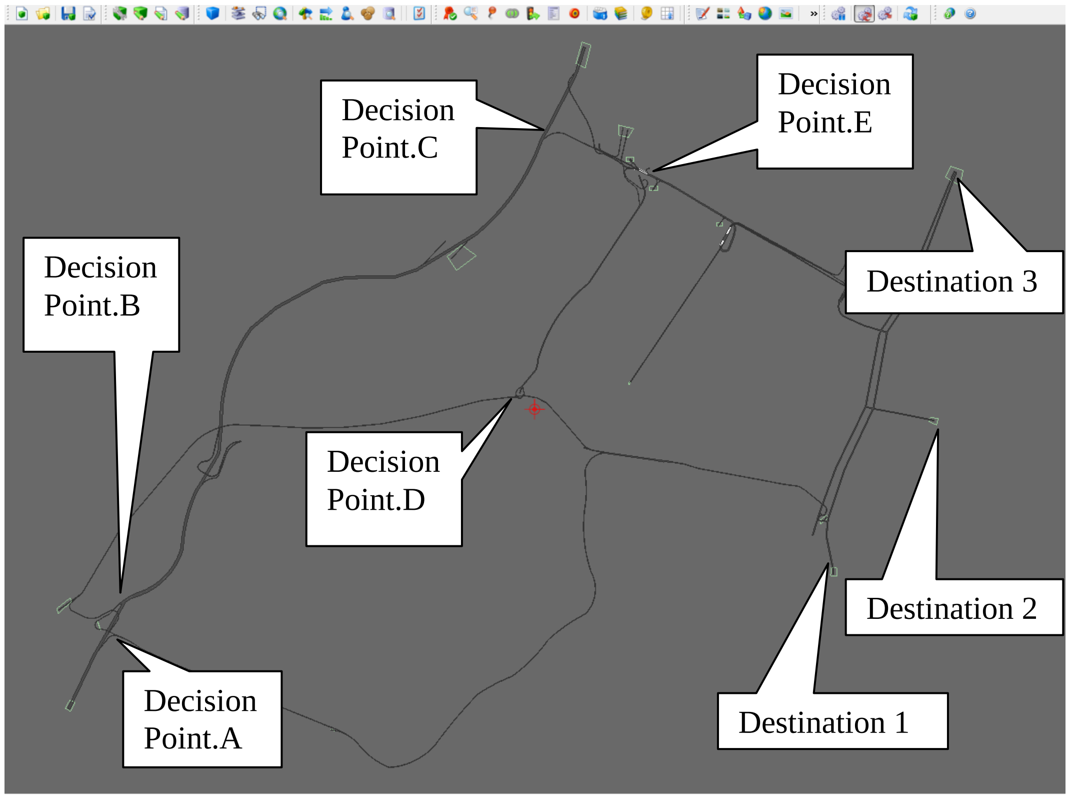

Figure 6-3: Decision and Destination Points for the Test Network

Traffic demand for the tunnels was collected from several sources. The New Jersey Turnpike exit counts were extracted with the help of the application which was developed by Rutgers Intelligent Transportation Laboratory. These counts were compared with the tunnel counts and the excess amount of demand was distributed to the remaining feeder links according to their respective capacity.

In the simulation single type of toll is considered for single type of vehicles. One of the reasons for doing this is the traffic counts we used for the tunnels are from 2007 and truck traffic in Holland Tunnel was forbidden between 2007 and 2010. Extending the current algorithm for multi-class traffic is left for the future studies.

Finally the coefficients used for the parameters in tolling algorithm are given in Table 6-1.

Table 6-1: Parameters Used in the Simulation

Parameter	**Coefficient**
α_1	0.5
α_2	0.02
β_1	0.1
β_2	0.1

6.2.3 Results

Simulation was run for several times to calibrate the network and the formulations in the provided algorithm which were plugged in through the API coding. Calibration procedure can be basically described as:

- Running the network without the API code to obtain the base case results with static tolling (which is the real case for the time being).

After plugging-in the API code;

- Obtaining the travel times for each alternative route for each decision point.
- Checking the probabilities generated for using one of the alternative routes considering the utility functions.
- Calibrating the coefficients in the utility function to obtain more realistic route choice decisions for every decision point.

- Checking the toll rates generated depending on the congestion at the crossings.
- Calibrating the coefficients of the toll rate equation to observe the effect of real time traffic conditions on the tolls.
- Observing the behavior of the simulation and calibrating the coefficients of each formulation to obtain a realistic toll rate window.

The change in toll rates throughout the simulation duration for the two crossings is shown in Figure 6-4. The graph shows that the Lincoln Tunnel started to get congested earlier than the Holland Tunnel therefore the toll rates get higher in the Lincoln Tunnel in the earlier stages of the simulation. Then when some of the Lincoln Tunnel users start to switch to the Holland Tunnel, traffic conditions become better and as a result toll rates have decreased. In the later stages of the simulation congestion level in the Holland Tunnel becomes more severe compared to the Lincoln Tunnel and higher tolls are observed in Holland Tunnel. It is also observed that at peak period shoulders, the lowest tolls are calculated as expected.

Driver behavior in response to dynamic toll rates is analyzed for every decision point. Figure 6-5 shows the probability of the New Jersey Turnpike users to choose the Holland Tunnel to travel to Manhattan. It is observed that with the increased level of tolls at the Holland Tunnel more people prefer to use the alternative crossing which is the Lincoln Tunnel.

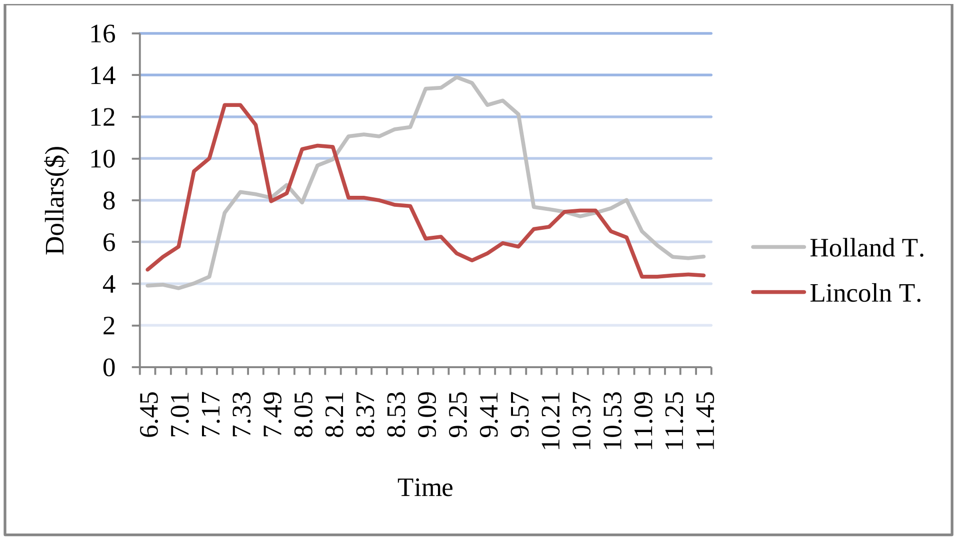

Figure 6-4: Time-dependent Toll Rates

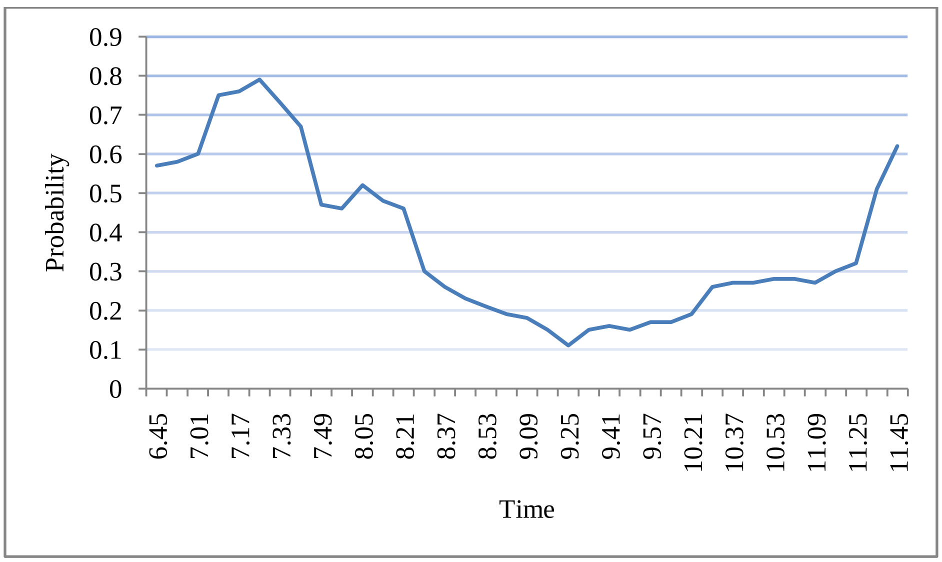

Figure 6-5: Time-dependent Change in Percentage of the New Jersey Turnpike Users Choosing the Holland Tunnel at the Decision Point A

Similar behavior can be observed at the Decision Point B, which is the exit from New Jersey Turnpike to the Pulaski Skyway. The Pulaski Skyway mostly carries traffic to Holland Tunnel therefore tolls at the Holland Tunnel mainly control the travelers behavior at this decision point. Although there is another decision point on the Pulaski Skyway which gives an option to switch the Lincoln Tunnel at a later, it is observed that most users which decide to use Lincoln Tunnel have continued their trips on the New Jersey Turnpike until the Lincoln Tunnel Exit (16E). Main reason for this behavior is the faster trip times on the New Jersey Turnpike, in spite of paying an extra toll for the next exit. It should be noted that the utility function used in the simulation gives twice as much weight to the travel times compared to the tolls.

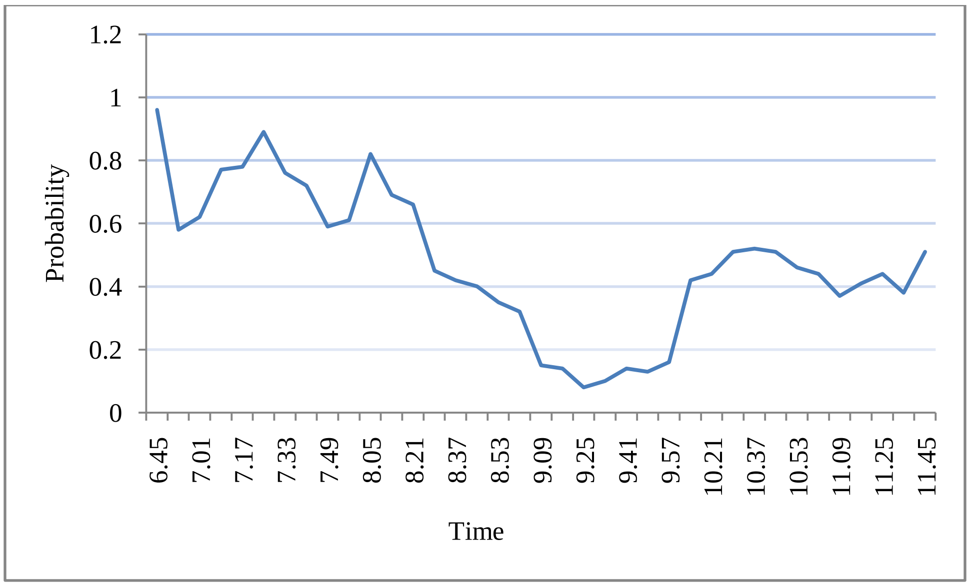

Figure 6-6: Time-dependent Change in Percentage of the New Jersey Turnpike Users Choosing the Holland Tunnel at the Decision Point B

Probability of users selecting the Lincoln Tunnel at Decision point C is shown in Figure 6-7. Again the correlation between tolls for the Lincoln Tunnel and the probability of selecting to travel in the Lincoln Tunnel can be observed in figure. It is assumed that no more than 20% of the users switch to the Holland Tunnel from this point. The reasoning is simply not to deviate too much from the traffic counts for the New Jersey Turnpike Exit 16E.

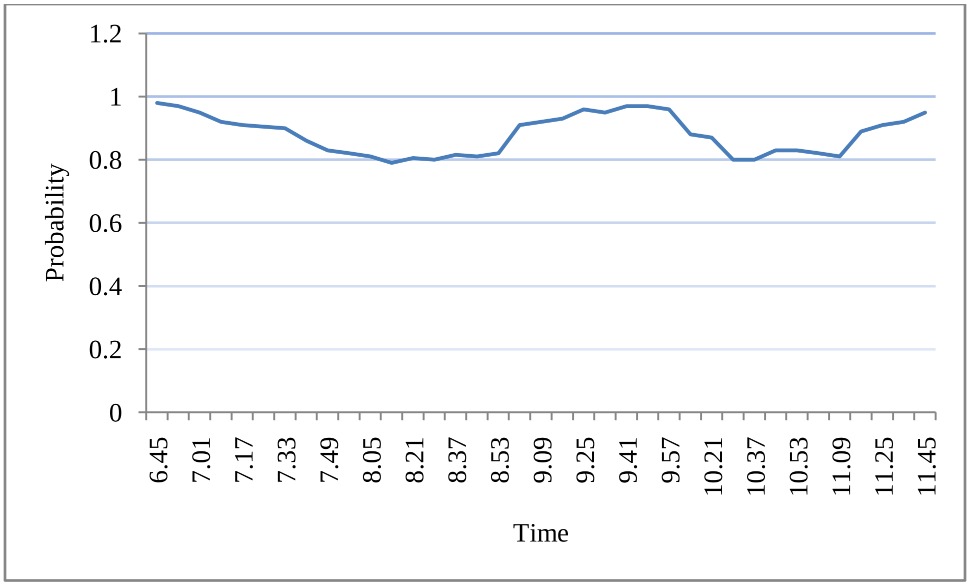

Figure 6-7: Time-dependent Change in Percentage of the New Jersey Turnpike Users Choosing Lincoln Tunnel at the Decision Point C

Figure 6-8 shows the probability of users to switch to the Lincoln Tunnel at Decision Point D. The probabilities are lower compared to the other decision points because for every destination point in Manhattan, the Holland Tunnel provides a shorter trip time under free flow travel conditions at this decision point. Therefore the probabilities increase when there is significant congestion in the Holland Tunnel. Again the correlation between the toll rates and the probability of switching can be observed at Decision Point D.

Finally the change in probability of users to switch to the Holland Tunnel at decision point E is shown in Figure 6-9. This figure shows that when the toll rate in the Lincoln Tunnel increases, more users tend to switch their routes to cross from Holland Tunnel.

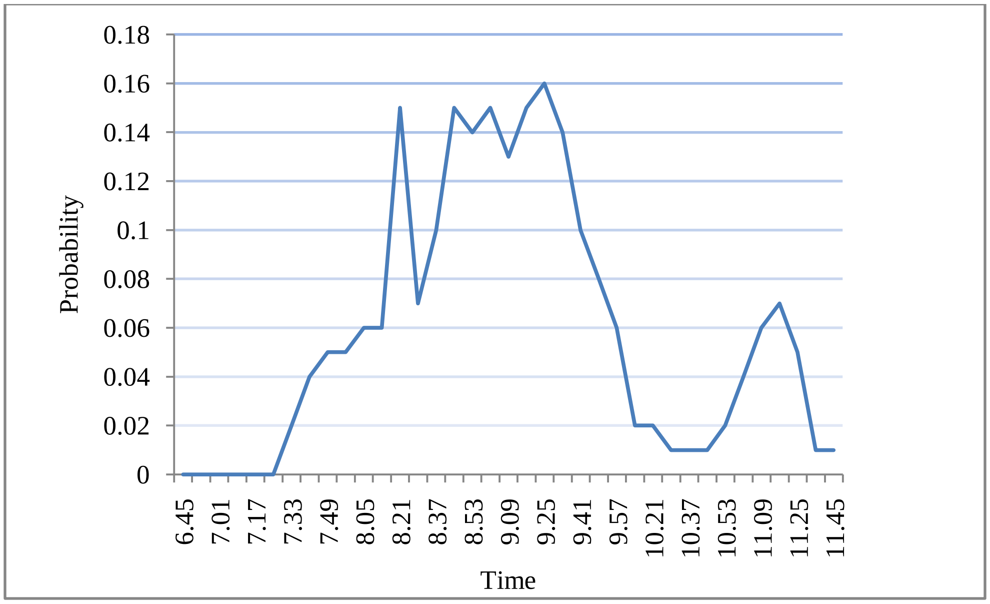

Figure 6-8: Time-dependent Change in Percentage of the New Jersey Turnpike Users Choosing the Lincoln Tunnel at the Decision Point D

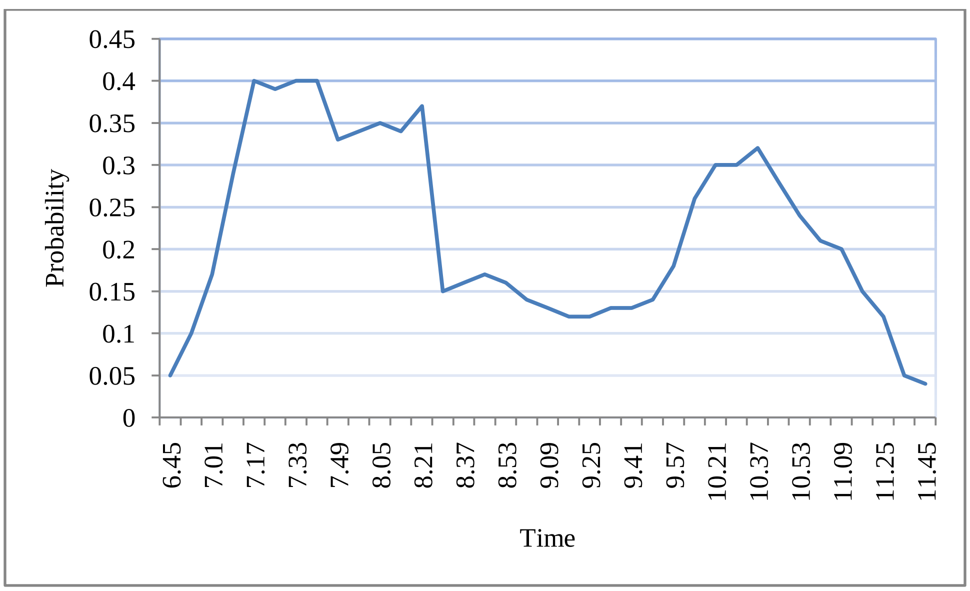

Figure 6-9: Time-dependent Change in Percentage of the New Jersey Turnpike Users Choosing the Holland Tunnel at the Decision Point E

Change in speeds in each tunnel is shown in Figure 6-10. The data is obtained from the detectors which are located to measure upstream traffic conditions. It can be seen that in earlier stages of the simulation, the Holland Tunnel has higher speeds.

However traffic conditions change when the users start to switch their routes and the Lincoln Tunnel has faster trips in later stages of the simulation. Although there is a difference in speeds between the two crossings, it is also observed that most of the time, speeds cannot exceed 20 mph for both tunnels.

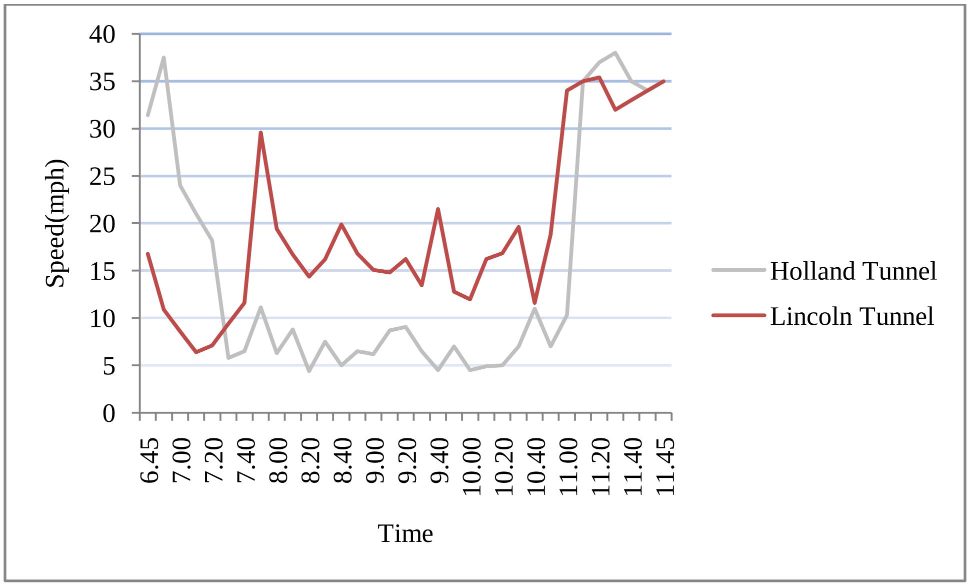

Figure 6-10: Time-dependent Speed Profiles at the Lincoln and Holland Tunnels

As a better measure of congestion, occupancy values are also obtained from the detectors. Figure 6-11 shows the changes in the occupancy values in two tunnels throughout the simulation. Similar to the speed data, the Holland Tunnel performs better in terms of congestion during the first hour of the simulation and for the later stages of the simulation, the Lincoln Tunnel has lower occupancy values which mean less congested traffic conditions.

Travel time is one of the two parameters in the utility function that determines the users' probability of choosing their routes. Therefore the change in travel times of the alternatives calculated at each decision gives the idea about the effects of the dynamic tolling algorithm on the route travel times.

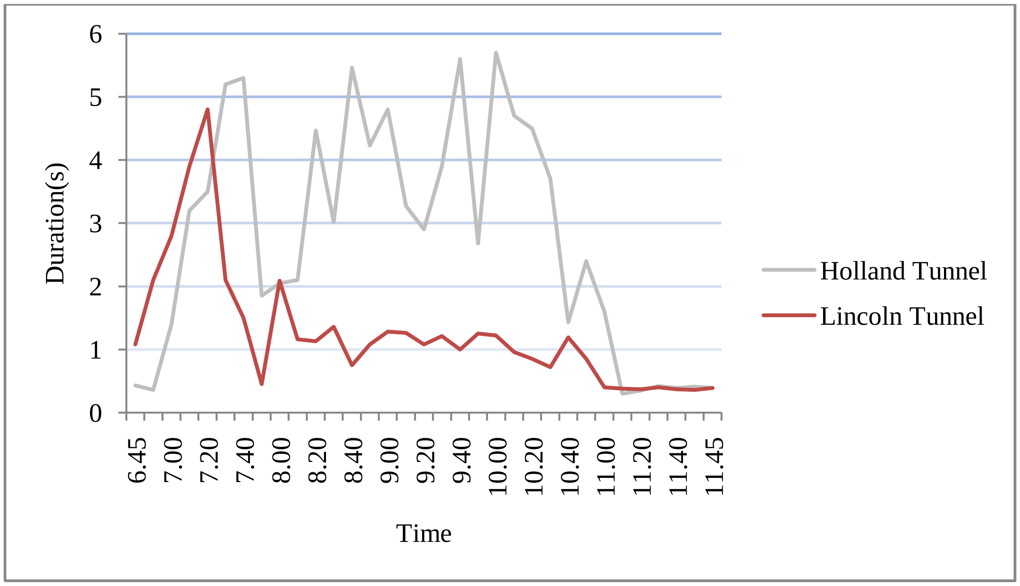

Figure 6-11: Time-dependent Occupancy Profiles at the Lincoln and Holland Tunnels

Generally, the algorithm tries to keep the difference between the two alternative route travel times within a certain range and does not allow dramatically high differences between the two travel times. In other words, when the difference between the two travel times gets higher for a time period, the algorithm tries to decrease the difference in the next time period.

Figure 6-12 shows the average travel time changes of the two alternative routes at Decision Point A. It is observed that although the distance is lower for the Holland Tunnel alternative for all three destination points, during the simulation at some time periods using the Lincoln Tunnel has lower average travel times. As expected, at the end of the simulation, when the congestion is mitigated, the Holland Tunnel again has lower average travel times.

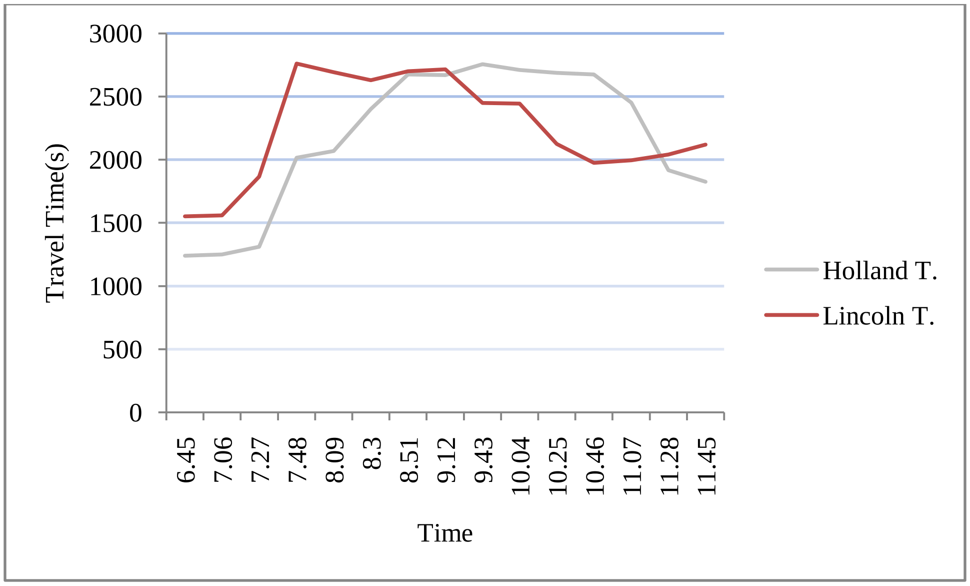

Figure 6-12: Time-dependent Travel Times for the Lincoln and Holland Tunnels at Decision Point A

Figure 6-13 shows the travel time changes at Decision Point B. Similar to the Decision Point A, under free flow conditions the Holland Tunnel has lower average travel times due to the shorter distances to the destination points. During the simulation, there are time periods when using the Lincoln Tunnel travelers experienced lower travel times in which the probability of using the Holland Tunnel from Decision Point B was relatively low.

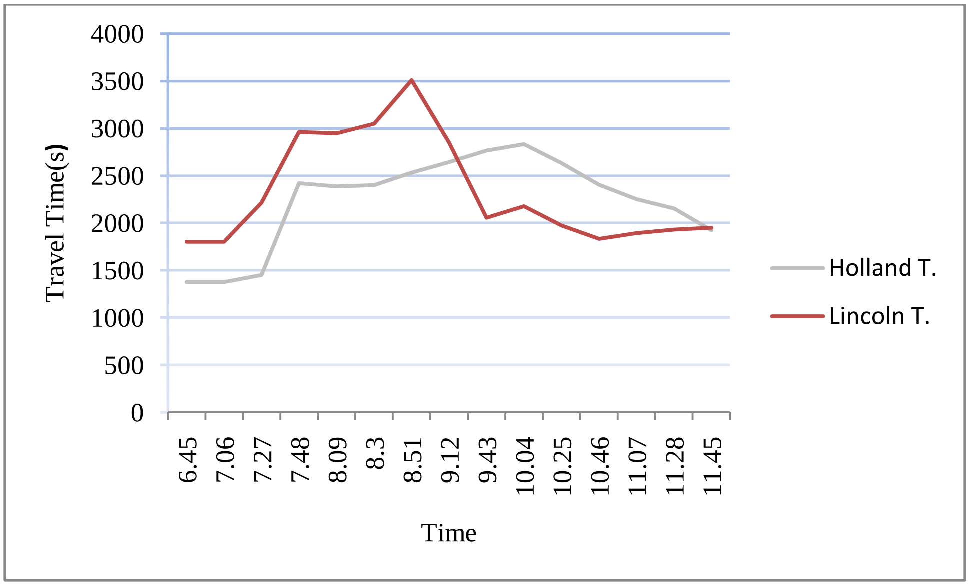

Figure 6-13: Time-dependent Travel Times for the Lincoln and Holland Tunnels at Decision Point B

Time-dependent change in average travel times from Decision Point C is given in Figure 6-14. This figure shows that from this decision point, the Lincoln Tunnel has faster travel time compared to the Holland Tunnel. It should be also noted that, at earlier stages of the simulation due to the severe congestion in the Lincoln Tunnel, there is a short period of time during which the Holland Tunnel has lower travel times. This, in turn, decreases the probability of using the Lincoln Tunnel at this decision point.

Average travel times for the alternative routes at Decision Point D are shown in Figure 6-15. At this point, the Holland Tunnel always has lower travel times. However at time periods where the difference in travel times between the two alternatives decreased the probability of using Lincoln Tunnel from this point increased.

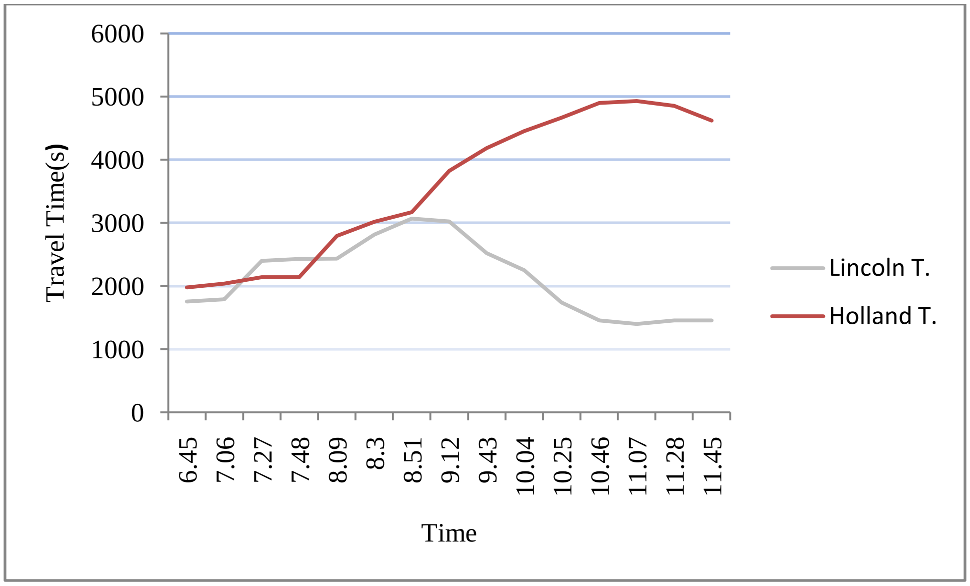

Figure 6-14: Time-dependent Travel Times for the Lincoln and Holland Tunnels at Decision Point C

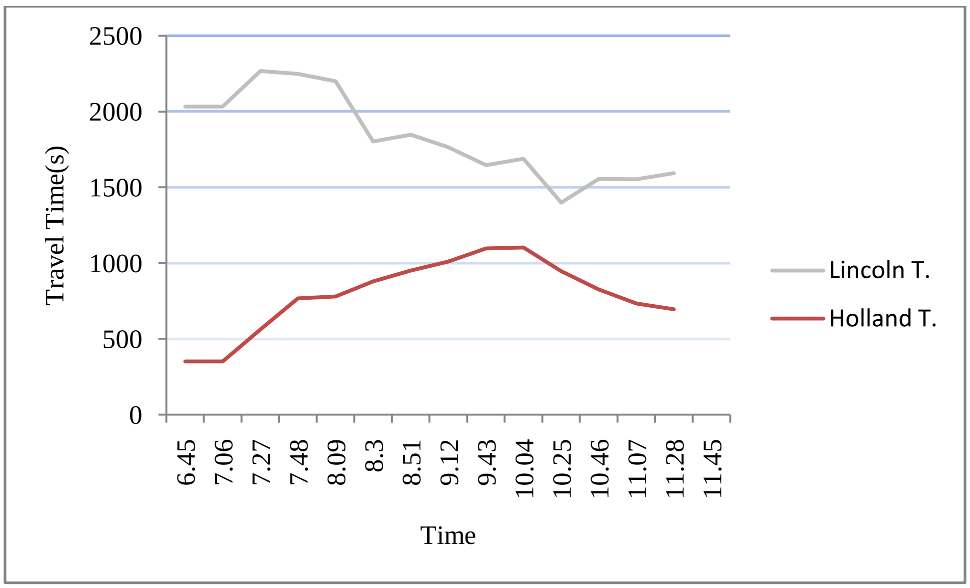

Figure 6-15: Time-dependent Travel Times for the Lincoln and Holland Tunnels at Decision Point D

Figure 6-16 shows the average travel time changes at Decision Point E. This point is very closely located to Lincoln Tunnel therefore it is expected that the Holland

Tunnel has higher travel times for every destination point. However in earlier stages of the simulation when the Lincoln Tunnel is highly congested the difference in travel times between the two alternatives is at its minimum.

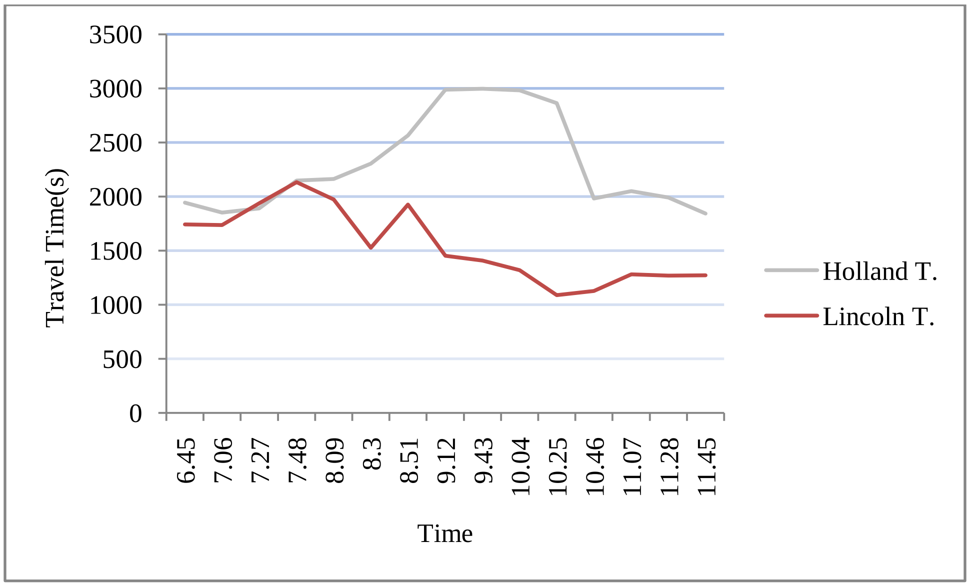

Figure 6-16: Time-dependent Travel Times for the Lincoln and Holland Tunnels at Decision Point E

Finally comparison between dynamic and static tolls is conducted in terms of average occupancies and average speeds on the crossings using the same demands for the same time periods. Measurements are done with point sensors located on each crossing. For the Holland Tunnel, dynamic tolls are found to be effective in decreasing the occupancies as shown in Figure 6-17. The main reason is the traffic that shifts to the Lincoln Tunnel in response to dynamic tolls which get higher when congestion increases. For the Lincoln Tunnel, on the other hand, occupancies are generally lower in the case of dynamic pricing but there are some short time periods when the occupancies are lower in static pricing. Figure 6-18 shows the occupancies in the

Lincoln Tunnel for the simulation scenarios with dynamic and static pricing alternatives.

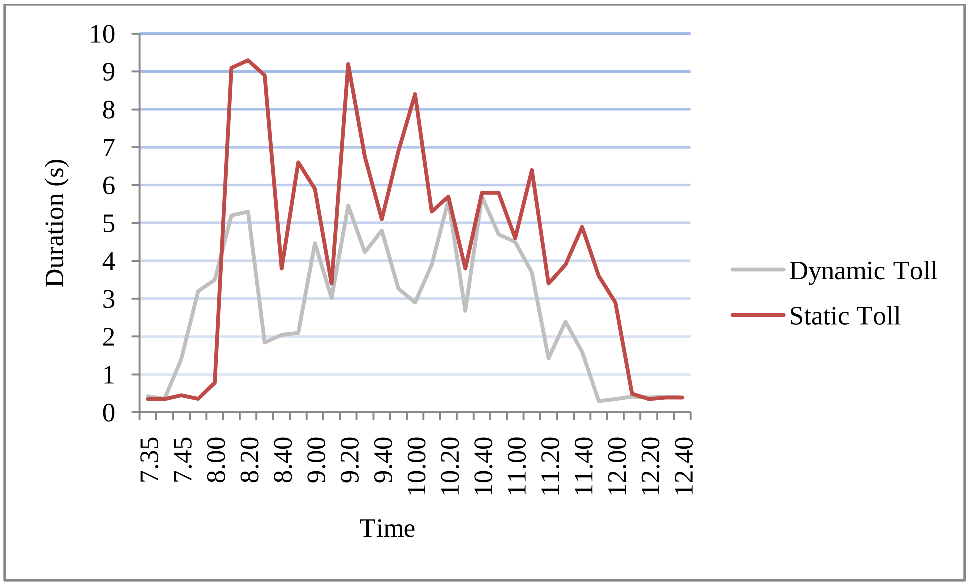

Figure 6-17: Time-dependent Average Occupancy Rates for the Holland Tunnel for Static and Dynamic Toll Strategies

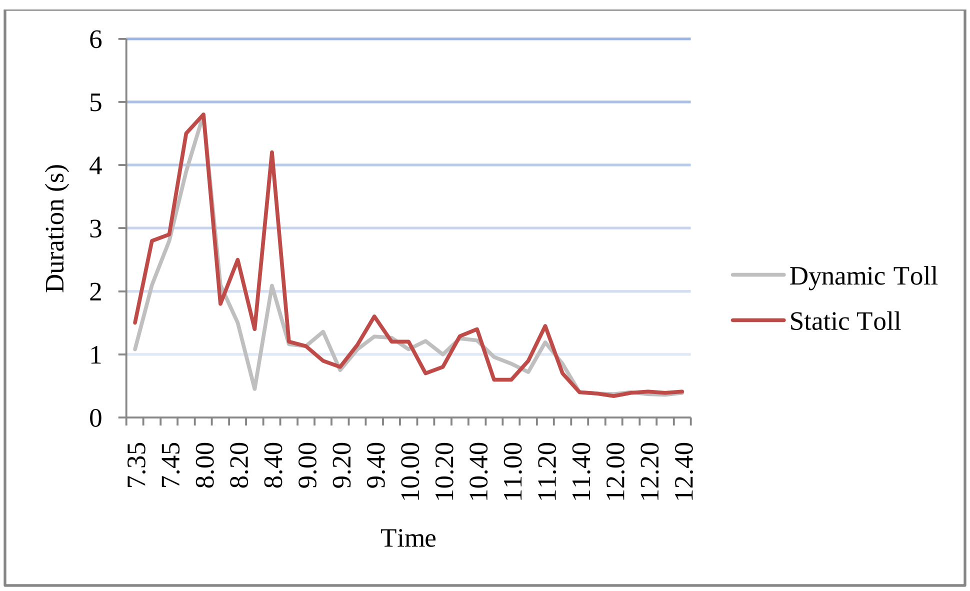

Figure 6-18: Time-dependent Average Occupancy Rates for the Lincoln Tunnel for Static and Dynamic Toll Strategies

Average speeds from the data collected for the two different simulation scenarios, with dynamic and static tolling respectively, are presented in Figure 6-19. Similar results can be seen in terms of the average occupancies, the Holland Tunnel dynamic toll scenario performs better than static toll scenario for the same crossing. For the Lincoln Tunnel for some short periods higher average speeds are observed for the simulation scenario with static pricing.

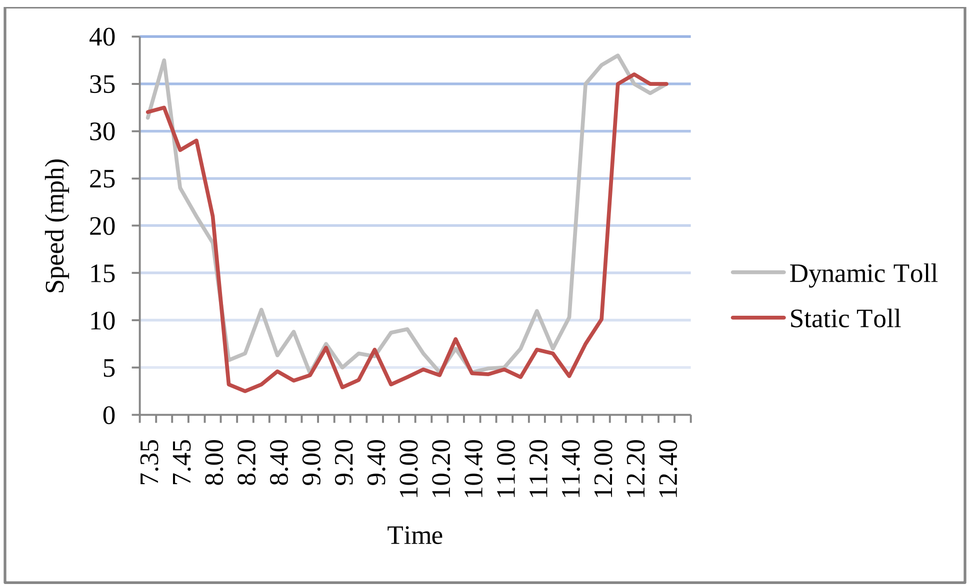

Figure 6-19: Change in Average Speed for the Holland Tunnel for Static and Dynamic Toll Strategies

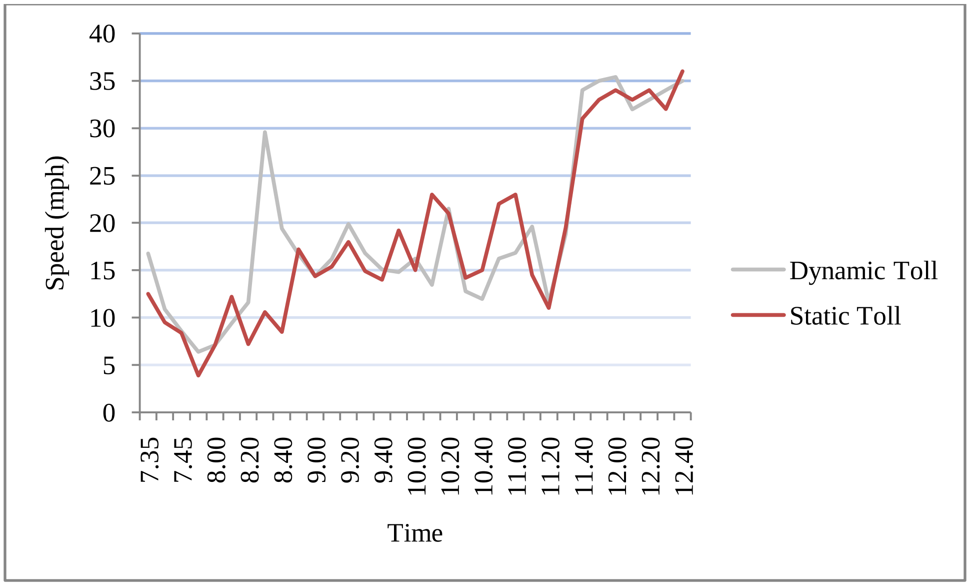

Figure 6-20: Change in Average Speed for the Lincoln tunnel for Static and Dynamic Toll Strategies

6.3 CONCLUSION

In this chapter simulation work using the proposed dynamic tolling algorithm is presented. A network including the Holland and Lincoln Tunnels and the connecting roads is created in Paramics. Dynamic tolling and route choice behavior is incorporated into the simulation model using an API code which is developed using C language. Observed demands for the morning peak period are used for the simulation scenarios.

It can be concluded that the dynamic tolling algorithm performed effectively to manage the peak period congestion. Route choice behavior as a result of the real-time toll changes is successfully simulated and logical route choices are observed at the decision points which are previously defined at junctions where users are most likely to switch their crossing choice to enter Manhattan.

Compared to the static tolling simulation, which is a representative of the situation which is applied in practice, dynamic tolling provided lower occupancies and higher speeds for most of the time for both crossings.

With further calibration of coefficients, toll rates can be more realistically distributed in simulation time and more realistic toll revenues can be obtained for comparison.

CHAPTER VII

SUMMARY AND CONCLUSIONS

7.1 SUMMARY AND CONCLUSIONS

This thesis has an objective of extending the idea of dynamic congestion pricing to a scenario of two major crossings between New York and new Jersey, namely the Holland and Lincoln Tunnels. Literature review showed that the studies conducted for dynamic pricing so far, only considered the HOT lane operations. Current HOT lane facilities which employ dynamic road pricing approaches are discussed in Chapter 2. A qualitative of the performance of these facilities shows that dynamic pricing provides promising improvements in terms of overall traffic conditions. User surveys which are conducted by Florida Department of Transportation (FLDOT) show that travelers are also satisfied with the dynamic pricing operations. In the same report it is stated that FLDOT will deploy similar dynamic toling systems at other roadways. Success of dynamic pricing applications is also proved by the fact that a number of states are proposing similar projects in the near future.

Dynamic pricing can be applied to the scenario of two major crossings as in the case of New York- New Jersey crossings when certain criteria are met. One of the biggest needs for a real-time pricing application is that when one crossing is priced dynamically, an alternative crossing should also exist within a reasonable distance so that users can switch in response to dynamically changing tolls. Another requirement should the availability of connecting routes between the two crossings so that users can easily switch from one alternative to the other.

Chapter 3 of the thesis focuses on commercial vehicle value of time estimation problem specifically for New York-New Jersey region. Literature review reveals that there are no studies done for estimating commercial vehicle value of time for this region. Using the trucker survey data which is conducted in 2004, average commercial vehicle value of time was found to be around $33.62/hr. This value which has an effect on driver behavior in response to toll rates is used in the case study as an input to the simulation model.

The first simulation study, which is used as the case study, is conducted to see the effects of dynamic pricing in a large network when all of the tolled crossings are priced dynamically. Manhattan network is selected for the simulation and crossings that carry inbound traffic from Bronx/Queens/Brooklyn side on east and from New Jersey side on west are included. For this large network mesoscopic scale simulation was run and simulation software TransModeler is used.

TransModeler is a software package which allows simulations for different fidelity options such as microscopic, mesoscopic and macroscopic. However, since TransModeler cannot be re-programmed using commonly used programming languages such as C/C++, in-built-in dynamic pricing modules were used. This default functionality allows the change of toll rates real-time based on the average occupancy level at the crossings.

The large network simulation is run for one full day and the results are given in detail for every crossing. It is observed that for most of the tolled crossings there are significant decreases in average occupancy values when the results are compared with the base case where static tolls are applied. Economical analysis is also done in terms of total toll revenues which show that dynamically priced tolls generate more revenue compared to the static congestion pricing. Another set of simulations are run with modified commercial vehicle demands. When the commercial vehicle demands are shifted to the night period, change in traffic conditions are observed and analyzed. When the effects of dynamic pricing obtained from the dynamic simulation model is compared with the results of the static network model it is seen that to get tangible enhancements in traffic conditions, larger tax incentives should be provided to shift enough vehicles to the night period.

In Chapter 5, an algorithm for dynamic tolling is proposed for a network that includes two crossings which are spatially close to each other. The algorithm is based on Zhang et al. (2008)'s dynamic pricing algorithm for HOT lane operations. According to the algorithm, when a user reaches the decision point, two utility functions are defined considering the travel time from each crossing and current toll rates. Using a logit function, a user's probability of choosing one route against others is calculated and the route choice decision is implemented accordingly.

The algorithm is tested using a Paramics simulation network which consists of the Lincoln and Holland Tunnels and the connecting roads on the New Jersey side, namely New Jersey Turnpike (NJTPK) and Route 1-9. Five decision points and three destination points for the users using NJTPK exits for the tunnels are identified.

Traffic demands obtained from NJTPK are compared with the bridge traffic count report which was issued by New York City Department of Transportation (NYDOT, 2008).

Paramics, microsimulation software is selected to test the dynamic pricing algorithm through the use of its Application Programmer Interface (API) feature. API feature allows users to plug in their own codes which can be developed in C/C++ coding language. The results of the simulation show that the developed algorithm can generate smooth behaving real-time toll rates. In response to these toll rates, users change their routes when the utility of the alternative route exceeds the regular route's utility. An important observation is the lower occupancy values for a significant portion of the simulation at both crossings under dynamic pricing scenarios when compared with the static pricing scenario. This result shows that as a result of dynamic pricing system can operate in a better way when vehicles move to the alternative crossings in case of high congestion.

The results of the simulations show that dynamic tolls can be considered as an effective method in decreasing the average occupancies and increasing the average speeds at New York-New Jersey crossings.

7.2 RECOMMENDATIONS FOR FUTURE RESEARCH

For future studies some of the recommendations are stated below:

- The algorithm for dynamic pricing employed in this thesis assumed single-class vehicle, and calculated a single toll rate for all types of vehicles. This model can be extended to simulate multi-class dynamic pricing problem just by defining different vehicle classes and updating the API code to calculate different toll rates for different vehicle classes. Also defining different classes will enable to set different value of times for different vehicles which will result in more realistic outcomes.

- One desirable improvement to the dynamic pricing algorithm can be to allow users to switch their departure times. In this thesis, fixed demands for individual time periods are assumed. Allowing users to switch between time periods might result in further improvements in traffic conditions
- Real-world implementation of this dynamic pricing algorithm needs comprehensive research on determining the parameter coefficients of the discrete choice model used to define likelihood of user decisions . This improvement will be helpful in obtaining more realistic toll rates.
- Value of time of commercial vehicles can be calculated using a different method such as Bayesian estimation techniques which gives more accurate results in case of limited sample size.

REFERENCES

1. Arnott, R, and Small, K.A. ,(1994), "The Economics of Traffic Congestion," *American Scientist*, Vol. 82, No. 5, pp. 446-455
2. Lindsey, C.R., Verhoef, E.T., (2000), "Traffic Congestion and Congestion Pricing*", Tinbergen Institute Discussion Paper TI2000-101/3. Accessed on 6/18/2009 at* www.tinbergen.nl/discussionpapers/00101.pdf
3. Parsons, Brinckerhoff, Quade & Douglas, Inc.,(*2005),"Truck Only Toll Facilities: Potential for Implementation in the Atlanta Region", Accessed on 6/18/2009 at* www.georgiatolls.com/PDFs/TOT_Final_Report_July2005.pdf
4. *Meyer, M.D., Saben, Larry, Shephard, W., Steavens,E.,(2006), "Feasibility of Truck-Only Toll Lane Network in Atlanta, Georgia", Transportation Research Record: Journal of the Transportation Research Board, No. 1960, Transportation Research Board of the National Academies, Washington D.C., pp. 57–67.*
5. Chu, H., Meyer, M.D., (2009), "Methodology for assessing emission reduction of truck-only toll lanes", *Energy Policy* ,Volume 37, Issue 8, August 2009, Pages 3287-3294
6. Poole, R.W., (2007), "Miami Toll Truckway: Preliminary Feasibility Study", Reason Foundation, Policy Study: 365, *Available on 6/18/2009 at: reason.org/news/show/1002856.html*
7. Lake, M., Ferreira L., (2002), "Demand For Toll Roads: A Summary of Elasticities, Travel Time Values and Modeling Approaches", *Transport Research Consortium*, Queensland University of Technology.
8. Holguin-Veras, J., Ozbay, K., de Cerreno, A.,(2005) "Evaluation Study of Port Authority of New York and New Jersey's Time of Day Pricing Initiative", FHWA/NJ-2005-005.
9. Vilain, P., Wolfrom, P., (2001). "Value pricing and freight traffic: issues and industry constraints in shifting from peak to off-peak movements". *Transportation Research Record* 1707, 64–72.
10. Bergkvist, E., (2001), "The value of time and forecasting of flows in freight transportation" ,*European Research in Regional Science*, vol. 11, Available on 6/18/2009 at http://www-sre.wu-wien.ac.at/ersa/ersaconfs/ersa01/papers/full/271.pdf
11. Ozbay,K., Yanmaz-Tuzel, O., Helguin-Veras, J.,(2006),"Evaluation of Impacts of Time-of-Day Pricing Initiative on Cars and Truck Traffic", *Transportation Research Record: Journal of the Transportation Research Board*, No. 1960, pp. 48–56.
12. Issues and Options for Increasing the Use of Tolling and Pricing to Finance Transportation Improvements, (2006), FHWA Report 05-002, Available on 6/18/2009 at www.ncppp.org/resources/papers/**tollissues**report606.pdf

13. "Interstate 80 Tolling Feasibility Study, Final Report",(2008), Parsons Brinckerhoff in association with PB Consult, Available on 6/19/2009 at http://www.thenewspaper.com/rlc/docs/2009/wy-toll80.pdf
14. "Corridors of The Future: Phase II Application", (2007) ,Available on 6/19/2009 at http://www.in.gov/indot/2355.htm Additional Information Available on 6/19/2009 at http://www.corridors.dot.gov/i70.htm,
15. Wilbur Smith Associates, (2003), I-10 National Freight Corridor Study: Phase II Report, Available on 6/19/2009 at http://www.i10freightstudy.org/7_reports.html
16. Verhoef, Erik T.,(2002),"Second-Best Congestion Pricing In General Static Transportation Networks With Elastic Demands", *Regional Science and Urban Economics* 32 (2002) 281-310
17. Verhoef, Erik , (1996), "Second-Best Congestion Pricing:The Case of an Untolled Alternative", *Journal of Urban Economics* 40, 279-302
18. Eliasson, J., (2001), "Road Pricing With Limited Information and Heterogeneous Users: A Successful Case", *The Annals of Regional Science*, Springer-Verlag, 35:595-604
19. Levinson, D.,(2005),"Micro-Foundations of Congestion and Pricing: A Game Theory Perspective", *Transportation Research Part A* 39 (2005) 691-704
20. De Palma, A., Kilani, M., Lindsey, R.,(2005), "Congestion Pricing on A Road Network: A Study Using The Dynamic Equilibrium Simulator METROPOLIS", *Transportation Research Part A* 39 (2005) 588-611
21. Holguin-Veras, J., Cetin, M.,(2009), "Optimal Tolls For Multi-Class Traffic: Analytical Formulations and Policy Implications", *Transportation Research Part A* 43(2009) 445-467
22. Pigou,A.C., (1920), The Economics of Welfare, MacMillan and Co. Ltd., London, accessed on 11/11/2009 at http://www.econlog.econlib.org/library/NPDBooks/Pigou/pgEW.html
23. Walters, A.A.,(1961),The Theory and Measurement of Private and Social Cost of Highway Congestion, Econometrica 29 (4), 676-699
24. Beckman, M.J., (1965), On Optimal Tolls For Highways, Tunnels, and Bridges, In: Edie, L.C., Herman, R., Rothery, R., (Eds), *Vehicular Traffic Scienc*e, American Elsevier Publishing Company, New York, 331-341
25. Vickrey,W.S.,(1963), Pricing and Resource Allocation In Transportation and Public Utilities: Pricing In Urban and Suburban Transport, *American Economic Review*, 53 (2), 452-465
26. Vickrey, W.S., (1969), Congestion Theory and Transport Investment, *American Economic Review*, 59 (2), 251-260
27. Arnott, R., De Palma, A., Lindsey, R., (1990),"*Economics of a Bottleneck*",Journal of Urban Economics,27 111-130

28. Hearn, D. W., Ramana, M.V. ,(1998),"*Solving Congestion Toll Pricing Models*",Equilibrium and Advanced Transportation Modeling, P.Marcotte and S.Nguyen (Eds), Kluwer Academics Publishers, pp. 109-124
29. Yang ,H., Haung, H., (1998) ,"*Principle of Marginal-Cost Pricing: How Does It Work In a General Network?*", Transportation Research A 32:45-54
30. Arnott, R., de Palma, A., Lindsey, R., (1998), *"Recent Developments In The Bottleneck Model."* In: Button, K.J.,Verhoef, E.T., (Eds.), *Road Pricing*, Traffic Congestion and the Environment: Issues of Efficiency and Social Feasibility. Edward Elgar, Cheltenham.
31. Teodorovic, D., Edara, P., (2007), *"A Real-time Road Pricing System: The Case Of A Two-Link Parallel Network"*, *Computers and Operations Research* 34(2007)2-27
32. Wie, B., Tobin, R., (1998), *"Dynamic Congestion Pricing Models For General Traffic Networks"*, *Transportation Research Part B* Vol. 32, No. 5, pp. 313-327
33. Joksimovic, D., Bliemer, M. C. J., Bovy, P. H. L., & Verwater-Lukszo, Z. (2005). *"Dynamic road pricing for optimizing network performance with heterogeneous users"*. In *IEEE* proceedings of the international conference in networking, sensing and control (pp. 407–412). Tucson, AZ.
34. Wie,B., (2007*),"Dynamic Stackelberg Equilibrium Congestion Pricing",*Transportation Research Part C 15 (2007) 154-174
35. Lu, C., Mahmassani, H., Zhou, X., (2008), *"A Bi-criterion Dynamic User Equilibrium Traffic Assignment Model and Solution Algoritm For Evaluating Dynamic Road Pricing Strategies",* Transportation Research Part C 16 (2008) 371-389
36. Mahmassani, H., Zhou, X., Lu, C.,(2005), *"Toll Pricing and Heterogeneous Users: Approximation Algorithms for Finding Bicriterion Time-Dependent Efficient Paths in Large-Scale Traffic Networks"*,Transportation Research Record: Journal of the Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 28-36
37. Killough, K., (2008), *"Value Analysis of Truck Toll Lanes in Southern California "*, Transportation Research Board Annual Meeting 2008, Paper Number:08-0140
38. Zhang, G., Wang, Y., Wei, H., Yi, P.,(2008), *"A feedback based Dynamic Tolling Algorithm for High-Occupancy Toll Lane Operations"*, *Transportation Research Record: Journal of the Transportation Research Board*, No.2065, Transportation Research Board of the National Academies, Washington, D.C., 2008, pp. 54-63
39. U.S. DOT Federal Highway Administration, Value Pricing Programs, accessed on 11/11/2009 at http://ops.fhwa.dot.gov/publications/fhwahop08023/02summ.htm
40. Blayac, T.,Causse, A., (2001), *"Value of time: A Theoretical Legitimization of Some Nonlinear Representative Utility in Discrete Choice Models"*, Transportation Research Part B 35 391-400

41. Haning, C. R., McFarland, W. F. , (1963). *"Value of time saved to commercial motor vehicles through use of improved highways"*. (Bulletin No. 23). College Station, Texas: Texas A & M University, Texas Transportation Institute.
42. Kawamura, K., (1999), *"Commercial vehicle value of time and perceived benefits from congestion pricing"*, Phd dissertation, University of California, Berkeley
43. Brian Smalkoski, Dr. David Levinson(2003), *"Value of time for commercial vehicle operators in Minnesota"* , Journal of the Transportation Research Forum 44:1 89-102
44. Ozbay, K., Yanmaz-Tuzel, O., (2008), *"Valuation of Travel Time and Departure Time Choice In the Presence of Time-of-day Pricing"*, *Transportation Research Part A* 42 (2008) 577-590
45. McDonald, J.F., d'Ouville, E., Louie, N., (1999), *"Economics of Urban Highway Congestion and Pricing"*, Transportation Research, Economics and Policy Volume 9, New York, ISBN 978-0-7923-8631-5
46. Small, K., Verhoef, E., (2007), *"The Economics of Urban Transportation"*,Routledge, New York, ISBN 978-0-415-28515-5
47. Smith, A., Erikson, E.,Lindberg, P., (1994), "*Existence of Optimal Tolls Under Conditions of Stochastic User-Equilibria"*, In: Johansson&Mattson(Eds), Road Pricing: Theory, empirical assessment and policy, pp. 65-87
48. De Palma, A., Lindsey, R.,(2004), *"Congestion Pricing With Heterogeneous Travelers: A General-Equilibrium Welfare Analysis"*,Network and Spatial Economics, 4 135-160
49. Ferrari, P.,(1995*),"Road Pricing and Network Equilibrium",* Transportation Research B 29, pp. 357-372
50. Yang, H., Bell, M., (1997), *"Traffic Restraint, Road Pricing and Network Equilibrium"*, Transportation Research Part B, 31(4), pp.303-314
51. Yang, H., Lam, W., (1996), *"Optimal Road Tolls Under Conditions of Queuing and Congestion"*, Transportation Research Part A:Policy and Practice 30(5), pp. 319-332
52. Mun, S. (1999), *"Peak-load pricing of a bottleneck with traffic jam"*, Journal of Urban Economics, 46(3), pp. 323-349
53. Braid, M, (1989), *"Uniform versus peak-load pricing of a bottleneck with elastic demand"*, Journal of Urban Economics, 26(3), pp.320-327
54. Hau, T. ,(1992), *"Economic Fundamentals of Road Pricing: A Diagrammatic Analysis"*, World Bank Policy Research Working Paper Series WPS 1070, The World Bank, Washington D.C., December 1992:1-96
55. Arnott, R., (2007), *"Congestion Tolling With Agglomeration Externalities"*,Journal of Urban Economics, 62(2), pp. 187-203
56. Sullivan, E., (2000), *"Continuation Study to Evaluate the Impacts of the SR-91 Value-Priced Express Lanes Final Report"*, State of California Department of Transportation

57. Mun, S, Konishi, K., Yoshikawa, K.,(2005), *"Optimal Cordon Pricing in A Non-monocentric City"*, Transportation Research Part A: Policy and Practice 39(7-9), pp. 723-736
58. Guiliano, G., (1994), *"Equity and fairness considerations of congestion pricing"*,In:Curbing Gridlock, Peak-Period Fees to Releive Traffic Congestion, Transportation Research Board Special Report 242, vol 2. Pp 250-279
59. Litman, T. ,(1996), *"Using Road Pricing Revenue, Econometric Efficiency and Equity Considerations"*, Transportation Research Record 1558, pp 24-28
60. Parry, I., Bento, Q., (2001), *"Revenue Recycling and the Welfare Effects of Road Pricing"*, Scandinavian Journal of Economics, 103(4), pp. 645-671
61. Kockelman, K., Kalmanje, S.,(2004), *"Credit-based Congestion Pricing: A Policy Proposal and Public's Response"*, Presented at the 83rd Annual Meeting of Transportation Research Board, Washington DC
62. Verhoef, E., Small, K., (2004), "*Product Differentiation on Roads-Constrained Congestion Pricing With Heteregoneous Users"*, Journal of Transportation Economics and Policy 38, 127-156
63. Ukkusuri, S., Karoonsoontawong, A., Waller, T., Kockelman, K., (2007), *"Congestion Pricing Technologies:Synthesis and an Evaluation Framework"*, Proceedings of the 84th Annual Meeting of The Transportation Research Board and Chapter 4 in New Transportation Research Progress, pp. 121-142
64. Friesz, T., Kwon, C., Chow, A., Heydecker, B., (2007), *"A Computable Theory of Dynamic Congestion Pricing"*, Sixth Triennial Symposium on Transportation Analysis (TRISTAN VI), Phuket Island, Thailand, 10-15 June 2007
65. Karoonsoontawong, A., Ukkusuri, S., Waller, S., Kockelman, K., (2008), *"Simulation-based Heuristic Approach For Dynamic Marginal Cost Pricing"*, Transportation Research Board Annual Meeting, 2008, Paper No. 08-0438
66. DeCarlo-Souza, P.,(1994), *"Applying the Cashing Out Approach to Congestion Pricing"*,Transportation Research Record,1450, pp. 34-37
67. Adler, J., Cetin. M., (2001), "*A Direct Redistribution Model of Congestion Pricing"*, Transportation Research Part B, 35, pp.447-460
68. Collier,T.,Goodin,G.,(2002),"Managed Lanaes: More Efficient Use of Freeway System: A Position Paper For Policy Makers", Texas Transportation Institute, Report 4160-5-P1
69. Satellic Traffic Management GmbH, "Road Charging drives mobility-the truck toll in Germany" accessed on 11/18/09 at http://www.t-systems.com/tsi/servlet/contentblob/t-systems.de/en/37536/blobBinary/Satellic_Maut-fuer-Mobilitaet-ps.pdf
70. News Release July 30.2009, Minnesota Department of Transportation, accessed on 11/18/09 at http://www.dot.state.mn.us/newsrels/09/07/30-express-lanes.html

71. Yin, Y., Lou,Y.,(2007), "Dynamic Tolling Strategies For Managed Lanes", Transportation Research Board Annual Meeting 2007 Paper no.07-1806
72. WADOT SR 167 HOT Lanes Pilot Project, First Annual Performance Summary, May2008-April 2009, accessed on 18/11/2009 at http://www.wsdot.wa.gov/NR/rdonlyres/31FB3D24-79CC-4332-82F7-EBECEBE1CA71/0/HOTlanesAnnualReport2009.pdf\
73. Supernak, J., Kaschade, C., Steffey, D.,(2003). "Dynamic Value Pricing on I-15 in San Diego: Impact on Travel Time and Its Reliability", Transportation Research Record 1839 Paper no. 03-4335
74. Brownstone, D., Ghosh, A., golob, T., Kazimi, C., Van Amelsfort, D., (2003), "Drivers' Willingness-to-pay to reduce travel time: evidence from the San Diego I-15 congestion pricing project", Transportation Research Part A:Policy and Practice, Volume 37, Issue 4, pp. 373-387
75. Supernak, J., Golob, J., Golob, T., Kaschade, C., KAzimi, C., Schreffler, E., Steffey, D., (2002), "San Diego's Interstate 15 Congestion Pricing Project: Attitudinal, Behavioral and Institutional Issues", Transportation Research Record 1812, Paper no.02-4170
76. Algers, S., Bergstrom, P., Dahlberg, M., Dillen, J.l, (1998), "Mixed Logit Estimation of the Value of Travel Time", Working Paper Series, Department of Economics, Uppsala University, USA
77. Calfee, J., Winston, C., (1998), "The Value of Automobile Travel Time: Implications For Congestion Policy", Journal of Public Economics 69, 83-102
78. Cirillo. C., Axhausen, K.W., (2006), "Evidence on The Distribution of Values of Travel Time Savings From a Six-Week Diary", Transportation Research Part A 40, pp.444-457
79. Ghosh, A., (2000), "To Pay or Not to Pay: Commuters; Mode Choice under Real Time Congestion Pricing", Working Ppaers, University of California, Irvine, USA
80. Hensher, D.A., (1996), "Extending valuation to controlled value functions and non-uniform scaling with generalized unobserved variances", In: Proceedings of The Theoretical Foundations of Travel Choice Modeling, Stockholm
81. Hultkrantz, L., Mortazavi, R., (2001), "Anomalies in The Value of Travel-Time Changes", Journal of Transport Economics and Policy 35 (2), pp.285-300
82. Leurent, F., (1998), "The Distribution of Car Commuters' Value of Time in Marseilles", Recherche Transports Securite 60, pp.19-38
83. Small, K., Rosen, H., (1981), "Applied Welfare Economics of Discrete Choice Models", Econometrica 49, pp.
84. Small, K., Sullivan, E.C., (2001), "Choice Models of Route, Occupancy, and Time-of-Day With Value Priced Tolls", In: Transportation Research Board 80th Annual Meeting, Washington, DC

85. Halvarson, R., Nookala, M., Buckeye, K.R., (2006), "High Occupancy Toll Lane Innovations: I-394 MnPass", Transportation Research Board, Paper No 06-1265

86. FLDOT, (2009), "95 Express Midyear Report", available from: http://www.sunguide.org/images/uploads/tmc_reports/95X_1A_UPA_Eval_Midyear_Report__10_30_2009__FINAL.pdf, accessed on 3/9/2010

87. GADOT, www.dot.ga.gov/i85hotlanes, accessed on 3/10/2010
88. I-595 Corridor Improvement website, http://www.i-595.com/default.aspx, accessed on 3/10/2010
89. Virginia HOT lanes website, http://www.virginiahotlanes.com/beltway-project-info.asp, accessed on 3/11/2010
90. http://www.metro.net/projects_studies/expresslanes/images/fl_plan.pdf, accessed on 3/10/2010
91. Morrison, S.A., (1986). A Survey of Road Pricing. *Transportation Research* **20A** 2; *Transportation Research* **87–97** 2
92. Texas Transportation Institute Report, 2007 accessed on 6/11/2010 at http://mobility.tamu.edu/ums/congestion_data/tables/national/table_2.pdf
93. SANDAG website, www.sandag.org accessed on 6/11/2010
94. MNDOT website http://dot.state.mn.us accessed on 6/11/2010
95. WSDOT website http://www.wsdot.wa.gov/Projects/SR167/HOTLanes accessed on 6/11/2010
96. New York City Bridge Traffic Volumes, 2007, New York City Department of Transportation, December 2008.
97. Yahoo maps http://maps.yahoo.com accessed on 6/11/2010
98. Caliper website http://www.caliper.com accessed on 6/11/2010
99. TransModeler Traffic Simulation Software, Version 2 Built 930 Caliper Corporation, website: http://www.caliper.com/transmodeler/default.htm accessed on 02/19/2010
100. Satellic Traffic Management GmbH, "Road Charging drives mobility-the truck toll in Germany" accessed on 11/18/09 at http://www.tsystems.com/tsi/servlet/contentblob/t-systems.de/en/37536/blobBinary/Satellic_Maut-fuer-Mobilitaet-ps.pdf
101. PANYNJ website http://www.panynj.gov/bridges-tunnels/tolls.html accessed on 6/11/2010
102. Iyer, S., (2010), "Estimating Traffic Impacts of an Off-Houe Delivery Program Using a Regional Planning Model", Master of Science Thesis, Rutgers University

103. Ozbay, K., Yanmaz-Tuzel, O., Holguin-Veras, J., (2006), "Theoretical Derivation of Value of Travel Time and Demand Elasticity", Transportation Research Record, Washington D.C.

104. Holguin-Veras, J., Wang, Q., Xu, N., Ozbay, K., Cetin, M., Polimeni, J., (2006), "The Impacts of freight carriers in a congested urban area: Implications to road pricing", Transportation Research Part A 40, pg. 744-766

105. Bureau of Labor Statistics, http://data.bls.gov/cgi-bin/cpicalc.pl, accessed on 6/11/2010