A DECISION SUPPORT SYSTEM TOOL FOR DYNAMIC PRICING OF MANAGED LANES

by

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Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

August 2016

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Acknowledgements

First and foremost, I would like to express my special gratitude to my doctoral advisor, Professor Siamak Ardekani for his unlimited support and exceptional guidance throughout this long journey. He has been a constant source of inspiration from the beginning. This dissertation would not have been possible without his encouragement and mentoring. I also would like to acknowledge all the invaluable guidance provided by my committee members, Dr. Mahmut Yasar, Dr. Stephen Mattingly, and Dr. James Williams at various stages of this research.

This research study was conducted through funding from the North Central Texas Council of Governments (NCTCOG). I would like to acknowledge the support and contributions of the technical staff at NCTCOG. In particular, I am grateful to Mr. Dan Lamers and Mr. Arash Mirzaei for their guidance and insights during the course of this study. Thanks are also due Mr. John Brady and Ms. Megan Rhodes of North Texas Toll Authority (NTTA) and Mr. Mohammad Al Hweil of the Texas Department of Transportation (TxDOT) Fort Worth District, and the technical staff at TxDOT, Fort Worth TransVision Center for their assistance in obtaining the necessary field data for the conduct of the study.

I am thankful to my dear friends and colleagues Anastasios, Margarita, Arezoo, Saeed, Sheida, and all the member of the Transportation Center at University of Texas at Arlington who were the source of motivation during the entire journey of my PhD study.

Finally, I would like to thank my family from the bottom of my heart. Special thanks to my role model, my mother, Fattaneh, who has been inspiring me in overcoming all challenges that have blocked my way to achieve my goals until now. I also want to thank my father, Lotfollah, for his unconditional love and supports and my sisters, Roshanak and Nina, for always being a true support and for loving me. I would like to dedicate this dissertation to my dear family.

Abstract

A DECISION SUPPORT SYSTEM TOOL FOR DYNAMIC

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The University of Texas at Arlington, 2016

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Congestion pricing and managed lanes (ML) have been recently gaining interest around the country as a congestion management tool and as a means of revenue generation for facility maintenance and expansion as well repayment of highway construction debts. Congestion pricing in MLs entails one of several strategies, including time of day pricing, dynamic pricing based on predicted/anticipated traffic conditions, and real-time dynamic pricing based on actual traffic conditions. The overall goal of this study has been to develop a Decision Support System (DSS) tool based on drivers' revealed willingness to pay (WTP) values. This should determine more effective dynamic toll pricing that achieves the ML corridors' operational goals. A key challenge has been estimating drivers' revealed WTP as influenced by their perceived values of time or by other factors such as enhanced safety and more reliable travel times.

While there are significant advances made in the available methods to estimate WTP, research still lacks in the area of dynamic pricing. Indeed, for dynamic toll pricing systems, setting real-time toll prices based only on drivers' average WTP values appears ineffective. However, the WTP values estimated through existing methods represent the average value of travel time saving and/or reliability (VOT and/or VOR) for the total

population. This makes the current approaches more compatible with static networks, which cannot efficiently address the nature of dynamic corridors. Another major drawback associated with current methods is that the travelers WTP values are measured in terms of price paid to save one unit of travel time (VOT). However, the travelers' WTP to use MLs has been shown to be for a number of intertwined reasons and not just for time savings.

This study suggests a number of unique approaches in estimating WTP values. These include a new revealed data source as well as an alternative analysis method for estimating WTP. To obtain more accurate results, the study was limited to the North Tarrant Expressway (NTE) drivers in North Texas and was conducted for different time periods. For this study, traffic count data were reduced from the camera images for different vehicle categories and for five different time periods, including AM and PM peaks, AM and PM inter-peaks, and off-peak periods. In addition, real-time toll prices associated with the study segment and the day and time of the data collection were obtained from the NTE website. The data analysis method involved an existing toll pricing model (TPM) developed in a former Texas Department of Transportation study for setting tolls for MLs. The model was modified and calibrated based on actual ML shares and associated toll prices for the NTE ML corridor. The modified version of TPM (version 5.0) can be employed as a DSS tool to estimate the WTP values for drivers of any vehicle class and for any time of day.

Values of about \$119, \$101, \$71, \$75, and \$59 per hours were estimated as the revealed average WTP for the NTE SOV drivers during AM peak, PM peak, AM inter-peak, PM inter-peak, and off-peak periods, respectively. In addition, a value of \$85 per hour was estimated for the mean revealed WTP (all periods inclusive) for the NTE SOV drivers. The results of this study showed relatively high WTP values and ML share percentages for the NTE drivers, indicating a high level of acceptance of MLs in the region.

Finally, this study suggested applying a new paradigm in WTP estimation studies. The employed data collection and analysis methods were two components of the new paradigm. Besides, the new paradigm recommended evaluating real-time WTP by time of day instead of average WTP values for dynamic pricing schemes. The last component was a recommendation to attribute the WTP values to the travelers' willingness to pay to drive one unit distance on toll lanes instead of to save one unit of travel time.

The DSS tool developed in this study for the NTE ML has the potential to be used by ML operators to measure the real-time WTP values for the ML users. The results of this new methodology may not directly address the questions about travelers' behavior in terms of their reasons to choose between the MLs and GPLs. However, these results can significantly contribute to decision making about transportation policies, in particular, the policies associated with dynamic congestion pricing for ML corridors.

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Chapter 1

Study Objective and Background

According to the United States Department of Transportation, the total number of vehicle miles traveled (VMT) in the United States during March 2016 was 273.4 billion vehicle miles. This number is an increase of 5 percent compared to the VMT in March 2015 [1]. Expanding roadway capacity in order to accommodate such rapid traffic growth has become one of the main challenges for transportation agencies. An effective solution needs to address several issues such as escalating construction costs, right-of-way constraints, and social and environmental impacts, especially in urbanized areas. Limited right-of-way in urban areas prohibits capacity expansion and leads to traffic congestion, delays, and excessive fuel consumption and emissions. Therefore, in order to effectively address mobility needs and provide travel options, the managed lanes (ML) concept has recently gained interest around the country. The operational benefits of MLs are widely discussed in the literature. However, there is still need for further research in the area of providing a decision support system for dynamic toll pricing of MLs to more effectively achieve facility managers' operational goals.

1.1 Problem Statement

Congestion pricing and managed lanes have been recently gaining interest around the country as a practical congestion management strategy as well as a mean to generate revenue to repay debt accrued in constructing and maintaining such facilities. Congestion pricing in MLs entails one of several strategies including time of day pricing, real-time (dynamic) pricing based on actual sensor-monitored traffic conditions, and real-time (dynamic) pricing based on predicted traffic conditions. In many current successful ML projects around the country, variable pricing strategies are used for different time periods (e.g., SH-91 Express Lanes in Orange County, CA) [2]. The dynamic pricing strategy, however, is not widely applied for setting toll prices. The best example of applying a dynamic pricing strategy is the IH-15 Express Lanes in San Diego, CA [2].

The concept of congestion pricing is well documented for the case of static networks, but research still lacks in the area of dynamic pricing. In this study, the optimal toll was sought to prevent MLs from becoming congested while simultaneously maximizing revenue subject to a number of constraints. This was achieved by applying a dynamic pricing strategy based on real traffic conditions on the corridor. A key factor to be considered was drivers' willingness to pay (WTP) tolls as influenced by their perceived values of time or other concerns such as enhanced safety and/or more reliable travel times. The existing data collection and analysis methods employed to estimate WTP cannot efficiently address the dynamic nature of the ML corridors. Despite the significant advances in WTP studies, further improvements seem to be possible and desired, especially with respect to ML dynamic pricing.

Accordingly, in this study, the revealed North Texas drivers' sensitivities to pay toll were assessed through an innovative data source and analysis method. In addition, a Decision Support System (DSS) for dynamic toll pricing was developed based on actual traffic conditions in the managed and neighboring general-purpose lanes while incorporating drivers' revealed willingness to pay values.

1.2 Research Objective

This study aimed at developing a Decision Support System for the dynamic pricing of MLs. A six-mile segment (segment one) of phase one of North Tarrant Expressway (NTE) in suburban Fort Worth, Texas, along IH-820 between IH-35W and SH-183, was selected as the study section (Figure 4-1) [3]. The selected segment was opened to traffic in October 2014 with four toll-managed lanes (two per direction) and four general purpose lanes (GPL) (two per direction). During the first six months, toll rates were static but variable with higher rates during peak hours. After this period, toll rates have fluctuated based on the level of congestion and demand for both MLs and GPLs and/or time of day in order to try to maintain a minimum speed of 50 mph in MLs [4].

In this study, the optimum price was sought in order to prevent the managed lane from becoming congested, with congestion defined as average speeds below 50 mph [4]. In other words, the dynamic prices should result in an acceptable and reasonable level of service for users who pay to use the managed lanes, i.e. at least a 50-mph operating speed. In this study, the field data was first augmented by monitoring the actual demand on the NTE managed lanes at different times of day and pricing conditions to capture the revealed preferences (RP) of north Texas drivers. The results were then compared with the WTP of the NTE's potential users estimated from a stated-preference (SP) survey from a Texas Department of Transportation (TxDOT) -sponsored study [5]. The results of drivers' sensitivity to toll values as obtained by SP surveys and adjusted by the RP results were then used as an input to modify a Toll Pricing Model (TPM) simulation package developed in a recent TxDOT study as a tool to model and price ML facilities [6,7]. After re-calibrating the TPM for the NTE users, various corridor demand levels and conditions were simulated. The outputs from the simulations were used to recommend dynamic toll pricing scenarios in response to various traffic conditions on MLs and adjacent general purpose lanes.

Based on the above objectives, the main outcomes of the research were as follows:

- Assessing revealed drivers' sensitivity to toll price obtained from the field data

- Developing a decision support tool of dynamic toll pricing by modifying and calibrating the existing TPM simulation package [6,7] based on field data from North Tarrant Expressway facility.

Chapter 2

Literature Review

The literature review of aspects related to this project including willingness to pay and dynamic toll pricing of managed lanes is presented in this chapter.

2.1 Willingness-to-pay Toll

2.1.1 Definition

The value of travel time savings (VTTS) or value of time (VOT) is one of the basic components of transportation investment evaluation. Travelers generally value their travel time savings due to one of the following reasons. First, they are able to obtain a monetary benefit through producing goods or providing services during the time saved. Second, they are able to spend the saved time to do something enjoyable or essential. Last, they are able reduce stress, frustration, and other negative attributes of travel delay [8]. However, travel time saving is not the only utility on which travelers place value. In the case of uncertain travel times, travelers have two options; either change their departure time, or choose a more reliable route or mode, with which a higher monetary cost might be associated [8]. The value of time reliability (VOR) indicates the monetary values travelers place on reducing the variability or improving the predictability of travel time by one unit [9,10]. There are several ways to measure travelers' VOR. Some of them include trip time variance or standard deviation, difference of trip time percentiles (usually between the 90th and 50th percentile trip time or between other convenient points on the distribution), or the probability of lateness beyond a fixed time [8,10]. Travelers' VOR is more complex to gauge than an average VOT. Furthermore, the relation between VOT and VOR does not follow a steady functional form and usually is not easy to understand or model [11].

Travelers generally choose their mode and time of travel to maximize their utility (e.g. travel time reliability) or more accurately, to minimize their disutility (e.g. unpleasant travel time) [12, 13]. People often do not treat the travel time just as a cost and budgetary constraint; but they believe it can also cause a direct utility or disutility to them [14]. Indeed, travel time savings depend both on the disutility of the time spent to travel and on the use to which the time saved is put. The disutility of the time spent travelling depends on factors such as the journey length or the effort, comfort, safety, travel time reliability, scenery and other attributes of the trip. Therefore, travelers might pay tolls to provide less disutility (i.e., a more pleasurable or a less stressful ride) for themselves [15]. As a result, it is difficult to separate the pure VOT from the premium placed on trip attributes that affect travelers' willingness to pay. Accordingly, the terminology adopted in this study is the travelers' willingness to pay (WTP) in lieu of the value of time (VOT).

There are various reasons that make the value of time analysis beneficial. Among them, Small [11] mentioned three reasons as the most important ones. First, VOT is critical in decision making about transportation policies. Second, it contributes to better understanding of human behavior that is of interest for fields such as economics. Third, it is one of the important components in travel demand modeling [11]. In the concept of ML toll pricing, it is critical to understand how travelers make their decisions between using General Purpose Lanes (GPLs) (for free) or paying tolls to use Managed Lanes (MLs) [11]. A number of research studies have been implemented to evaluate VOT or VOR, which underscores the importance of both values in this regard [16, 17]. Different data sources and data analysis methods have been employed in these studies. In the following, the most common methods utilized are discussed.

2.1.2 Existing data sources

According to the literature, the more common data sources employed in WTP studies include Stated- and Revealed- Preference (SP and RP) survey data. SP data are based on the elicitation of respondents' statements to hypothetical scenarios. RP data are based on actual drivers' behavior in their real world mode choice experiments. Recently, other sources of revealed data, including loop detector data, Global Positioning System (GPS) data, and dynamic toll data have been introduced to the field [18,19,20,21,22]. In previous WTP studies, one or a combination of these data sources has been used. Survey data, stated preference (SP) and revealed preference (RP), are the traditional sources used in travelers' behavior studies. However, there are a number of disadvantages associated with both. First, a SP survey is able to only capture the mode choice decisions made for hypothetical scenarios offered by the survey questionnaire. This leads to biased estimates since individuals actual decisions may not reflect their responses to the survey questions. To overcome this shortcoming, RP surveys are designed to detect the mode choice decisions made in real-word experiences. However, it is difficult or impossible to measure all the existing factors associated with the decision makers' situations (e.g. VOR or unobserved heterogeneity [8, 11]). In addition, covering only the limited number of surveyed or observed conditions is also pointed out as a drawback of both approaches.

The various capabilities and shortcomings of each data source might result in different datasets obtained for the same population. This leads to different VOT/VOR values estimates. Therefore, in some studies, both SP and RP data have been employed [23,24]. Combining SP and RP data allows detection and correction of any systematic biases in SP results based on RP data [25]. This method still suffers from a number of deficiencies, including non-response bias, and the fact that collecting RP data is typically expensive and time consuming [20]. To overcome some of the shortcomings associated with survey data, loop detector and GPS data are used as alternative data sources in some more recent studies [18,19]. While the previous drawbacks might be addressed by these new methods, the former lacks the resolution of disaggregate data, and the latter is costly due to new equipment installation requirement. The GPS data collection methods also require considerably more time and effort to find volunteers to participate. More recently, dynamic toll data are used as an alternative source in some studies [20,21,22]. Since only two variables, toll and travel time savings, can be provided through this source, the results are considered to be biased. This is especially caused by not considering travel time variabilities (reliabilities) [21]. To overcome this problem, dynamic toll data were combined with loop detector data in a recent study by He et al. [20]. While the lack of travel time reliability in WTP estimation was addressed, the results were still prone to bias. This was due to the unavailability of adequate data associated with travelers' socio-demographic characteristics and trip attributes. Another major weakness of employing dynamic toll pricing data to estimate VOT/VOR was that only data associated with ML users could be provided and GPL users' information were not available. In another research project conducted by Sheikh [22], a combination of two data sources including revealed field data and household level socio-economic data was employed [22]. The revealed data included disaggregated, automated Express Lane use and non-use data. Therefore, the data associated with both MLs and GPLs were provided. In addition, the socioeconomic backgrounds of the users were also represented in his model. However, there were possible sources of bias associated with the suggested data sources. First, matching the revealed data with the vehicle registration database could result in biased estimates. Additionally, lack of data regarding trip attributes information could be another source of bias.

The methods mentioned above are the common data sources that have been used in available literature for WTP studies. Despite the significant improvements made in data collection efforts, these are still some possibilities for biased results, as discussed above. This indicates a need for further improvements in data collection efforts.

2.1.3 Existing data analysis method

Regardless of the methods used to obtain data, all the studies employed the same method to analyze the data. The travelers' WTP is often estimated through discrete travel choice modeling as the marginal rate of substitution (MRS) between time and monetary cost [26]. The results obtained from these models are subject to change based on different factors. First, the accuracy of the results strongly depends on the data source, as different sources capture different aspects of the users' behavior. Indeed, VOT/VOR estimates are not strong functions of the explanatory variables used in the models. Finding more observable explanatory variables, for both travelers' socio-economic characteristics and trip attributes, could lead to significant enhancements.

In order to better measure the travelers' sensitivity to different tolls, it is critical to understand how people implicitly value their travel time savings. The literature shows that a number of factors affect the travelers' WTP. These include factors such as travelers' characteristics (e.g., age, gender, and income), and their trip attributes (e.g., time of day trip taken, trip purpose, trip characteristics (level of congestion), trip length, travel mode, and size of the travel time savings) [11,12,14].

In a study conducted by Algers et al. [27], it was observed that travelers aged 45 or younger seemed more sensitive to travel time than older travelers. According to Patterson et al. [28], female commuters were often less time sensitive than male commuters. Other studies showed that the travelers' income affected the value they place on their travel time savings [29]. In previous research studies, the prevailing average wage rates of potential facility users were usually used to determine the WTP [30]. However, according to both theoretical and empirical research, the current wage rate of an individual would not be a good estimator of WTP. Indeed, travelers' willingness to pay could be significantly higher or lower than their wage rate [14]. Cherlow [31] studied the estimated

WTP from previous studies, which varied from 9% to as high as 140% of the wage rate. He suggested that there was no single value of travel time savings for different individuals in different circumstances. Small pointed out that travelers' VOT increased with income or wage rate, but not proportionally [27]. In a study recently conducted for the IH-85 HOT Lane in Atlanta, no relation was observed between income and using toll lanes [32].

Wardman showed that travelers had generally greater WTP for commuting than leisure trips [33]. In another study, the travelers' behavior was studied in different situations including one normal situation versus six urgent ones [34]. The results showed higher WTP values for travelers in an urgent situation than those in normal situations [34]. It was also shown that the value of motorists' time also varies with the level of traffic congestion [35]. In another study by Wardman [36], a "congestion multiplier" was suggested and estimated for travelers. Any such "congestion multiplier" could be explained by more difficult and accident-prone conditions with a higher sense of frustration and greater unreliability [37]. Wardman et al. recommended that to study travelers' behavior, a finer categorization of traffic congestion (i.e., free flow, busy, light congestion, heavy congestion, stop-start, and grid lock) should be considered instead of the simple dichotomy of congested and uncongested traffic conditions [37].

On the other hand, the factors affecting the travelers' mode choice decision are not all measurable (e.g., individual tax rates, ability to use time saved productively, fatigue from travel and congestion, non-flexible work-hours [11]), or even not known to researchers. In addition, all the models cannot address the observed and unobserved heterogeneity of the drivers [11]. The inaccuracies of the results would still not be resolved by employing more advanced models such as mixed logit models. For example, the different choice of distribution function for the random coefficient can yield different coefficient estimates [11]. These are some of the major barriers in VOT/VOR studies that are mostly caused by the data analysis method.

The studies mentioned above are just a few examples of studies on travelers' WTP. There are some points that should be further investigated. First, in addition to the factors considered in the models, travelers' WTP can be strongly affected by other possible but unknown factors. Second, the existing methods in the field mainly measure the average behavior of the system. While this is more compatible with static networks, it cannot efficiently address the nature of dynamic ones. Third, as shown in the literature, different factors definitely influence travelers' WTP. However, all the individual travelers are not affected in similar ways. Using the population average WTP estimated through current methods to individual travelers would not address the dynamic nature of ML networks. Accordingly, despite the significant progress made in this field, there are still potentials for more enhancements.

Furthermore, WTP values vary among different times and regions. Most recently, some research studies focused on estimating the WTP of users on specific MLs. The WTP of passenger car drivers for Metro Atlanta was estimated by GDOT from $7 to $15 per hour [38]. According to their estimates, WTP varied for trucks from $10 for 2-axle trucks to $28 for 6-axle trucks [38]. In another study conducted by FDOT [39], WTP was estimated to vary widely from $2.27 to $79.32 per hour for IH-95 travelers. These indicate a wide variation in WTP in various regions and hence, a further impetus to determine the revealed WTP for the North Texas drivers and implement a more effective dynamic toll pricing scheme.

2.2 Dynamic Toll Pricing of Managed Lanes

Road pricing is being considered as a financing mechanism for infrastructure maintenance in many countries worldwide. It may also help with roadway congestion problems and reduce system-wide delays, fuel consumption, and emissions. However, this is only one of the strategies of a total management package and congestion problems would not be solved by only using this strategy.

Due in part to early Federal Highway Administration (FHWA) Value Pricing Pilot Program efforts in 1991 Intermodal Surface Transportation Efficiency Act (ISTEA) and the Transportation Efficiency Act for the 21st Century (TEA-21), the ML concept has gained increasing attention in the United States [2]. The expected increase in MLs popularity is considered a potential factor in the over-use and congestion on managed lanes [2]. Therefore, the congestion on MLs should be, to the extent possible, controlled or it would defeat the purpose of having MLs as a congestion mitigation tool. One potential approach could be to adopt pricing strategies to keep MLs at an acceptable level of service. Indeed, the toll should ideally be set at an optimum price that results in a reasonable speed on MLs and maximized throughput for the corridor as a whole.

2.2.1 Definition

Congestion pricing, also known as congestion-relief tolling, has been practiced under different schemes including fixed-rate pricing, variable pricing, and dynamic pricing. Flat rate schemes do not change the toll price while in variable pricing the price of toll is influenced and varies by different factors including time-of-day (peak-hour period versus non-peak-hour period and weekday versus weekends), facility location, season, day-of-week, or air quality conditions. On the other hand, in dynamic pricing systems, toll rates fluctuate with operating conditions that reflect current congestion levels [40]. In order to dynamically estimate the optimum toll price for managed lanes, congestion levels should be monitored in real-time.

Dynamic toll schemes vary the toll price in real time (or near real time) as a function of prevailing or historical traffic conditions [41,42]. Thus, if congestion occurs in GPLs, the toll can be raised in order to limit the number of drivers who enter the ML during the disruption. The principal challenge is to set the price at a sufficiently high rate before the congestion/breakdown occurs in the MLs. To do so, a proactive (anticipatory) approach has been developed by Dong et al., which proves to be more effective to control the congestion [43]. In this approach, instead of prevailing or historical traffic data, predicted traffic data were used by a proactive pricing strategy. Therefore, any probable significant changes in network conditions, such as incidents, during an individual's travel through a ML was considered by the model in order to provide the expected level of service and a more reliable travel time due to the amount of toll which was paid [43].

2.2.2 Better-known ML facilities in the United States

As indicated in Table 2-1, some of the existing ML facilities around the country are practicing dynamic toll pricing schemes. The IH-15 Express Lanes in San Diego, California is the best example of using this type of pricing scheme. The price varies by entrance location and is a rate per mile multiplied by the distance of travel for that trip. Tolls range from $0.50 to a maximum of $8 per trip, which is set via a distance-based dynamic pricing system. In order to ensure a free-flow speed on the MLs, every three minutes, the per-mile toll rate is recalculated according to the level of congestion on MLs [44].

Table 2-1 Better-known Managed Lane Facilities in the United States

Name	Location	Length (miles)	Congestion Pricing Schemes
SR-91	Orange County, CA	10	Variable
IH-15	San Diego, CA	20	Dynamic
IH-680	San Francisco, CA	14	Dynamic
IH-10	Houston, TX	12	Variable
US-290	Houston, TX	15	Variable
IH-95	Miami-Ft. Lauderdale, FL	7	Dynamic
IH-394	Minneapolis-St. Paul, MN	22	Dynamic
IH-35W	Minneapolis-St. Paul, MN	26	Dynamic
IH-25	Denver, CO	7	Variable
IH-15	Salt Lake City, UT	62	Dynamic
SR-167	Seattle, WA	10	Dynamic
IH-85	Atlanta, GA	15.5	Dynamic

In some of the other facilities, toll prices are adjusted based on algorithms in response to traffic conditions. For example, to provide the IH-15 Express Lanes users in Salt Lake City with speeds around 55 mph, toll prices vary between $0.25 to $1 per zone based on congestion levels, with the highest prices during peak traffic times [45]. The Salt Lake Express Lanes are divided into six payment zones. In the IH-680 Express Lanes in San Francisco, toll rates vary from a minimum of $1 per trip during the morning peak to a minimum of $0.30 during off-peak periods in response to the level of demand [46]. According to the level of congestion, the average peak period toll prices vary between $1 and $4 per toll zone for the IH-35W and IH-394 Express Lanes in Minnesota [47]. On IH-95 Express Lanes in Florida, tolls vary from $0.20 to $0.80 per mile based on the level of congestion of the express lanes only, and not based on the adjacent GPL conditions [39].

2.2.3 Challenges in dynamic toll pricing

Uncertainties in the network are caused by uncertainty on the supply-side (e.g., the effect of an incident or maintenance activities), uncertainty on the demand-side (e.g., due to prediction errors in demand forecasting), and/or travel behavior [35, 48]. In terms of congestion management, short-term capacity disruptions (e.g., poor weather, incidents, or short-term maintenance activities) critically affect even the long term planning for managed lane corridors [48]. In a study, Boyles et al. [49] examined the toll pricing problem under stochastic supply conditions. The results showed that toll schemes, which consider uncertainty in supply involve significantly higher prices.

Travel demand and network capacity are major factors affecting network performance. The stochastic nature of travel demand and network capacity in managed lane corridors pose a challenge for toll pricing strategies that attempt to predict the potential users of MLs based on toll prices. Moreover, these uncertainties in traffic conditions affect the drivers' WTP a certain toll rate to use the managed facilities. Therefore, reliable data on drivers' WTP is considered a critical component to successfully model the impacts of tolls on travel demand and network performance [14].

While the concept of congestion pricing is well documented for the case of static networks, research still lacks in the area of dynamic pricing. The dynamic nature of ML corridors requires a method that allows capturing the frequent fluctuations in the corridors' condition and demand. Developing a decision support system (DSS) tool for ML dynamic toll pricing seems essential. As discussed, the existing methods employed to estimate WTP values cannot efficiently capture the uncertainty in the ML corridors' demand and supply. To estimate and use the average WTP values, which might be significantly different from an individual traveler's real-time WTP, can be mentioned as the major drawback with the current dynamic pricing practices.

Recently, a regionally supported managed lane system has been developed in the Dallas-Fort Worth (DFW) region. Recently, the North Tarrant Expressway (NTE) (first and second segments), Lyndon Baines Johnson (LBJ) TEXpress lanes, and the DFW airport connector TEXpress lanes have opened to traffic as part of this ML network [50]. To operate these facilities, a dynamic pricing method is implemented for setting the toll rates. After six months from the opening of each facility, toll rates began fluctuating based on the level of congestion and demand on both MLs and GPLs and/or time of day to try to maintain a minimum of 50 mph speed on MLs. Real-time rates are calculated based on the actual traffic data monitored by roadside equipment [4]. Typical toll prices on each TEXpress toll segment may range from $0.15 to $0.35 per mile during non-peak periods, and from $0.45 to $0.75 during peak periods [50].

This study aims at using a new data source and analysis method that could contribute to improving the dynamic toll pricing effectiveness. A literature review presented in this chapter was conducted to understand the state-of-the art in WTP and the dynamic pricing schemes for managed lane toll pricing as well as the existing shortcomings in this field. In the next chapters, the new data collection efforts and analysis method will be presented. The new approach is suggested as an alternative source to the traditional methods used in this field to develop an efficient DSS tool to more effectively achieve facility managers' operational goals.

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Chapter 3

Study Approach

The overall goal of this study was to enable planners to more accurately model the demand on dynamically managed lanes. This was not likely without assessing the revealed preference (RP) of drivers in terms of their sensitivities to toll prices. The WTP is one of the basic components of transportation investment evaluation. In the concept of managed lanes toll pricing, it is critical to understand how people implicitly value their travel time.

The study of driving behavior is often complex and error-prone. If it is conducted through different data collection and analysis methods, the results are often not consistent with each other and with field behavior. Another complication in studying travel behavior is that it is spatially and temporally sensitive. Indeed, it varies from region to region and time of day as well as from individual to individual. Even for a single individual, it varies by many factors such as time of day, day of week (weekday versus weekend), and trip purpose.

Accordingly, it is essential to implement specific dynamic toll pricing schemes based on different regions and time periods with allowance for variability across individuals. The focus of this study was to develop a decision support tool for dynamically pricing the North Texas region ML tolls by studying the NTE TEXpress corridor as a case study. To consider the effects of time on the sensitivity of the drivers to toll rates, five different time periods were considered for data collection; two peak periods (AM peak (6:00 AM- 9:00 AM) and PM peak (4:00 PM- 7:00 PM)), an off-peak period, and two inter-peak periods (AM inter-peak (11:00 AM- 12:00 PM) and PM inter-peak (7:00 PM- 8:00 PM)).

The approach to this study can be summarized as follows:

- Determine the stated WTP through an SP survey,
- Determine the average WTP through field observations,

- Determine the distribution of revealed WTP values through simulation runs that match the ML/GPL volume splits observed in the field,
- Select a distribution of revealed WTP values, which yield the same average values as those observed in the field.

3.1 Determining the Stated WTP through the SP Survey

The travelers' WTP is usually estimated by conducting SP studies. In the case of a toll pricing study, the SP survey is designed to gain information related to hypothetical choices for a range of different toll levels and travel time savings scenarios. The data obtained by SP methods are analyzed via discrete travel choice models. Accordingly, the stated preference of a WTP toll is calculated as the marginal rate of substitution (MRS) between time and monetary cost in the model. Due to time and budget constraints, we were unable to conduct a SP survey as part of this study. Instead, we used the data obtained from the SP survey conducted for TxDOT in 2006 for the first phase of the NTE [5] and estimated by AECOM Enterprises as part of the NTE-Traffic and Revenue Forecast study in 2009 [52]. In Chapter 4, more details about the survey administration and questionnaire design are presented. The stated WTP for different times of day that was estimated through the SP surveys was used as a starting point for the simulation of the study section through Toll Pricing Model (TPM).

3.2 Determining the Average WTP from Field Data

For the purpose of this research, traffic count data were reduced from the camera images for different vehicle categories and different time periods. In addition to the traffic count data, toll prices associated with the study segment and the day and time of the data collection were obtained from the NTE website [51].

First, based on the assumed traffic flow model that was most representative of the traffic flow characteristics of the study corridor, the speed (mph) and travel time (minutes) for the observation points were estimated. The travel time savings (minutes) associated with each prevailing toll charge were then obtained through the differences between the associated travel time on the MLs and the travel time on the GPLs. The average WTP value was estimated by the average toll paid divided by the average travel time saved by Single Occupant Vehicle (SOV) drivers for each respective study period.

3.3 Determining the Revealed WTP through TPM

The Toll Pricing Model (TPM-5.0) used in this study was a modified version of the Toll Pricing Model (TPM-4.3), which was developed based on a recent study conducted for TxDOT [6,7].

As mentioned earlier in this chapter, the stated WTP was used as a starting point to simulate the field data through the TPM. The initial WTP distribution scenario from the SP surveys was then modified until the output of simulation runs produced similar ML/GPL flow splits as the field observations. The simulation runs were based on trial and error attempts of different WTP distribution scenarios. To determine which of the WTP distribution scenarios would best represent the revealed WTP, two criteria were considered, as follows:

- Simulation runs using the WTP distribution being examined must result in the same split between the ML and GPL as observed in the field,
- The WTP distribution must also yield the same average WTP as obtained from the regression models on the field data.

Accordingly, the output of the simulation runs was compared to the field observations. The price sensitivities within the TPM were tweaked until simulation runs produced similar splits as observed volume splits in the field. In cases when more than one

WTP distribution scenario yielded the same split as observed in the field, the average, which was obtained from the linear regression models was used as a second criterion to choose among those alternatives. For the WTP distribution scenarios, which led to the same traffic split in TPM as in the field, the average WTP value was calculated. To do so, the mid-values of the WTP intervals in each scenario were multiplied by the percent of the population distribution belonging to the respective WTP intervals. The average WTP for each distribution scenario was then calculated by aggregating these values over all the intervals to obtain a weighted average.

The WTP distribution scenario, which led to the same volume split as the field and also yielded the same average WTP as obtained from the field data was considered to best represent the revealed WTP for the associated period. These WTP values were then used to modify the TPM into a decision tool for toll pricing.

The next chapter presents the data collection process used in this study. As mentioned earlier, this study employed an alternative data source to the existing ones using the WTP studies.

Chapter 4

Data Collection

The overall goal of this study was to enable planners to more accurately model the demand on dynamically managed lanes by assessing the revealed preference (RP) of drivers in terms of their sensitivity to toll prices. This required data to be collected from potential and current travelers who were using MLs or who had an option of using MLs.

This study first used the data collected from the North Tarrant Expressway (NTE)'s potential users through the stated-preference (SP) surveys, which were conducted for TxDOT in 2006 [5]. Then, traffic counts were made by monitoring the actual demand on the NTE managed lanes and general purpose lanes at different times of day and pricing conditions to capture the actual usage of toll lanes. The result of drivers' sensitivity to toll values obtained by SP surveys and RP results obtained from the field were then used as an input to modify a Toll Pricing Model (TPM) simulation package [6,7] developed in a recent TxDOT study as a tool to model and price ML facilities. Details of the study section as well as the process of data collection are presented in this Chapter.

4.1 Site Description

The study section for this research is a 6-mile segment (segment one) of the first phase of the North Tarrant Expressway (NTE) in suburban Fort Worth, along IH-820 between IH-35W and SH-183. The NTE is dedicated to improving mobility along north IH-35W, northeast IH-820 and SH-121/183 Airport Freeway through a regionally supported managed lane system. This project is one of six major Dallas-Fort Worth TEXpress corridors that will form the regional TEXpress Lanes network [3]. The selected segment was completed and opened to traffic in early October 2014. The corridor had four main lanes and four TEXpress (toll-managed) lanes, two each direction. By 2030, frontage roads and auxiliary lanes would be completed and two additional GPLs would also be added to the corridor. During the first six months, toll rates were static but variable, with higher rates during peak hours. After this period, toll rates fluctuated based on the real-time level of congestion and demand for both MLs and GPLs and/or time of day to maintain a minimum of 50 mph speed on MLs [3].

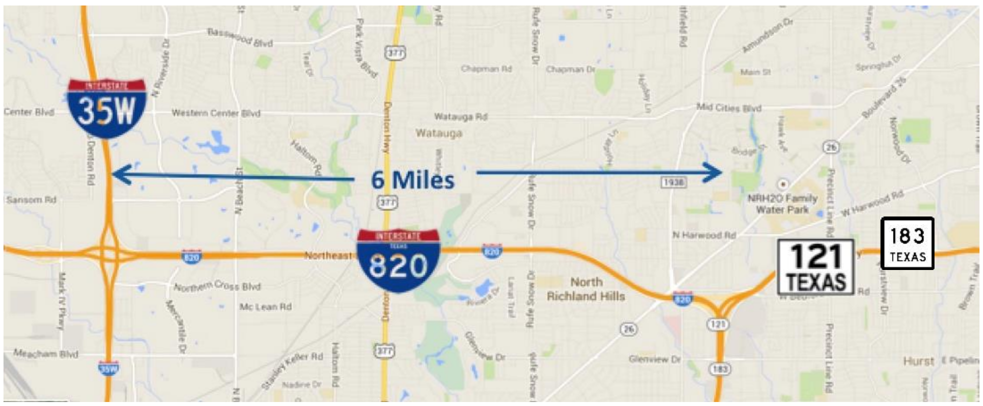


Figure 4-1 Study Section [53]

4.2 Stated Preference Survey Data

The value of time (VOT) is one of the basic components of transportation investment evaluation. In the concept of managed lanes toll pricing, it is critical to understand how people implicitly value their travel time. Travelers' VOT is often estimated by conducting stated-preference (SP) studies. In the case of a toll pricing study, the SP survey is designed to gain information related to hypothetical choices for a range of different toll levels and travel time savings scenarios. The data obtained by SP methods is analyzed via discrete travel choice models. Accordingly, the stated preference of WTP toll is calculated as the marginal rate of substitution (MRS) between time and monetary cost in the model. Due to the budget constraints, I was not able to conduct a SP survey for the purposes of this study. Instead, we used the data obtained from the SP survey conducted for TxDOT in 2006 for the NTE first phase. In the following sections, more details about the survey administration and question design are presented.

4.2.1 Survey administration

This study used data from the survey conducted by Resource System Group, Inc. (RSG) for the IH-820/ SH-183 Travel Study for TxDOT in January 2006 [5]. As documented in an AECOM report [52], the design, implementation, and analysis of the survey were directed by Wilber Smith Associates (now CDM Smith) and a total of 1,930 individuals completed the survey. The results were documented by RSG in two sections, including the raw data in SPSS format containing all the stated preference data and the corresponding background data and the document with summarized results in PDF format. For the purpose of this study, both reports [5, 8] were obtained through a Public Information Act request from TxDOT in November 2014.

Travelers between Dallas and Fort Worth who either had used or could have used IH-820 or SH-183 for trips longer than 15 minutes were asked to take the survey. The focus was mainly on sites adjacent to the study corridor, which provided access to travelers with work and non-work purposes as well as travelers with airport and non-airport trips.

To gather the data, a computer-assistant self-interview (CASI) instrument with both Internet and field-intercept administration techniques were used as follows:

- Survey at field intercept sites
- Online survey to businesses within the study corridor
- Online survey to individuals who participated in an origin-destination study and agreed to be contacted for this study [52].

4.2.2 Stated preference questionnaire design

The survey consisted of five main parts: context questions that asked for details of the respondent's trip (a recently made one-way trip that was longer than 15 minutes and was or could have been made through the study section of IH820/ SH183), an introduction to the proposed IH-820/ SH-183 Managed Lanes, stated preference questions that offered hypothetical travel alternatives with different levels of toll, different travel time and other vehicle occupants, if applicable, followed by a series of background questions.

Each respondent was presented a total of eight trade-off scenarios with two, three or four distinct hypothetical travel alternatives in each choice set for a trip similar to the one the respondent had described in the first section. The information obtained from the first section had been used to customize the scenarios' options based on its characteristics. The options in each scenario were as follows:

- Option 1: GPLs with no toll
- Option 2: New MLs, driving alone with an electronic toll tag
- Option 3: New MLs, driving in a carpool with an electronic toll tag
- Option 4: Staying with the respondent's current route.

Note that option 3 was shown only to the respondents who recently had traveled in a vehicle with two or more occupants, and option 4 was presented only when the respondents had not used IH-820/ SH-183 for their recent trips.

To ensure that the greatest possible amount of information could be obtained from the fewest possible experiments, a fixed fractional factorial orthogonal experimental design was used. This allowed assigning the specific values in each SP survey, with the resulting orthogonal design for this survey containing 16 experiments. A randomly selected and randomly ordered set of eight of these experiments was presented to each of the participants. Each experiment included up to eight attributes, and five of them were independently varied. For those who had not used the study portion of IH-820/ SH-183, the presented experiments included an option for staying with their current travel route, which had two attributes of time and cost.

Finally, a series of general socio-demographic questions were asked in order to allow a comparison of the sample population to the whole population that would be served by the new managed lanes. These questions contained household size, number of total and young children in the household, number of vehicles owned by the household, age, gender, employment status, and the annual household income.

4.3 Field Data

For the purpose of this research, five different time periods were considered for data collection; two peak periods (AM peak and PM peak), an off-peak period, and two inter-peak periods (AM inter-peak and PM inter-peak). Obtaining field data was a challenge, as both TxDOT Forth Worth and North Texas Tollway Authority (NTTA) were reluctant to provide access to the records from their live cameras. To start, some preliminary field data were gathered for AM peak periods by visiting the Fort Worth Transvision center and using the live camera feeds at the center. However, the study required traffic counts from the field for different vehicle categories. This was not possible through live camera images since it would increase the probability of errors in counting without options to slow the camera images, pause, or rewind them. Finally, NTTA and TxDOT agreed to provide recorded camera images at a specific site midway through the NTE section under study.

In addition to the traffic count data, toll prices associated with the study segment and the day and time of the data collection were obtained from the NTE website. The detailed process and results of data collection are explained in the following sections.

4.3.1 Traffic count data

The field data was recorded from one of the NTTA cameras, which was located at the intersection of the NTE study section and U.S. 377 (Denton Hwy). Figure 4-2 shows the location of the camera along the study segment.

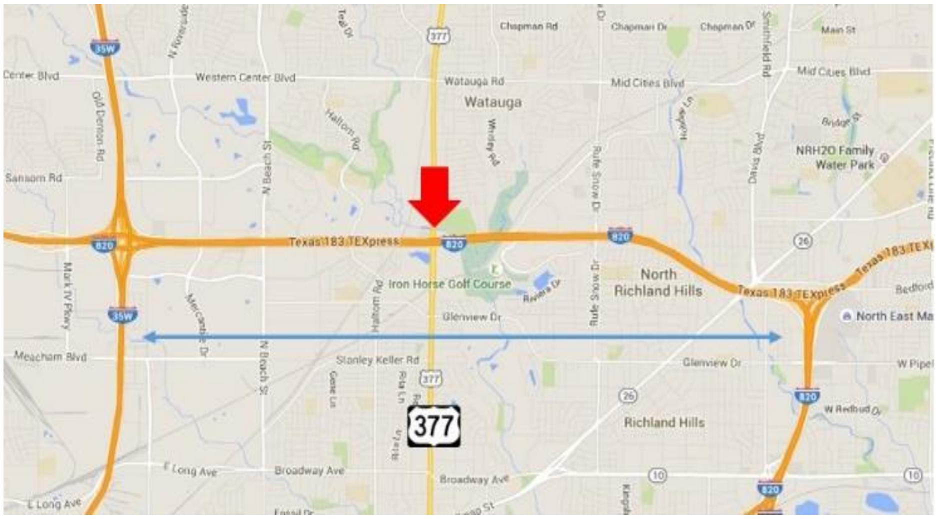


Figure 4-2 Location of the Camera Used for Data Collection [53]

The data were collected for different days of the week (weekdays and weekends) and different times of the day (AM and PM periods) and different traffic conditions (peak, off peak, and inter-peak periods). Table 4-1 summarizes the obtained data from the field by period of the day, date, and day of the week.

Table 4-1 Period, Date and Day of Data Collection

Period	Date	Day of the Week
AM Peak	Nov-03-2015	Tuesday
	Dec-08-2015	Tuesday
	Dec-09-2015	Wednesday
	Dec-10-2015	Thursday
PM Peak	Oct-30-2015	Friday
	Dec-08-2015	Tuesday
	Dec-09-2015	Wednesday
	Dec-10-2015	Thursday
Off Peak	Oct-31-2015	Saturday
	Nov-05-2015	Thursday
	Nov-08-2015	Sunday
AM-inter Peak	Nov-04-2015	Wednesday
PM-inter Peak	Nov-02-2015	Monday

Toll prices on the NTE managed lanes vary by the size class of the vehicle instead of the number of axles [51]. The purpose of this study was to develop a decision support tool to dynamically set the toll prices, which could be used for any managed lane corridors. Therefore, the definition of the different vehicle classes presented by NTTA was modified based on the classes defined in the Highway Capacity Manual [54]. Hence, this classification would be generally recognized in applying the TPM software for modeling any other corridors. These new classes were then used to categorize the traffic count data as reduced from the video recordings as well as to modify the TPM software. Table 4-2 shows the different vehicle classes and the associated toll policies, which were used in this study to collect and analyze the data.

Table 4-2 Vehicles Classes and Associated Toll Policies

Vehicle Class	Prevailing Toll Factor [1]
Single Occupancy Vehicles (SOV)- Class 12[2]	1.0 × (Base Toll Rate)
Registered High Occupancy Vehicles (HOV) and Motorcycles- Class 12	0.5 × (Base Toll Rate)[3]
SOV, +1 trailers- Class 13	2.0 × (Base Toll Rate)
Single-unit Trucks- Class 14	3.0 × (Base Toll Rate)
Semi-trailer Trucks- Class 15	4.0 × (Base Toll Rate)
Semi-trailer Trucks, Double or Triple Trailers- class 16, 17	4.0 × (Base Toll Rate)
Special Vehicle or Special Permit Vehicles- class 18	5.0 × (Base Toll Rate)

The traffic count data obtained from the video recordings were stored in Excel format. Table 4-3 presents a sample of traffic count data for the eastbound direction in terms of different vehicle classes, collected for the AM peak period on Tuesday, November 3, 2015 (6:00 AM to 9:30 AM).

As mentioned, video recordings supplied by NTTA were used to obtain traffic count data. This procedure imposed a number of constraints on data accuracy. First, for the last vehicle class, Special Vehicle or Special Permit (class18), it was not possible to positively recognize them from the images. This was because the vehicles' weight was also an attribute in defining this class. In the same way, vehicles that were required to obtain a special permit from authorities to use the facility could not be recognized. Note that the focus of this study was only on the SOV class drivers and other vehicle classes were just considered in terms of their impact on the corridor's traffic conditions. The changes in the traffic conditions would definitely affect the SOV class drivers in their decision to use or not use the ML. Therefore, it was assumed that the percent of the vehicles in the corridor which

[1] *http://www.ntetexpress.com/pricing/check-past-rates*
[2] *The class numbers are related to the NTTA suggested vehicle classification*
[3] *The 50% discount is only offered to registered HOV (+2) and motorcycles and only during peak periods.*

belonged to such special classes would be negligible. However, considering them could capture their impact on the SOV drivers' decisions. These special classes included semi-trailer trucks, and double- or triple-trailer vehicle classes. As shown in the records, no traffic count data in the last vehicle class was ever observed during any of the five observation periods listed inTable 4-1.

Travel behavior studies are essentially dependent on the data collected from trips and travelers. For this study data, the stated WTP for potential NTE users which was estimated from the SP survey was obtained. In addition, traffic volume splits between the MLs and GPLs was collected from the field as well as the associated toll for MLs. Details of the data collection process were presented in this chapter (Chapter 4). The analysis carried out on these data for achieving the study objectives is presented in the next chapter.

Table 4-3 A Sample of Collected Data for AM Peak in One Day

Time	Base Price ($/6 miles)	SOV (Base Price) (v/5-minute)		Registered HOV and Motorcycles (0.5× Base Price) (v/5-minute)		SOV, +1 Trailers (2× Base Price) (v/5-minute)		Single-unit Trucks (3× Base Price) (v/5-minute)		Semi-Trailer Trucks (4× Base Price) (v/5-minute)		Semi-Trailer Trucks, Double or Triple Trailers (4× Base Price) (v/5-minute)		Special Vehicle or Special Permit (5× Base Price) (v/5-minute)		Total (vph)		
		ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	Total
6:00- 6:05	2.67	67	246	1	82	0	0	2	7	6	9	0	0	0	0	912	4128	5040
6:05- 6:10	3.21	82	207	2	69	0	1	1	4	5	10	0	0	0	0	1080	3492	4572
6:10- 6:15	3.3	85	194	2	65	0	0	1	5	2	5	0	0	0	0	1080	3228	4308
6:15- 6:20	3.3	80	215	1	72	0	0	1	6	1	10	0	1	0	0	996	3648	4644
6:20- 6:25	3.3	83	209	2	70	0	2	4	1	3	8	0	0	0	0	1104	3468	4572
6:25- 6:30	3.3	105	202	2	67	0	0	6	6	1	7	0	0	0	0	1368	3384	4752
6:30- 6:35	3.54	111	207	2	69	0	1	2	4	3	14	0	0	0	0	1416	3540	4956
6:35- 6:40	3.9	108	219	2	73	1	2	5	2	0	6	0	1	0	0	1392	3636	5028
6:40- 6:45	3.9	92	221	2	74	3	0	4	4	1	9	1	0	0	0	1236	3696	4932
6:45- 6:50	3.9	99	236	2	79	0	2	2	8	5	5	0	0	0	0	1296	3948	5244
6:50- 6:55	3.9	88	222	2	74	1	0	3	8	4	6	1	0	0	0	1188	3720	4908
6:55- 7:00	3.9	119	225	2	75	1	1	4	7	3	7	0	0	0	0	1548	3780	5328
7:00- 7:05	4.02	91	231	2	77	3	4	3	4	5	4	2	0	0	0	1272	3840	5112
7:05- 7:10	4.2	103	231	2	77	1	2	5	3	4	8	0	0	0	0	1380	3852	5232
7:10- 7:15	4.2	99	248	2	83	2	0	1	1	8	8	2	0	0	0	1368	4080	5448
7:15- 7:20	4.2	94	215	2	72	2	1	2	1	2	7	0	0	0	0	1224	3552	4776
7:20- 7:25	4.2	79	250	1	83	1	4	1	2	6	1	0	0	0	0	1056	4080	5136
7:25- 7:30	4.2	74	233	1	78	1	5	2	3	6	13	0	0	0	0	1008	3972	4980
7:30- 7:35	4.2	77	229	1	76	1	2	2	9	2	4	0	2	0	0	996	3864	4860
7:35- 7:40	4.2	89	247	2	82	0	5	4	3	4	3	0	1	0	0	1188	4092	5280

Table 4-3-*Continued*

Time	Base Price ($/6 miles)	SOV (Base Price) (v/5-minute)		Registered HOV and Motorcycles (0.5× Base Price) (v/5-minute)		SOV, +1 Trailers (2× Base Price) (v/5-minute)		Single-unit Trucks (3× Base Price) (v/5-minute)		Semi-Trailer Trucks (4× Base Price) (v/5-minute)		Semi-Trailer Trucks, Double or Triple Trailers (4× Base Price) (v/5-minute)		Special Vehicle or Special Permit (5× Base Price) (v/5-minute)		Total (vph)		
		ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	ML	GPL	Total
7:40- 7:45	4.2	70	243	1	81	0	2	3	2	2	9	0	0	0	0	912	4044	4956
7:45- 7:50	4.2	83	223	2	74	0	5	2	2	9	12	0	0	0	0	1152	3792	4944
7:50- 7:55	4.2	74	216	1	72	1	8	4	9	5	7	1	0	0	0	1032	3744	4776
7:55- 8:00	4.2	81	206	1	69	0	1	2	6	7	13	0	0	0	0	1092	3540	4632
8:00- 8:05	4.2	90	209	2	70	1	0	2	6	6	10	1	0	0	0	1224	3540	4764
8:05- 8:10	4.2	74	203	1	68	0	3	5	4	10	3	0	0	0	0	1080	3360	4440
8:10- 8:15	4.2	91	205	2	68	0	8	8	8	6	12	0	0	0	0	1284	3612	4896
8:15- 8:20	4.2	69	209	1	70	1	1	3	5	8	7	1	0	0	0	996	3504	4500
8:20- 8:25	4.2	82	201	1	67	0	3	2	7	6	7	1	0	0	0	1104	3420	4524
8:25- 8:30	4.2	90	179	2	60	1	3	2	5	5	11	0	1	0	0	1200	3096	4296
8:30- 8:35	4.2	69	203	1	68	1	4	3	2	2	7	0	0	0	0	912	3408	4320
8:35- 8:40	4.2	59	197	1	66	0	7	3	6	5	15	0	0	0	0	816	3480	4296
8:40- 8:45	4.2	57	197	1	66	1	4	7	8	4	12	1	0	0	0	852	3432	4284
8:45- 8:50	4.2	46	172	1	57	0	2	1	5	2	18	1	0	0	0	612	3048	3660
8:50- 8:55	4.2	54	158	1	53	1	1	1	11	5	19	2	1	0	0	768	2904	3672
8:55- 9:00	4.2	59	178	1	59	1	1	3	8	12	16	0	1	0	0	912	3156	4068

Second, there was a similar problem in gathering the data associated with the registered HOV and Motorcycles classes. The number of individuals in each vehicle could not be captured on video recordings. Therefore, the number of vehicles in the corridor belonging to this class was unknown. Moreover, the toll discount (50% off the base toll rate) applied only during peak periods on weekdays (AM peak: 6:30 to 9:00 and PM peak: 15:00-18:30). The HOV drivers with a minimum of one additional passenger and motorcycles should obtain a valid digital toll tag and register as HOV2+ to be eligible for the discount [51,52]. For the purpose of this study, the traffic volume of registered vehicles on managed lanes belonging only to this category during the AM and PM peak periods were estimated by the average percent of transactions associated with this class as obtained from NTTA. These numbers were 1.8% of the total transactions made during AM peak periods and 1.4% of the total transactions made during PM peak periods. For example, suppose the total number of vehicles on the managed lanes during the AM peak period were 106 vehicles per 5-minute interval. Then, the 106 vehicles could be divided between SOV and HOV classes as 104 SOVs and 2 HOVs (98.2% × 106= 104 SOVs per 5 minutes and 1.8% × 106= 2 registered HOVs per 5 minutes).

For the GPLs, the average vehicle occupancy rate was used to split the recorded numbers of vehicles between SOV and HOV classes. Based on the 2009 National Household Travel Survey [55], the average vehicle occupancy rate for suburban areas in Texas was 1.36. Inversing this occupancy rate (1.36^{-1}=0.74) could roughly show the fraction of vehicles in the corridor that could be considered to be SOVs, with the remainder being HOVs. Accordingly, for the toll-free lanes in the study section, a 75/25 split was assumed for the SOV/HOV ratio. Assuming for example, a combination of 291 (SOV+HOV) vehicles in 5 minutes, 218 (= 75% × 291) vehicles were categorized as SOVs and 73 (= 25% * 291) vehicles were categorized as HOVs.

4.3.2 Toll price data

As shown in Table 4-2, the toll prices associated with the study segment and the day and time of the data collection were obtained from the NTE website. All past rates for the last 180 days can be accessed through the website [51]. In the drop-down menus, the appropriate entry and exit points for the study section were selected. For the eastbound direction trips, the IH-820 east entrance from IH- 35W was picked as the entry point and the SH-26 exit was picked as the end of the trip on the study section. For the westbound direction trips, the two points were selected in reverse. The associated toll rate data were obtained by entering the exact date and time of the data collection and the respective vehicle classes (toll rates were available for every minute). Figure 4-4-3 shows an example NTTA website screen shot showing the prevailing toll prices at the time.

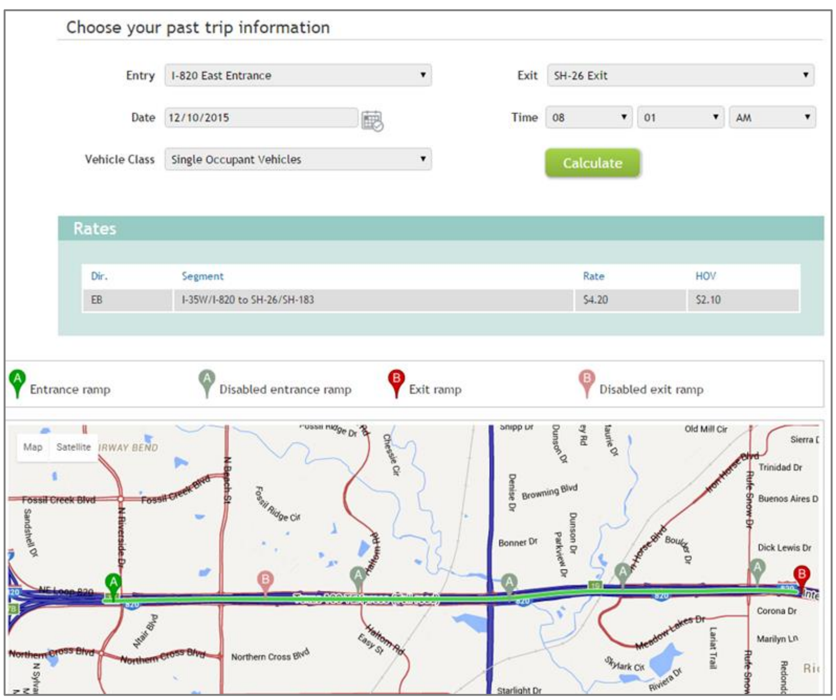


Figure 4-4-3 Example of Using NTTA Website to Check the Prevailing Toll Rates [51]

Chapter 5

Data Analysis and Results

The primary goal of this study was to gain a better understanding of manage lane (ML) travelers' sensitivity to tolls rates. To obtain more accurate results, the study was limited to the NTE drivers in North Texas and was conducted for different time periods. In addition, the field data were collected for different vehicle types categorized based on their size, weight, and the toll rates paid. The analysis carried out to contribute towards achieving the objectives of this study is described in this chapter. First, data were analyzed to obtain an overall picture of the sample population regarding their preferences to use the MLs. The results derived from a preliminary analysis were helpful in finding the general trend of the population in their mode choice decision between MLs and GPLs. Next, a more in-depth analysis of the field data resulting in average revealed Willingness-To-Pay (WTP) estimations for the NTE SOV drivers is presented.

5.1 Preliminary Analysis

The MLs is a relatively new concept in the nation's freeway system. Recently, a limited number of MLs or TEXpress lanes have been introduced to the DFW highway system [3]. In addition, the conventional toll pricing methods are being replaced by an emerging scheme called dynamic toll pricing. In the new system, instead of setting the price based on time of day, the price is continually adjusted according to actual traffic conditions to maintain an acceptable level of traffic. Since these new concepts are still in their early stages, the level of acceptance by users is not yet well specified. Thus, to get a better understanding of the users' responses to the new concepts, an initial analysis was performed on field data obtained from the first segment of NTE ML corridor. These results are presented as follows.

5.1.1 Travel time estimation

According to the National Household Travel Survey (NHTS), travel time is one of the important factors that influenced individuals' choice of transport [56,57]. Specifically, in the case of MLs, travelers mainly pay a toll to reduce their travel time [13,58]. There are also other reasons than travel time savings that explain why people choose to drive on MLs. These reasons include travelers' perception of improved safety and/or more reliable travel time provided by toll lanes [58,59,60]. However, while the impacts of the latter factors might not be negligible, they are not directly measurable. To capture their effects on the drivers' mode choice decision, it would be beneficial to apply other data collection methods such as SP and RP surveys. However, according to the data collected in this study, the overall impacts of travel time savings and toll rates on the sample population could only be examined.

On the other hand, the data obtained from the field (video images from the field) could not directly provide any information about the speed and travel time on the corridor. But, other information including traffic count data for different vehicle categories were reduced from the records. In addition, the geometric attributes of the corridor provided the length of trips (6-mile corridor). Therefore, the speed and travel time could be estimated based on the traffic flow characteristics and the geometric information of the corridor.

To do so, the relationship among the corridor's flow, density and speed was to be first specified. Due to budget and time limitations for this study, we were not able to directly calibrate the existing traffic flow models to find out which one best represents the traffic characteristics of the study section. Instead, we used the Drake model to characterize the NTE corridor's flow-density-speed relationship. This model was used based on recommendations from a previous study by Nepal in 2008 [61]. His study showed that the

Drake model was the best fit for the data collected for two freeway sections in the Dallas-Fort Worth area [6,61]. The general equation of the Drake model is as follows [62]:

$$u = u_f e^{[-0.5(k/k_c)^2]} \tag{5-1}$$

Where:

u = speed (mph)

u_f = free-flow speed (mph)

k = density (pcpmpl)

k_c = density at capacity (pcpmpl)

One way to estimate the model parameters, free-flow speed (u_f) and density at capacity (k_c) is calibrating the model based on the data obtained from the site. However, in this study, these parameters were directly measured based on the data observed in the field. The process of data collection and measurement for the Drake model's parameters is explained as follows:

<u>Free-flow speed</u> (u_f) - is an average free-flow speed (in mph) in the study corridor. In order to estimate u_f value, the vehicles' speeds on the NTE eastbound direction were measured using hand-held K&E Radar. The measurements were performed when the corridor was under free-flow condition, on Tuesday, December 30, 2014 between 10:30 PM and 11:00 PM. At the time, the weather condition was dry and clear. The experiment was done on Tuesday, December 30, 2014 between 10:30 PM and 11:00 PM, at the intersection of IH-820 with Rufe Snow Drive in Fort Worth, TX. The following tables show the speeds measured for both facilities. The free-flow speed was estimated as the average of the measured speeds for each facility. In this way, the free-flow speeds of 73 mph and 63 mph were estimated for the MLs and the GPLs, respectively.

Table 5-1 Free-Flow Speeds Measured for NTE MLs (mph)

Speed (mph)				
73	72	72	71	75
75	69	72	73	74
71	73	73	73	75
68	74	82	70	76
74	81	74	80	76
75	75	70	72	73
Average	73 mph			

Table 5-2 Free-Flow Speeds Measured for NTE GPLs (mph)

Speed (mph)				
60	58	60	60	66
62	63	64	65	65
62	63	64	64	65
61	64	67	70	60
65	61	63	65	63
60	63	69	70	62
Average	63 mph			

Density at capacity (k_c) – is the concentration at which flow is maximum, i.e. the corridor is operating at the capacity. This parameter was estimated by following the relationships between flow, speed, and density (Equation 5-2) as well as the Drake Model.

$$q = u \times k \tag{5-2}$$

Where:

$q =$ flow (pcphpl)

$u =$ speed (mph)

$k =$ density (pcpmpl)

For the calculations, the corridor capacity was considered to be 2200 (pcphpl) for both MLs and GPLs. This assumption was in line with the former study conducted for NTE [51]. In this way, values of k_c were estimated as 50 (pcpmpl) and 58 (pcpmpl) for the MLs and the GPLs, respectively.

Table 5-3 shows some examples of speed and travel time estimations for both ML and GPL facilities. The travel time saving was estimated by subtracting MLs' travel time from respective travel time on GPLs.

Table 5-3 Speed and Travel Time Calculation based on Drake Model for the AM Peak in One Day

Time	ML			GPL			Travel Time Saving (minute)
	Volume (vph)	Speed (mph)	Travel Time (minute)	Volume (vph)	Speed (mph)	Travel Time (minute)	
6:00- 6:05	912	72.4	4.98	4128	45.6	7.90	2.93
6:05- 6:10	1080	72.1	4.99	3492	53.1	6.78	1.79
6:10- 6:15	1080	72.1	4.99	3228	55.1	6.54	1.55
6:15- 6:20	996	72.3	4.98	3648	51.6	6.97	1.99
6:20- 6:25	1104	72.1	5.00	3468	53.5	6.73	1.74
6:25- 6:30	1368	71.6	5.03	3384	53.9	6.67	1.65
6:30- 6:35	1416	71.5	5.03	3540	52.5	6.86	1.82
6:35- 6:40	1392	71.5	5.03	3636	52.1	6.91	1.87
6:40- 6:45	1236	71.8	5.01	3696	51.4	7.00	1.99
6:45- 6:50	1296	71.7	5.02	3948	48.6	7.41	2.39
6:50- 6:55	1188	71.9	5.01	3720	51.1	7.04	2.03
6:55- 7:00	1548	71.2	5.06	3780	50.5	7.13	2.07
7:00- 7:05	1272	71.7	5.02	3840	50.2	7.17	2.15
7:05- 7:10	1380	71.5	5.03	3852	49.9	7.21	2.18
7:10- 7:15	1368	71.5	5.03	4080	47.1	7.64	2.60
7:15- 7:20	1224	71.9	5.01	3552	52.9	6.81	1.80
7:20- 7:25	1056	72.1	4.99	4080	47.5	7.57	2.58
7:25- 7:30	1008	72.2	4.99	3972	47.9	7.51	2.52
7:30- 7:35	996	72.3	4.98	3864	49.5	7.27	2.29
7:35- 7:40	1188	71.9	5.01	4092	46.9	7.67	2.66
7:40- 7:45	912	72.4	4.97	4044	47.4	7.59	2.62
7:45- 7:50	1152	71.9	5.00	3792	50.28	7.16	2.16
7:50- 7:55	1032	72.2	4.99	3744	50.58	7.12	2.13
7:55- 8:00	1092	72.1	5.00	3540	52.45	6.86	1.87
8:00- 8:05	1224	71.8	5.01	3540	52.62	6.84	1.83
8:05- 8:10	1080	72.0	5.00	3360	54.30	6.63	1.63
8:10- 8:15	1284	71.7	5.02	3612	51.63	6.97	1.95
8:15- 8:20	996	72.2	4.99	3504	53.08	6.78	1.80
8:20- 8:25	1104	72.1	5.00	3420	53.58	6.72	1.72

Table 5-3-*Continued*

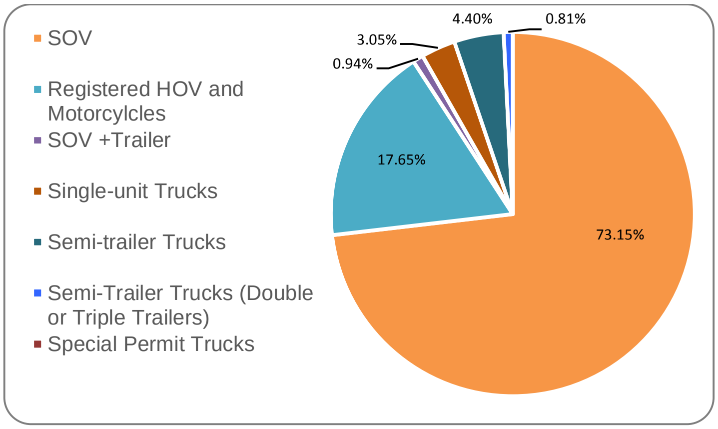
Time	ML			GPL			Travel Time Saving (minute)
	Volume (vph)	Speed (mph)	Travel Time (minute)	Volume (vph)	Speed (mph)	Travel Time (minute)	
8:30- 8:35	912	72.4	4.97	3408	53.87	6.68	1.71
8:35- 8:40	816	72.5	4.97	3480	52.73	6.83	1.86
8:40- 8:45	852	72.4	4.97	3432	53.21	6.77	1.79
8:45- 8:50	612	72.7	4.95	3048	55.66	6.47	1.52
8:50- 8:55	768	72.5	4.96	2904	56.20	6.41	1.44
8:55- 9:00	912	72.3	4.98	3156	54.95	6.55	1.57

As mentioned, the corridor was not investigated to find the traffic flow model, which best represented its characteristics. Therefore, this could affect the accuracy of the outcomes. To get more precise results, a further study would be beneficial to calibrate the traffic flow models for the corridor. Due to the dynamic nature of ML corridors, it is unlikely to describe various stochastic behavior of travelers' solely using a deterministic traffic flow model. The deterministic single-regime speed-density traffic flow models characterize the average systems behavior [63]. Therefore, more advanced models are required to capture the corridor's uncertainties. Wang et al. [63] proposed a stochastic speed-density relationship to overcome the shortcomings of deterministic models. In another study, to accurately estimate the freeway travel time, a (modified) dynamic traffic flow model was presented. The model used fixed-point detector data to describe and predict the corridor travel time under transition and congestion conditions [64]. In the concept of ML and dynamic toll pricing, further studies are useful to come up with more accurate traffic flow models.

5.1.2 Descriptive analysis

For this study, 426 data points (traffic volume counts and SOV toll rates for 5-minute intervals) were collected from the field. This section presents the initial analysis, including a description of the corridor vehicle mix as well as the ML share percentages in each vehicle class for different time periods. The analysis also involved the ML share comparisons for different times of day and different amounts of toll charged. This analysis can be used to evaluate the prevailing tendency of the sample population with respect to their mode choice decisions between MLs and GPLs.

Individual travelers' choice of mode is affected not only by their socio-economic characteristics but also by their trip attributes such as trip purpose or time of day the trip is taken [66]. Also, WTP distributions vary among drivers of different vehicle classes [65,66,67,68]. Accordingly, the field data were examined based on time periods and vehicle classes to which the observations belonged. The results revealed how variations in mode choice decisions occurred during different time periods and among different vehicle classes (figures 5-1 to 5-5).



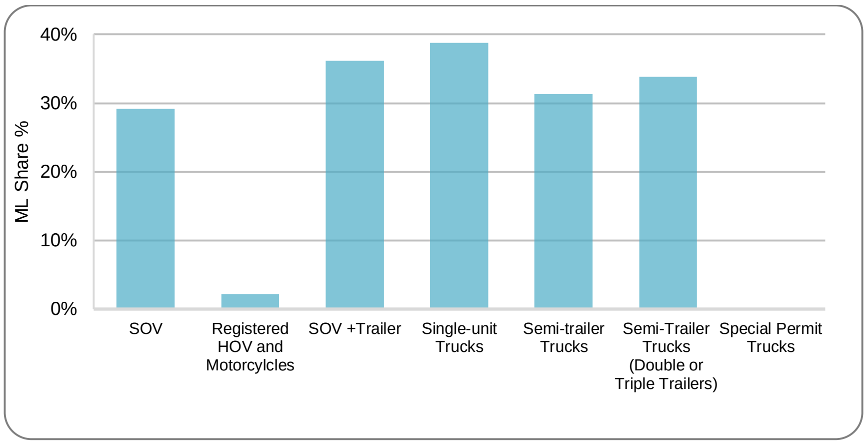
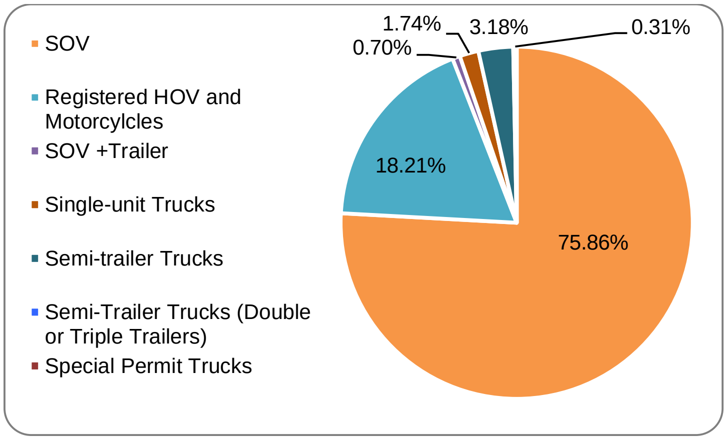


Figure 5-1 Corridor Total Volume Mix- ML Share Percentage for Different Vehicle Classes - AM Peak Period



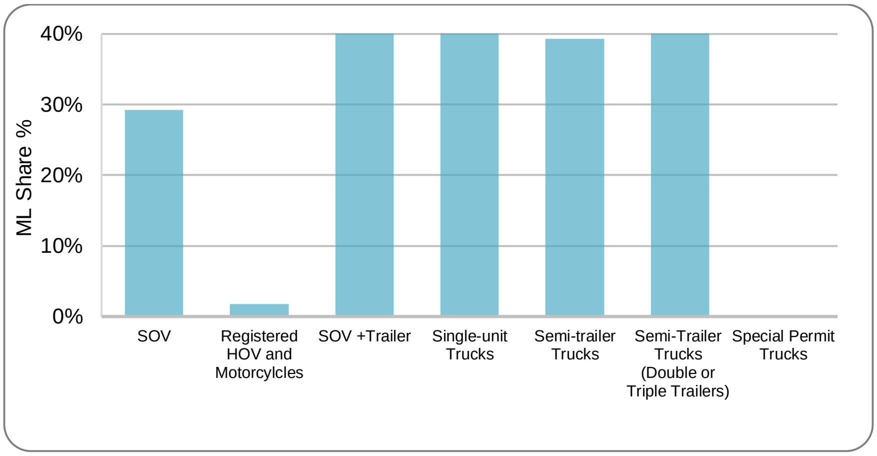
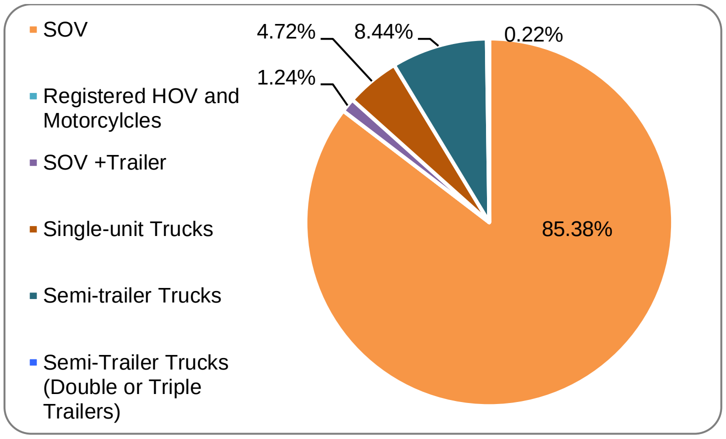


Figure 5-2 Corridor Total Volume Mix- ML Share Percentage for Different Vehicle Classes- PM Peak Period



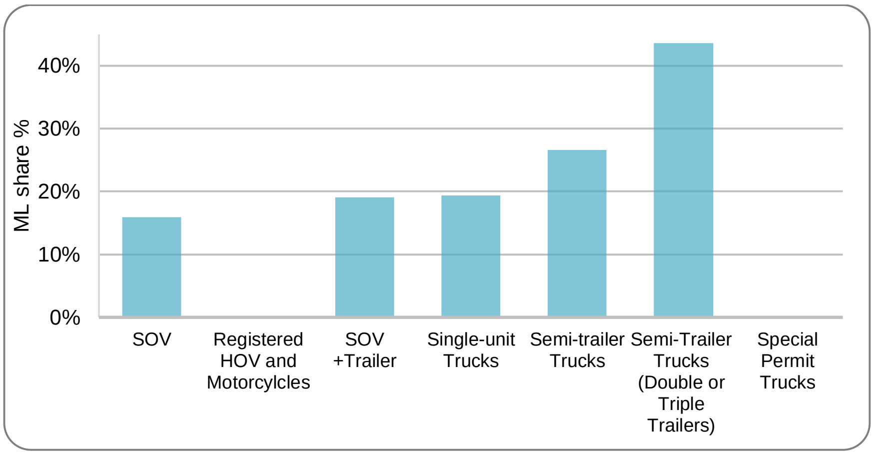
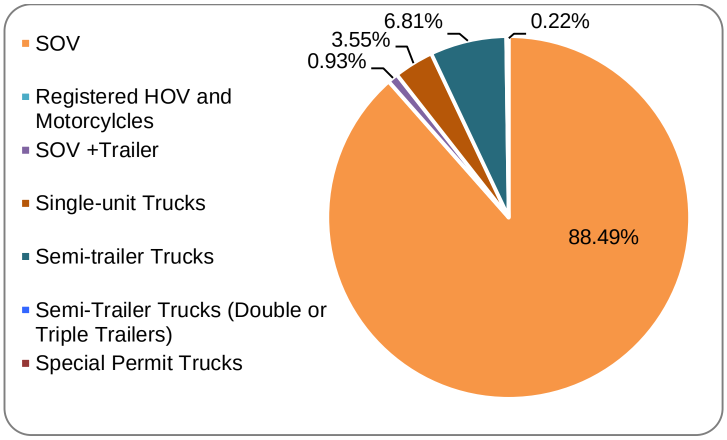


Figure 5-3 Corridor Total Volume Mix -ML Share Percentage for Different Vehicle Classes- AM Inter-Peak Period



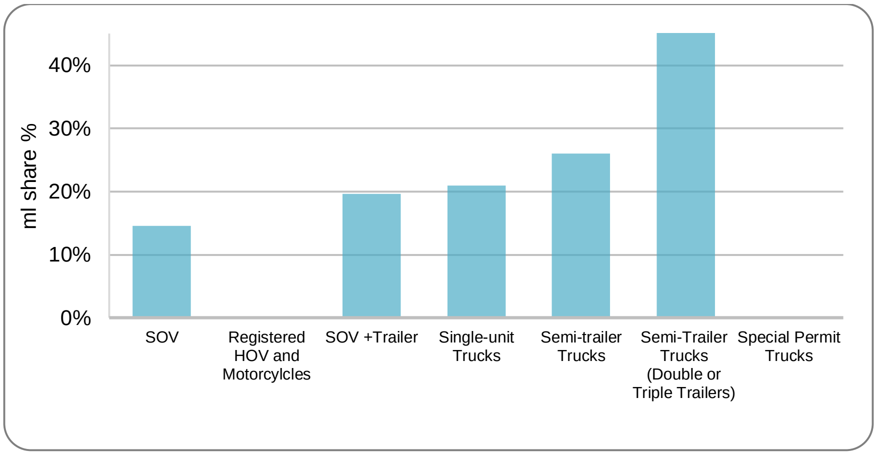
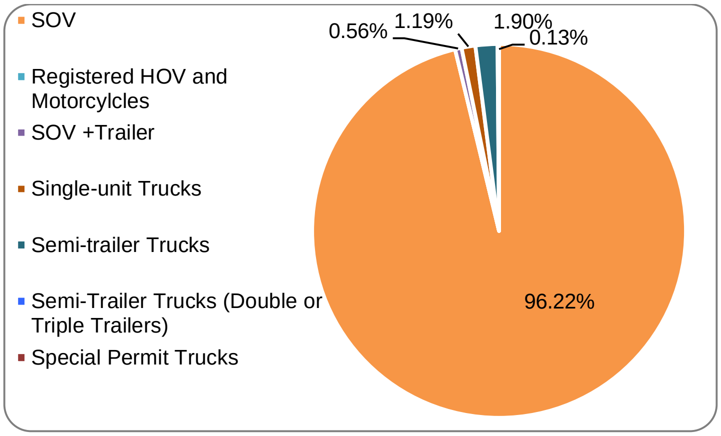


Figure 5-4 Corridor Total Volume Mix- ML Share Percentages for Different Vehicle Classes- PM Inter-Peak Period



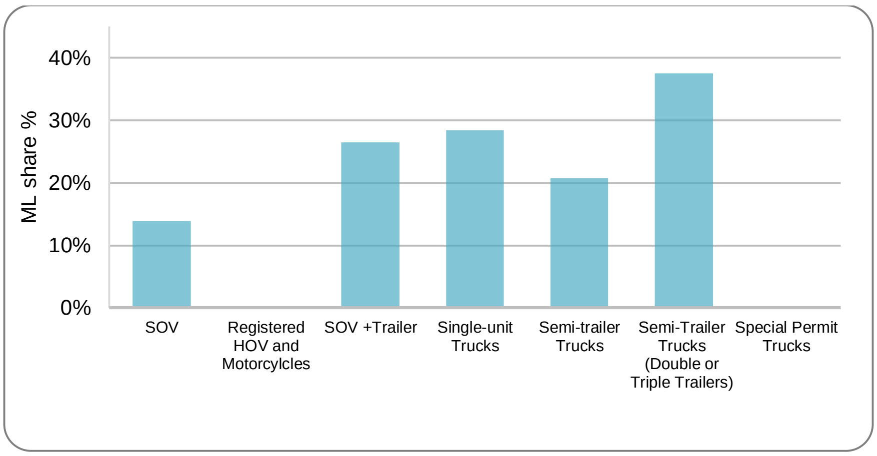


Figure 5-5 Corridor Total Volume Mix- ML Share Percentage for Different Vehicle Classes- Off-Peak Period

For each time period, the figure on top displays the corridor's vehicle mix and the one on the bottom shows the ML share percentage for each vehicle class. The ML share is defined as the ratio of the traffic volume on MLs to the total volume of the corridor (MLs and GPLs). For example, as shown in Figure 5-1 for AM peak periods, on average almost 4% (196 vehicles) of the total corridor's volume (4451 vehicles) were semi-trailer trucks, of which 31.4% (61 vehicles) used the MLs. Furthermore, as it can be observed from the figures, for all non-peak periods (AM and PM Inter-peak and Off peak periods), the number of vehicles belonging to the "Registered HOVs and Motorcycles" class was shown as zero. It did not mean that there were no registered HOVs or motorcycles on the corridor during those periods. However, recall from Chapter 4 that for the purpose of this study, the vehicles were categorized based on their differences in the tolls charged. The discount (0.50 × base toll) was available to the registered HOVs and motorcycles only during peak periods. Therefore, during non-peak periods, the share of traffic volume belonging to this class, if any, was considered under the SOV class, as both paid the same toll rates (1.00 × base toll).

Once more, the emphasis of this study was only on examining the travel behavior of SOV drivers. However, data associated with the other vehicle classes were also collected in order to provide the simulation model with the same traffic conditions as observed in the field. Accordingly, the analysis and results are only presented for SOV travelers. Future work can be done on studying travel behavior of drivers belonging to other vehicle classes.

Based on the figures, during peak periods (AM and PM), as it was expected, SOV drivers were more willing to pay tolls and switch to the MLs compared with non-peak periods. It is shown that almost one-third of the SOV population chose to drove on MLs instead of using GPLs. The next high ML share percentages can be recognized for the inter peak periods (16% AM inter-peak and 15% PM inter-peak periods) followed by the off peak period (14%). Peak-period trips are more likely to be oriented around work commuting purpose while during non-peak periods trip purposes mainly switch to non-work trips [69]. My data did not have information about trip purposes. However, the time of day and trip purpose variables are likely correlated and thus affect the travelers' WTP values. Table 5-4 and Figure 5-6 summarize the SOV average ML share percentages and SOV average toll rates charged for different time periods. The average values were estimated from all data collected for five-minute intervals during each time period.

Table 5-4 SOV Average ML Share and Average Toll Price for Different Time Periods

Time Period	SOV Average ML Share%	SOV Average Toll Charge ($/6 miles)
AM Peak	29.2%	$3.90
PM Peak	29.2%	$3.29
AM Inter-peak	15.9%	$1.74
PM Inter-peak	14.6%	$1.92
Off-Peak	13.9%	$1.22

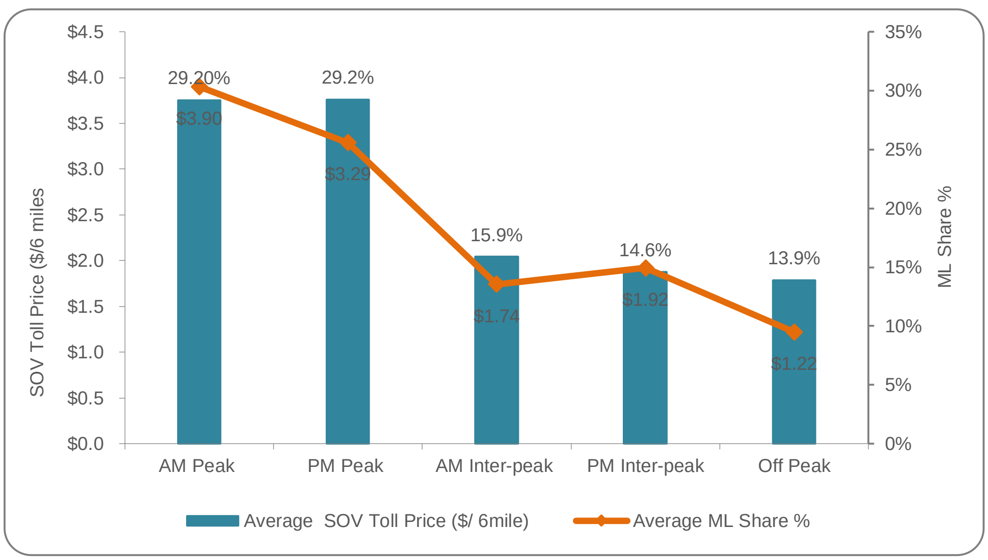


Figure 5-6 SOV Average ML Share and Average Toll Price for Different Time Periods

The results showed that NTE travelers were willing to pay higher tolls to use MLs during peak periods. During the AM and PM inter-peak periods, both ML share percentages and toll rates dropped by nearly 50 percent. The decrease was likely due to the general shifts in the purpose of trips from work commute trips. Also, the considerable drop (about 30 percent) in the level of congestion on the corridor, which led to a decrease in travel time savings, could make toll lanes less appealing to the drivers. However, as shown in Table 5-4, the ML share percentage during off peak periods did not dramatically drop compared to the inter-peak periods. It can be therefore concluded that travelers' WTP values might not be merely explained by time savings as a reason. During off peak periods, ML users were probably looking to increase and/ or decrease their other utilities and/or disutilities by choosing MLs over GPLs. Perceiving a higher speed limit, improved safety, and more reliable travel time could be among their other reasons to switch to the MLs. With regard to the noticeable percentages of drivers on the MLs during non-peak periods, it is critical to consider the effects of these factors in travelers' WTP studies.

5.1.3 Travelers' general tendency towards using NTE MLs

The data collected for this study were used to model the revealed travelers' mode choice decisions. Three variables associated with the drivers' real route choice, including travel time, out-of pocket monetary cost (toll), and times of day the trip taken were captured by the dataset. The data were initially analyzed to determine how the travel time saved by the users affected their WTP tolls. Figure 5-7 shows the travel time savings and the toll paid by the SOV drivers for various time periods. It shows that during peak period hours, no significant relation can be observed between travel time savings and toll. This can be partially due to the data insufficiency or inaccuracy in estimating travel time savings. However, it also reveals other potential aspects of the NTE travelers' behavior with respect to the MLs. First, it might be indicative of the differences between the actual and perceived travel time savings by drivers. A former study conducted for the MLs in the Houston area showed that travelers generally overestimated the amount of time saved by using the MLs [70]. Trip purpose was shown to be one of the important factors affecting their perceptions. Accordingly, no obvious relation between time savings and toll during peak hours could be partially due to this reason. Some travelers might have paid tolls to save their travel time, however, their perceived travel time savings might have been overestimated by some of them. Additionally, it might show that the travelers may value travel time reliability more than travel time savings. The results of another study conducted for the MnPASS Express lanes in Minneapolis showed that MnPASS users were willing to pay a toll for travel time reliability rather than for travel time savings [20]. In particular, travel time reliability was shown to be more valuable than travel time savings for morning peak since travelers were shown to be more concerned about travel time reliability than travel time savings [20]. This could also help explain the NTE drivers' behavior, especially during peak hours. Specifically, due to the dynamic toll pricing system employed by facility operators, drivers could infer that the higher rates indicate a higher level of congestion in GPLs. In addition to more reliable travel times, other potential advantages offered by MLs as well as drivers' socio-demographic characteristics and trip attributes (e.g. trip purpose, length) might affect the travelers' mode choices. Therefore, it seems that NTE drivers probably did not pay tolls to only save travel time. However, the other potential reasons to switch to the MLs cannot be investigated through the data associated with toll and time savings.

Nonetheless, as shown in Figure 5-7, travel time savings were a better predictor of the NTE users' mode choice decisions during non-peak hours. Except for the AM inter-peak hours, which follow the same pattern as the peak periods, a positive relation can be detected during other non-peak periods. Therefore, it can be concluded that travel time saving was one of the main motivations for the NTE users to pay a toll during PM inter-peak and off-peak hours. These findings are in line with the results of a previous study, which indicated the VTTS values estimated for, off-peak through mixed logit models were largely affected by travel times and toll rates [71].

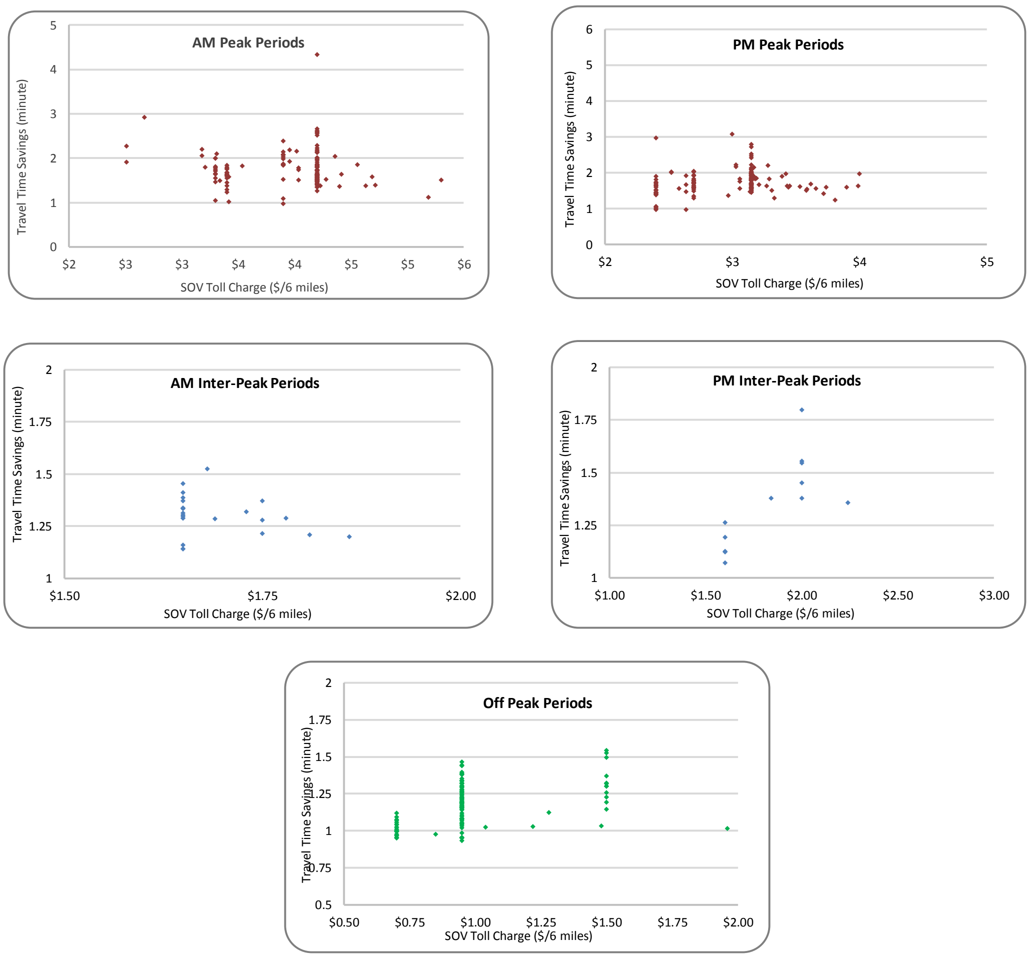


Figure 5-7 SOV Travel Time Savings versus Toll Rates - Different Time Periods

Following the analysis, a general trend in users' ML versus GPL choice decision between ML and GPL, independent of time of day, was obtained for the NTE users. In doing so, data over all the time periods were considered together. Figure 5-8 presents the corridor total volume versus the SOV toll rates.

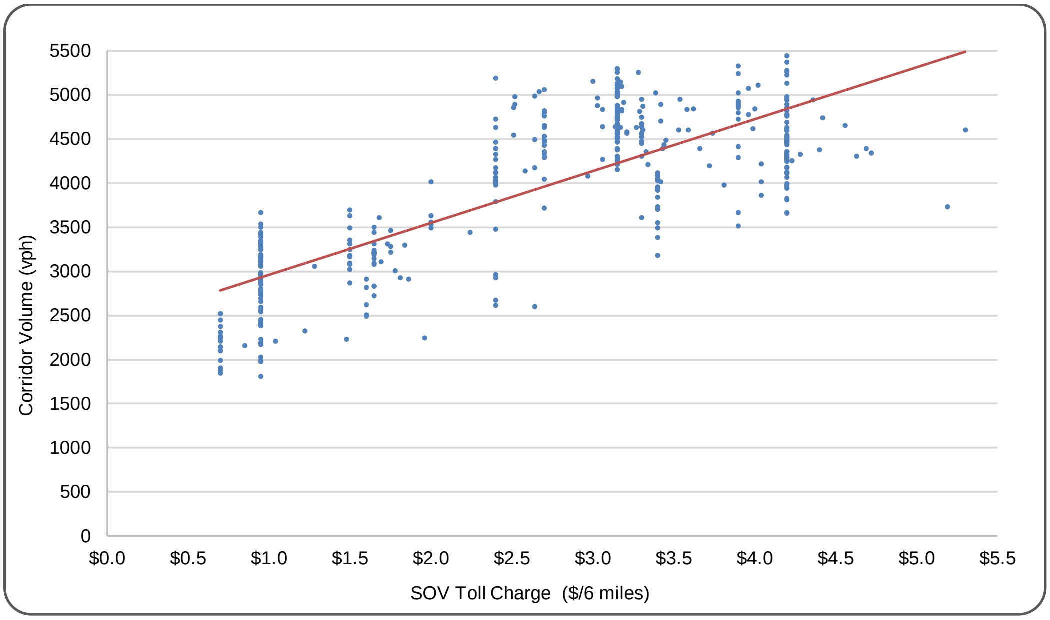


Figure 5-8 Corridor Total Volume versus SOV Toll - All Time Periods

It can be seen from Figure 5-8 that toll rates increased as traffic volume increased on the corridor. As GPLs became more congested, the travel time saving and reliability offered by MLs increased. This made MLs more appealing to the drivers whose WTP were higher than tolls charged. As a result, toll rates increased in order to prevent MLs from becoming congested. The level of congestion is differently defined for different toll facilities. For the NTE managed lanes, the minimum speed should be no slower than 50 mph [4].

Figure 5-9 shows the variations in ML shares in response to fluctuations in toll prices. As shown in Figure 5-9, a counterintuitive positive relation is observed between the two variables. Indeed, contrary to what was expected, the overall percentage of ML share increased with an increase in toll rates. The trend can partly be explained due to the influence of peak-period data. The higher ML shares associated with the higher toll rates were mostly associated with the peak periods. This can also be observed in Table 5-4 and Figure 5-6, i.e. travelers were willing to pay higher tolls during peak periods. Their higher WTP could be due to the dominated peak-period trip purpose (mainly work trips) and their perceptions about more reliable travel time offered by MLs [70].

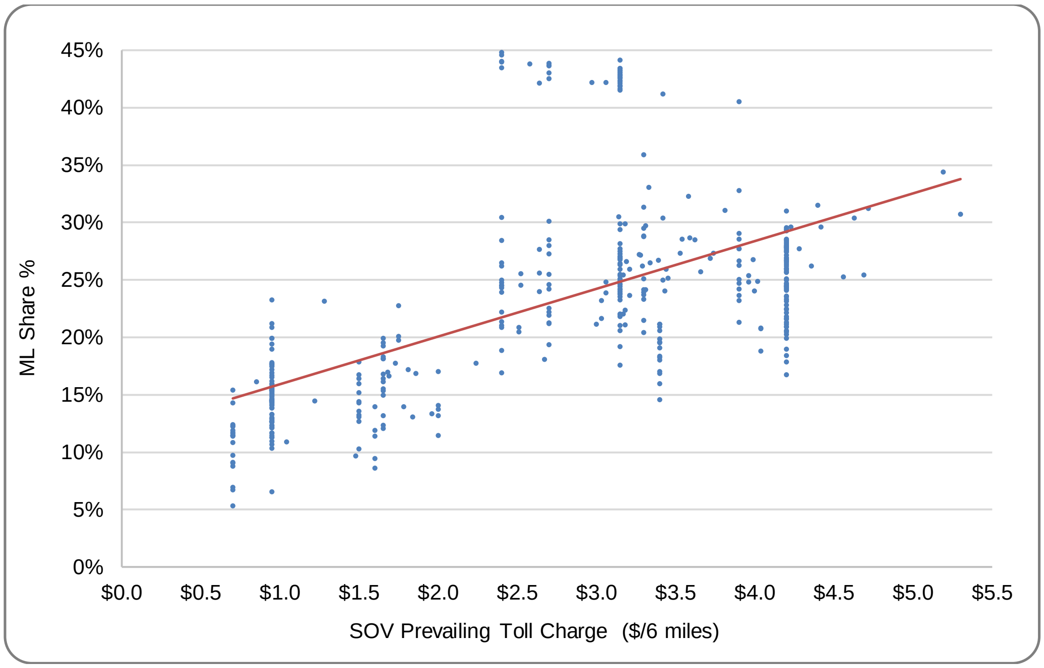


Figure 5-9 ML Share Percentage- SOV Prevailing Toll Charges for All Time Periods

Figure 5-10 displays the relation between toll paid and associated travel time saved by SOV drivers. An overall positive trend can be observed from the figure, which indicates that drivers were generally willing to pay higher tolls in order to save more time. However, this is not a strong trend since the value of R^2-adjusted for the linear regression fit is only 0.40. Based on Figure 5-7, as discussed earlier, the travel time savings might not be the major reason behind drivers' decision to pay tolls for both peak periods and the AM inter-peak hours.

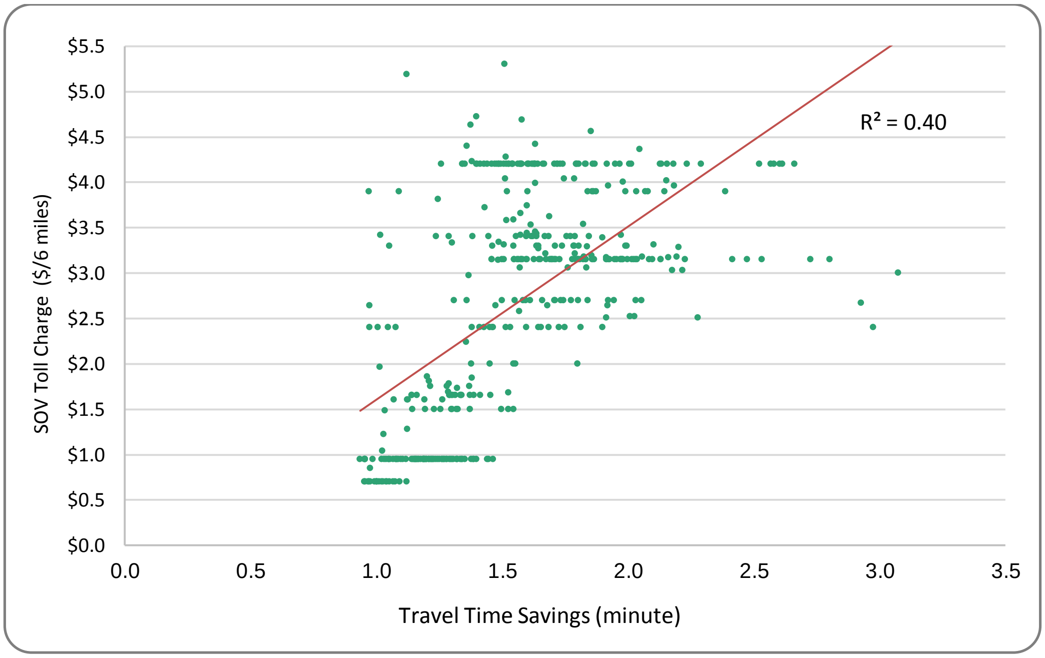


Figure 5-10 SOV Average Toll Prices versus Average Travel Time Savings for All Time Periods

As it can be further observed from Figure 5-10, drivers paid different tolls to save the same amount of time in some instances the difference in tolls exceeded $2. In the same way, for different travel time savings (at times more than one-minute difference in 6 miles) drivers paid different tolls. This demonstrates a relatively wide range of WTP values among the NTE ML users. Note that the data in Figure 5-10 were associated with different time periods.

As mentioned, a wide range of variation can be observed in tolls paid to save a similar amount of time. A wide range of variation can be also observed in travel time savings obtained for similar tolls paid. To obtain a stronger trend for the sample population, a data aggregation method was applied to smooth the data on toll values paid versus the time saving periods. The results of data smoothing yielded a more statistically significant trend to describe the average behavior among the users in paying tolls for time savings. Figure 5-11 shows the general linear trend acquired by regressing the average toll rates against the average time savings, which were smoothed over 0.2-minute travel time saving intervals. The data now display a more obvious positive linear trend between travel time savings and toll paid. This result confirms the key role of travel time saving in the travelers' mode choice decisions and WTP values [27]. However, near the upper end of the linear fit, data deviate from the positive linear trend. This can most likely be caused by the maximum toll allowed by regional policy; the amount of toll cannot exceed a fixed maximum rate. So, when the toll rate reaches that amount, even if the congestion grows on the corridor and more time savings can indeed be realized by ML drivers, the toll price will not increase anymore.

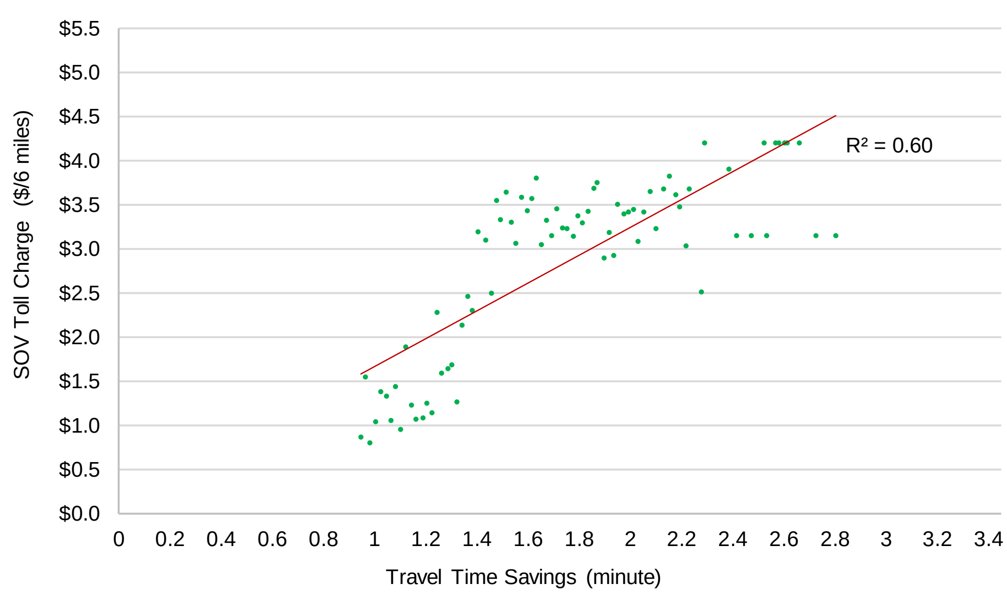


Figure 5-11 SOV Average Toll paid versus Average Travel Time Savings - All Time Periods

5.2 Revealed WTP Analysis

The main goal of this study was to determine the NTE SOV drivers' revealed WTP for different times of day. The former studies in this field were mainly conducted based on the SP and RV survey data. Other sources of data were also employed in some recent studies, which were discussed in Chapter 2. For data analysis, while the main method to estimate the WTP values has been discrete choice modeling, this study suggested a new method based on revealed data. This method involved an existing toll pricing model (TPM) developed in a former TxDOT study [6,7] for setting the tolls for MLs. The model was modified and calibrated based on actual ML shares and associated toll prices for the NTE ML corridor.

According to the objectives of this study, the data obtained from the field were prepared for each vehicle class and time period. Then, the analysis carried out to find the WTP values based on the revealed data. First, to find the revealed average WTP, the TPM was calibrated according to the geometry and traffic characteristics of the study section. In addition, to achieve the objectives of this study, some modifications were also made to the algorithm of the model. The field data were then simulated through the TPM based on different trial and error attempts of the WTP distribution. To begin, the WTP distribution scenarios derived from the SP survey were used as the initial trial and error attempts. Each simulation run through the TPM resulted in a volume split between MLs and GPLs. The goal was to find the WTP distribution scenario resulting in the same ML/GPL volume split as observed in the field. However, the same split as the field was obtained through simulating the model for more than one WTP distribution scenario at times. Thus, based on the first criterion, there were multiple WTP distribution scenarios which could probably represent the average WTP of the NTE users. Therefore, it was necessary to involve another criterion to narrow down the probable WTP distribution scenarios to the one that best represented the field data. Thus, the average WTP values estimated from the field data were used as the second condition. The process of data preparation and analysis carried out to find the revealed WTP values for the NTE drivers are summarized as the following:

- Data Aggregation
- Determining Stated Preference WTP through Survey Data
- Determining the Revealed Average WTP through the TPM

5.2.1 Data aggregation

Since a key objective of this study was to estimate the revealed WTP for different time periods, traffic volume versus toll data were aggregated over each time period. This reduced the variance in the data so that trends could be more easily identified. However, the accuracy of the results would naturally be reduced due to inevitable errors resulting from the data aggregation effort [72]. In this regards, the results obtained from the aggregated data present the average revealed WTP of the NTE travelers for different times of day. So, the results should not be generalized to other time intervals and/or facilities without further investigations.

Tables 5-5 to 5-9 present the results from the data aggregation for various time periods. As reported in the following sections, the results were used as input to the TPM to obtain the revealed WTP values.

Table 5-5 Aggregated Field Data - AM Peak Periods

Vehicle Classes	Average Corridor Vehicle Mix Volume (vph)	Average Corridor Vehicle Mix (%)	Average ML Volume (vph)	Average GPL Volume (vph)	Average ML Share (%)
SOV	3256	73.15	951	2305	29.2
Registered HOVs and Motorcycles	786	17.65	17	768	2.22
SOV, +Trailer	42	0.94	15	27	36.18
Single-unit Trucks	136	3.05	53	83	38.75
Semi-trailer Trucks	196	4.40	61	135	31.34
Semi-Trailer Trucks (Double or Triple Trailers)	36	0.81	12	24	33.82
Special Permit Trucks	0	0.00	0	0	0.00

Table 5-6 Aggregated Field Data - PM Peak Periods

Vehicle Classes	Average Corridor Vehicle Mix Volume (vph)	Average Corridor Vehicle Mix (%)	Average ML Volume (vph)	Average GPL Volume (vph)	Average ML Share (%)
SOV	3460	75.86	1012	2448	29.2
Registered HOVs and Motorcycles	830	18.21	14	816	1.7
SOV, +Trailer	32	0.70	13	19	41.5
Single-unit Trucks	79	1.74	40	40	49.9
Semi-trailer Trucks	145	3.18	57	88	39.3
Semi-Trailer Trucks (Double or Triple Trailers)	14	0.31	7	7	48.8
Special Permit Trucks	0	0.00	0	0	0.0

Table 5-7 Aggregated Field Data - AM Inter-Peak Periods

Vehicle Classes	Average Corridor Vehicle Mix Volume (vph)	Average Corridor Vehicle Mix (%)	Average ML Volume (vph)	Average GPL Volume (vph)	Average ML Share (%)
SOV	2708	85.38	430	2278	15.9
Registered HOVs and Motorcycles	0	0.00	0	0	0.0
SOV, +Trailer	39	1.24	8	32	19.1
Single-unit Trucks	150	4.72	29	121	19.4
Semi-trailer Trucks	268	8.44	71	197	26.6
Semi-Trailer Trucks (Double or Triple Trailers)	7	0.22	3	4	43.6
Special Permit Trucks	0	0.00	0	0	0.0

Table 5-8 Aggregated Field Data - PM inter-Peak Periods

Vehicle Classes	Average Corridor Vehicle Mix Volume (vph)	Average Corridor Vehicle Mix (%)	Average ML Volume (vph)	Average GPL Volume (vph)	Average ML Share (%)
SOV	2814	88.49	411	2402	14.6
Registered HOVs and Motorcycles	0	0.00	0	0	0.0
SOV, +Trailer	30	0.93	6	24	19.7
Single-unit Trucks	113	3.55	24	89	21.0
Semi-trailer Trucks	217	6.81	56	160	26.1
Semi-Trailer Trucks (Double or Triple Trailers)	7	0.22	4	3	53.0
Special Permit Trucks	0	0.00	0	0	0.0

Table 5-9 Aggregated Field Data - Off Peak Periods

Vehicle Classes	Average Corridor Vehicle Mix Volume (vph)	Average Corridor Vehicle Mix (%)	Average ML Volume (vph)	Average GPL Volume (vph)	Average ML Share (%)
SOV	2686	96.22	373	2313	13.9
Registered HOVs and Motorcycles	0	0.00	0	0	0.0
SOV, +Trailer	16	0.56	4	12	26.5
Single-unit Trucks	33	1.19	9	24	28.4
Semi-trailer Trucks	53	1.90	11	42	20.8
Semi-Trailer Trucks (Double or Triple Trailers)	4	0.13	1	2	37.5
Special Permit Trucks	0	0.00	0	0	0.0

5.2.2 Determining stated preference WTP through survey data

For the purpose of this study, the results from SP survey carried out for TxDOT in January 2006 were used to find the stated WTP for NTE drivers [5]. The analysis of the data was done by AECOM Enterprises as part of the NTE-Traffic and Revenue Forecast study in 2009 [52]. The SOV drivers' stated values of time were estimated through Multinomial Logit modeling. According to Microeconomic Theory, the value of time is defined as the marginal cost of travel time and toll [26]. The results were just estimated for AM, PM, and Off peak periods. No results were available for AM and PM Inter-peak periods [5]. To use the 2006 stated WTP values reported by AECOM for this study, the values were converted to their equivalent monetary values in 2015 (year of data collection). This was done through the CPI Inflation Calculator available on the Bureau of Labor Statistics website [73]. The following table shows the resulting SOV stated WTP values in both 2006 and 2015 equivalent monetary values.

Table 5-10 SOV Average Stated WTP in 2006 and 2015 Equivalent Values [52,73]

Time Period	Average WTP	
	2006 Monetary Value ($/hr)	2015 Equivalent Monetary Value ($/hr)
AM Peak Periods	14.44	16.98
PM Peak Periods	15.03	17.67
Off Peak Periods	14.40	16.93

In addition, the SOV WTP distributions for different time periods were retrieved from the charts presented in the report [52], as summarized in Table 5-11, values of time intervals presented in the table were also converted to the 2015 equivalent monetary values. In addition, the number of intervals was reduced from 27 to 10 to match the number of intervals required by TPM. These values were used later as the initial WTP distribution scenario to simulate the field data for each of the associated time periods.

Table 5-11 SOV Stated Value of Time Distributions for Different Time Periods [52,73]

WTP ($/hr) 2015 Monetary Value	Frequency (%)		
	AM Peak Period	PM Peak Period	Off Peak Period
0-5	3.3	3.9	0.0
5-10	17.8	19.3	5.5
10-15	30.2	29.9	34.0
15-20	15.5	12.5	17.0
20-25	9.5	11.0	9.7
25-30	6.5	8.2	8.2
30-35	4.7	5.9	9.0
35-40	3.7	1.6	6.7
40-45	4.0	4.2	5.5
45+	5.1	3.5	4.4

5.2.3 Determining the revealed average WTP through TPM

The Toll Pricing Model (TPM-5.0) used in this study was a modified version of an existing Toll Pricing Model (TPM-4.3), which was developed based during a former TxDOT study [6,7]. ML facilities are intended to offer a lower travel time compared to the adjacent GPLs. Therefore, Wardrop's first principle based on equal travel times cannot directly explain the users' equilibrium condition for these facilities. The model instead, was established based on a new paradigm in user equilibrium. In the following, the concept of this new paradigm is briefly presented followed by an analysis carried out to find the revealed average WTP values through TPM. More details about the logic and components of TPM are presented in Chapter 6.

5.2.3.1 The Toll Pricing Model (TPM) framework

The ML equilibrium paradigm which was employed to develop TPM entails two important components including Cost of Time Saving (CTS) and Willingness-to-pay (WTP) [7]. The volume assignments in the ML networks are significantly affected by these two factors. On managed lane corridors, CTS is defined as the amount per mile that drivers pay for saving one unit of time (usually measured in minutes) if they choose to take the MLs. While WTP is the amount that drivers are willing to pay for one unit of time saved [7].

$$CTS = \frac{Toll\ per\ mile\ (\$)}{Travel\ Time\ saving\ per\ mile} \tag{5-3}$$

$$CTS = \frac{T}{[(L_{GPL} \times t_{GPL}) - (L_{ML} \times t_{GPL})]/L_{ML}} \tag{5-4}$$

In Equation 5-5, travel time saving per mile is an average time that is expected to be saved by driving one mile on MLs compared to travel time on GPLs. In Equation 5-6, T is a ML toll per mile. L_{GPL} and L_{ML} are the lengths of the GPL and ML facilities and t_{GPL} and t_{ML} are the travel times spent for traveling one mile on each of the facilities, respectively [6,7]. The travel time calculations are based on the Bureau of Public Roads (BPR) function [7] as the follows:

$$t_{GPL} = 0.8 \times \left[1 + \left(\frac{V_{GPL}}{C_{GPL}}\right)^4\right] \quad (5\text{-}5)$$

$$t_{ML} = 0.8 \times \left[1 + \left(\frac{V_{ML}}{C_{ML}}\right)^4\right] \quad (5\text{-}6)$$

Here, V is the traffic volume per lane and C is the respective capacity per lane on either GPL or ML. At the initial volume assignment state, when there is no charge for driving on the MLs, the volume is expected to be equally assigned to both MLs and GPLs. In this case, the cost of time savings does not exist. However, when a toll is charged on the MLs, drivers whose WTP values are higher than CTS will switch to the MLs. On the other hand, drivers whose WTP are lower than the CTS will choose to drive on the GPLs. This changes in volume assignments between ML and GPL will in turn affect the travel time savings. Therefore, CTS is re-estimated and compared with the current ML users' WTP [6,7].

$Toll = 0, CTS = 0;\ V_{GPL} = V_{ML}$ ……………………………….Initial Loading Condition

$Toll > 0, CTS <\ WTP_i;\ V_{GPL} = V_{ML}$ ……………………………………. ML is Chosen

$Toll > 0, CTS \geq WTP_i;\ V_{GPL} = V_{ML}$ ……………………………..…….. ML is not Chosen

The process explained above continues until the network becomes stable, i.e. no one else switches lanes. At this point, the user's WTP is equal to the corridor's CTS and the network reaches its equilibrium condition. Indeed, according to the above equilibrium concept, under users' equilibrium conditions the model splits the traffic volume in such a way that ML users' WTP are higher than or equal to the corridor's CTS and the GPL users' WTP are lower than the corridor's CTS [6,7].

5.2.3.2 TPM simulation runs

All vehicles were allowed to travel on the NTE MLs regardless of the class to which they belonged. However, toll rates charged were different for each of the classes [52]. In addition, former studies showed that the WTP values were different among drivers of different classes [65,66,67]. Therefore, to model the corridor in TPM, it was not accurate to assume that vehicles traveling on the MLs were homogenous. Accordingly, the TPM was designed to incorporate separate traffic volumes and WTP values for each vehicle class. However, the focus of this study was only on finding the SOV drivers' revealed WTP. In addition, the simulation runs to find the WTP values were based on trial and error attempts of different WTP distribution scenarios. It was almost impossible to simultaneously change WTP distributions for different vehicle classes to find the ones that best represented the field data.

For this research, data associated with all the vehicle classes were collected from the field. Although, the drivers of the SOV class were the specific focus of this study, classes other than SOV were also studied. In this study, their impacts on the corridor's traffic condition and consequently on SOV drivers' route choice decisions were incorporated. To do so, the TPM was equipped with an additional option. The new option allowed the user to include or exclude any vehicle classes in or from equilibrium assignment. Therefore, during the initial loading state in TPM, the traffic counts associated with the excluded classes were fixed and assigned to respective MLs and GPLs. Next, when a toll was charged, for the corridor to reach its equilibrium condition, only traffic counts associated with the remaining (included) vehicle classes were switched between ML and GPLs. Eventually, the model included all the vehicles regardless of their class during re-estimating the corridor's CTS. Thus, the traffic volumes associated with the excluded vehicle classes were also considered as part of the corridor's flow in estimating the corridor's travel time. In this study, in running the simulation, all the classes except for SOV were excluded from participating in the equilibrium process. This did not expect to impact the equilibrium results significantly since the percent of non-SOV classes in the mix were relatively low. Furthermore, their impacts on travel time for the ML were incorporated regardless.

5.2.3.2.1 Stated WTP simulation runs through TPM

The simulations were run on the field data individually for each time period. Data including toll rates and traffic volumes were averaged across vehicle categories for each time period as shown in Table 5-5 through Table 5-9. Different WTP distribution scenarios were used as inputs to the model. The stated WTP distribution scenarios (as shown in Table 5-11) were used as the initial input. The following figure shows the results obtained through the TPM for the stated WTP distribution scenario compared with the actual traffic volume split observed in the field. The figure shows the results just for AM, PM, and off peak periods since the stated WTP results were only available for these time periods [52].

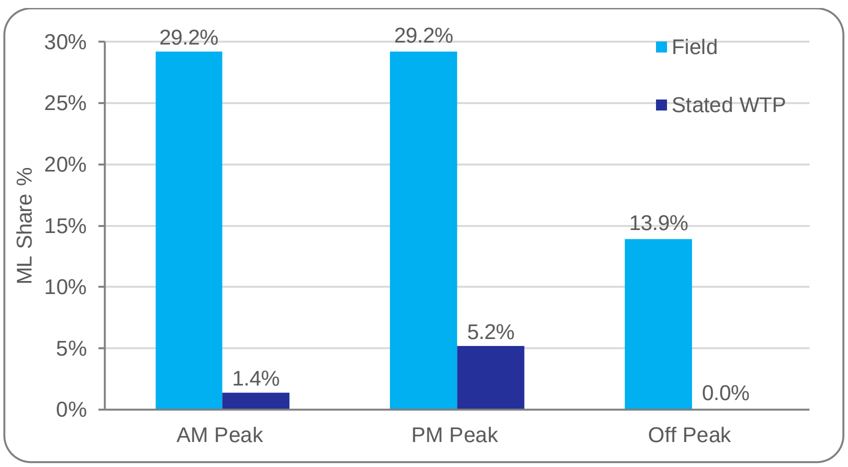


Figure 5-12 SOV ML Share Percentages- Field and Stated WTP data

As it can be observed from Figure 5-12, the traffic volume splits from the stated WTP distribution scenarios are significantly lower than the actual splits observed in the field. These differences can be partially explained by the drawbacks associated with the SP surveys [27]. Besides, several other reasons may also help explain these differences.

First, the SP survey used in this study was conducted in 2006. For this study, the values of WTP obtained from the survey were converted to the current monetary values. However, the survey results were completely out-of-date to contribute to any practical outcomes. The discrete choice model used to estimate the SP WTP values was a Multinomial Logit Model, while applying more elaborate and complex models may yield more reliable estimates [27,75]. Additionally, the survey was conducted for a traffic and revenue study before the start of the NTE ML construction project. At the time, the concept of a ML was in its early stages and there was no ML facility built in the DFW area. So, the answers could be more based on the respondents' personal perceptions about MLs rather than their real-life experiences. Additionally, there could be the probability of biased responses to the survey questions. Indeed, some individuals might have deliberately answered in such a way to reflect their objection to the concept of MLs. This opposition was observed among the comments of some respondents [5]. Another possible explanation can be that the estimated SP WTP values just measured the travelers' VOT. Other factors such as the values of travel time reliability, safety, smoother geometry, and higher speed limits might also influence the revealed values of WTP. However, the stated WTP results from the survey were useful in providing an overall perspective of the NTE travelers' willingness to pay trends for different time periods.

5.2.3.2.2 Determining revealed average WTP through simulation

Since the results from the initial simulation run were so different from the field splits, the initial WTP distribution scenario was modified through trial and error attempts. The output of the simulation run yielded from any single attempt was then compared to the field observations. In the case of non-similarity, the WTP distribution scenario was re-modified. This process was continued until any of the trial attempts yielded similar (with ± 0.05 error threshold) ML/GPL split as observed in the field. Different WTP scenarios and distribution scenarios were defined through the simulation process. The following tables show some examples of different WTP distribution scenarios developed based on trial and error attempts. Each of the WTP scenarios are different in the ranges of WTP values. For example, as shown in Table 5-12, in the first scenario, ($0- $175+) per hour is defined as the range of WTP values. This range is increased to ($0- $270+) per hour in the fourth scenario. All the WTP scenarios are introduced in 10 consecutive intervals in order to be compatible with the TPM input module.

Table 5-12 Sample of Different WTP Scenarios

WTP ($/hr.)			
Scenario 1	Scenario 2	Scenario 3	Scenario 4
0-15	0-20	0-25	0-30
15-30	20-40	25-50	30-60
30-45	40-60	50-75	60-90
45-60	60-80	75-100	90-120
60-75	80-100	100-125	120-150
75-100	100-120	125-150	150-180
100-125	120-140	150-175	180-210
125-150	140-160	175-200	210-240
150-175	160-180	200-225	240-270
175+	180+	225+	270+

Table 5-13 displays a number of different probable frequencies for each of the WTP intervals. For this study, more than 250 different frequency distributions were defined, each representing one trial and error attempt. Each WTP scenario was used along with different frequency distributions until one of these combinations yielded the same volume split as observed in the field. For convenience, each of the trial and error attempts was labeled based on the number associated with each of the WTP scenarios and frequency distributions used. For example, in try 1-70, as shown in Table 5-14, the first WTP scenario and the 70th frequency distribution were combined.

Table 5-13 Sample of Different Frequency Distributions

Frequency Distribution (%)					
Dist. 70	Dist. 71	Dist. 72	Dist. 73	Dist. 74	Dist. 75
31	31	30	31	31	31
23	23	24	23	23	23
13	13	13	12	13	13
10	11	10	11	11	10
6	6	6	5	5	7
4	4	4	5	5	4
4	4	4	4	3	3
3	3	3	3	3	3
3	3	3	3	3	3
3	2	3	3	3	3

Table 5-14 Example of Labeling the Trial and Error Attempts: Try 1-70

WTP ($/hr.) Scenario	Frequency Distribution (%)
Scenario 1	Dist. 70
0-15	31
15--30	23
30-45	13
45-60	10
60-75	6
75-100	4
100-125	4
125-150	3
150-175	3
175+	3

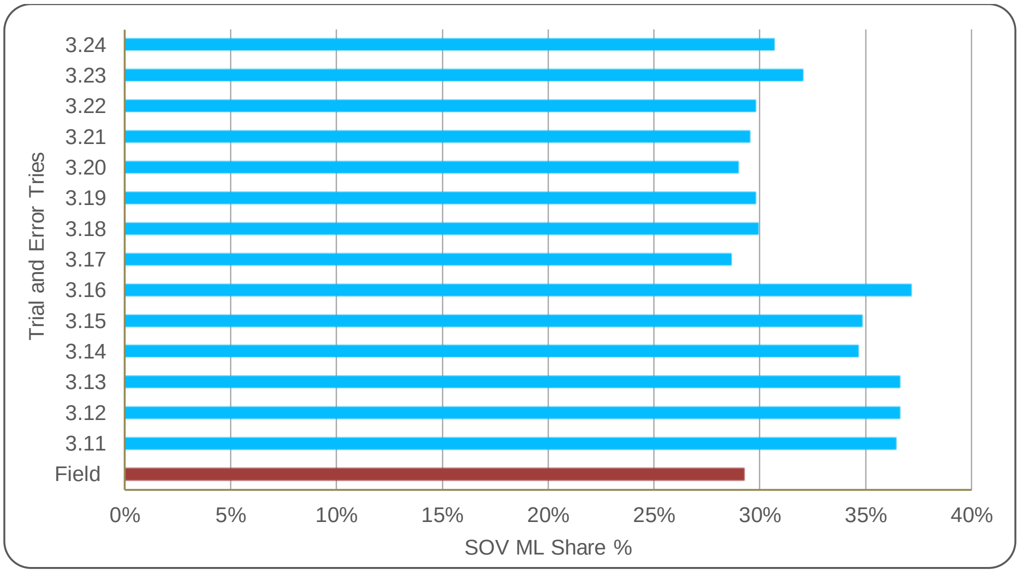


Figure 5-13 Sample of Simulation Results through TPM-AM Peak Period

Different WTP distribution scenarios were investigated through the TPM for different periods of day. Figure 5-13 shows some examples of the simulation results obtained for the AM peak period data. In the figure, the red bar shows the ML share percentage observed in the field. The bars in blue show the results obtained through the simulation runs using trials 3-11 to 3-24, as shown in Table 5-15. The details associated with these tries are displayed in Table 5-16. As it can be observed in Figure 5-13, more than one WTP distribution scenario yielded the same volume splits as the field, considering the ±0.05 error threshold. This was also the case for the other time periods, as shown in Table 5-16 to Table 5-20. Note that the tables just present a sample of the tries that yielded the same split as what was observed in the field.

Through this step, multiple WTP distribution scenarios were selected for each time period as the probable NTE users' revealed WTP. To narrow them down to achieve the desired results, a second criterion was imposed, as discussed in the next section.

Table 5-15 WTP Distribution Scenarios Associated to Trials 3-11 to 3-24

WTP ($/hr.) Scenario 3	Dist. 11 (%)	Dist. 12 (%)	Dist. 13	Dist. 14 (%)	Dist. 15 (%)	Dist. 16 (%)	Dist. 17 (%)	Dist. 18 (%)	Dist. 19 (%)	Dist. 20 (%)	Dist. 21 (%)	Dist. 22 (%)	Dist. 23 (%)	Dist. 24 (%)
0-25	7	7	7	6	6	5	15	11	11	13	13	13	13	12
25-50	7	7	7	7	6	6	14	12	11	13	13	13	12	12
50-75	8	7	7	8	8	7	13	12	12	13	13	12	11	12
75-100	8	8	7	9	8	8	12	14	13	13	12	12	10	11
100-125	9	9	7	9	9	9	11	14	14	13	11	11	10	11
125-150	11	11	13	14	14	11	9	6	9	7	9	9	10	9
150-175	12	12	13	13	14	12	8	6	9	7	8	8	10	9
175-200	12	13	13	12	12	13	7	8	8	7	7	8	9	8
200-225	13	13	13	11	12	14	6	8	7	7	7	7	8	8
225+	13	13	13	11	11	15	5	9	6	7	7	7	7	8

Table 5-16 Samples of Tries Yielded the Same Volume Split as the Field Data- AM Peak Periods

Number of Try													
4-40	4-41	4-43	4-47	4-52	4-136	4-142	4-143	4-144	4-145	4-156	4-157	4-165	4-169
Frequency Distribution (%)													
25	25	27	33	28	23	22	22	22	22	22	22	22	22
14	11	14	10	12	11	12	12	12	12	12	12	11	11
13	11	12	10	12	12	12	12	12	12	12	11	11	11
11	11	11	10	9	13	13	13	13	12	11	11	12	12
10	11	10	10	10	9	9	9	9	10	11	12	12	12
6	10	6	9	8	7	7	6	6	6	5	5	5	6
6	6	5	8	7	8	7	6	6	6	6	6	6	6
5	5	5	5	6	6	6	7	6	6	7	7	7	6
5	5	5	5	3	6	6	7	7	7	7	7	7	7
5	5	5	0	5	5	6	6	7	7		7	7	7
ML Share (%) through TPM Simulation Runs													
28.1	29.3	27.8	28.1	28.7	30.6	30.6	30.6	30.6	30.6	30.6	30.6	30.6	30.6

Table 5-17 Samples of Tries Yielded the Same Volume Split as the Field Data- PM Peak Periods

Number of Try													
3-40	3-43	3-47	3-52	3-58	3-136	3-143	3-144	3-147	3-153	3-156	3-168	3-171	3-179
Frequency Distribution (%)													
25	27	33	28	30	23	22	22	22	23	22	22	21.5	21
14	14	10	12	18	11	12	12	12	12	12	11	11	10
13	12	10	12	12	12	12	12	12	12	12	11	11	10
11	11	10	9	7	13	13	13	12	12	11	12	12.5	12.5
10	10	10	10	7	9	9	9	10	10	11	12	12	14.5
6	6	9	8	7	7	6	6	6	5	5	6	5	5
6	5	8	7	6	8	6	6	5	5	6	6	6	6
5	5	5	6	5	6	7	6	7	7	7	7	7	7
5	5	5	3	4	6	7	7	7	7	7	7	7	7
5	5	0	5	4	5	6	7	7	7	7	6	7	7
ML Share (%) through TPM Simulation Runs													
28.4	28.2	28.4	29.0	27.8	29.7	29.7	29.7	29.7	29.6	29.7	29.7	29.7	29.7

Table 5-18 Samples of Tries Yielded the Same Volume Split as the Field Data- AM Inter-Peak Periods

Number of Try													
2-70	2-74	2-78	2-83	2-85	2-97	2-100	2-184	2-191	2-200	2-210	2-215	2-221	2-222
Frequency Distribution (%)													
31	31	31	31	31	31	31	27	23	21.5	16.5	14	11	10.5
23	23	23	23	23	23	23	21	16	15	15	15	15	15
13	13	13	12	12	13	13	14	18	16	16	16	16	16
10	11	11	10	10	9	10	14	16	19	24	25	25	25
6	5	6	8	8	6	5	6	8	9.5	9.5	11	14	14.5
4	5	4	3	3	5	4	5	6	6	6	6	6	6
4	3	3	4	3	3	4	4	4	4	4	4	4	4
3	3	3	3	4	3	3	3	3	3	3	3	3	3
3	3	3	3	3	4	4	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3
ML Share (%) through TPM Simulation Runs													
15.8	16.3	15.3	15.3	15.3	16.3	16.4	16.2	16.6	16.6	16.6	16.6	16.6	16.6

Table 5-19 Samples of Tries Yielded the Same Volume Split as the Field Data- PM Inter-Peak Periods

Number of Try													
2-200	2-204	2-210	2-216	2-220	2-222	2-225	2-229	2-230	2-231	2-232	2-235	2-236	2-237
Frequency Distribution (%)													
21.5	19.5	16.5	13.5	11.5	10.5	9	7	6.5	6	6.5	9	10	7.8
15	15	15	15	15	15	15	15	15	15	15	15	15	15
16	16	16	16	16	16	16	16	16	16	16	16	16	16
19	21	24	25	25	25	25	25	25	25	24.5	22	22	23.4
9.5	9.5	9.5	11.5	13.5	14.5	16	17.5	17.5	17.5	17.5	17.5	17.5	17.5
6	6	6	6	6	6	6	6.5	7	7.5	7.5	7.5	7.5	7.4
4	4	4	4	4	4	4	4	4	4	4	4	3	3.9
3	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3
ML Share (%) through TPM Simulation Runs													
16.6	15.0	15.0	15.0	15.0	15.0	15.0	15.1	15.2	15.3	15.3	15.3	14.9	15.3

Table 5-20 Samples of Tries Yielded the Same Volume Split as the Field Data- Off Peak Periods

Number of Try													
1-40	1-41	1-43	1-45	1-52	1-53	1-238	1-239	1-240	1-241	1-242	1-243	1-244	1-245
Frequency Distribution (%)													
25	25	27	32	28	26	27	26	25	25	25	24	24	24
14	11	14	9	12	16	13	13	14	14	14	15	15	15
13	11	12	12	12	11	12	13	13	12	12	12	12	13
11	11	11	11	9	12	12	12	12	12	12	11	12	11
10	11	10	10	10	10	11	11	11	12	11	11	10	10
6	10	6	6	8	5	5	5	5	5	6	6	6	6
6	6	5	5	7	5	5	5	5	5	5	6	6	6
5	5	5	5	6	5	5	5	5	5	5	5	5	5
5	5	5	5	3	5	5	5	5	5	5	5	5	5
5	5	5	5	5	5	5	5	5	5	5	5	5	5
ML Share (%) through TPM Simulation Runs													
14.4	14.4	14.4	14.4	14.0	14.4	14.4	14.4	14.4	14.4	14.4	14.4	14.4	14.4

5.2.3.2.3 Determining the average WTP from field data

The second criterion to find the best WTP distribution scenario which represented the field data was defined as the average WTP values estimated from the field data. These values were obtained by estimating the average of the toll paid by SOV drivers divided by the average time they saved by driving in the MLs. The estimated SOV average WTP values are shown in Table 5-21 for each time period.

Table 5-21 SOV Average WTP from Field Data for each Time Period

Time Period	Average Toll Charge ($/6 miles)	Average Time Savings (minutes)	Average WTP ($/hr)
AM Peak	3.90	1.9	123
PM Peak	3.29	1.87	106
AM Inter-peak	1.74	1.48	71
PM Inter-peak	1.92	1.53	75
Off Peak	1.22	1.24	59

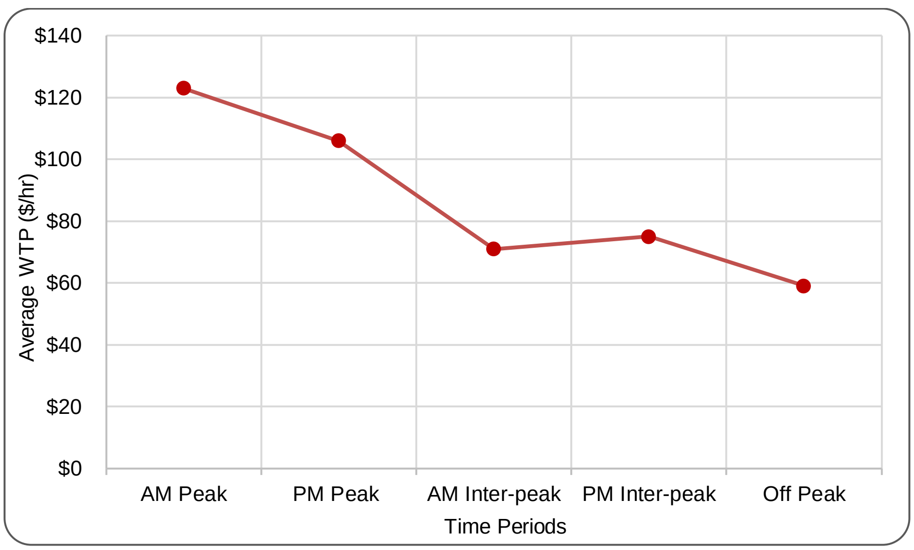


Figure 5-14 SOV Average WTP from Field Data - Different Time Periods

Based on data from the field, during peak hours, the average travel time on the MLs was almost 35 to 40 percent shorter than the average travel time on the GPLs. Also, as it can be seen in Table 5-21 and Figure 5-14, the NTE drivers had higher WTP values during the peak periods compared to the non-peak periods. During the AM and PM inter-peak periods, the WTP values considerably dropped indicating that drivers became more sensitive to toll prices. During these periods, the average travel time on the MLs was almost 25 percent shorter than the average travel time on the GPLs. The lowest values of WTP belonged to the users who travelled during off peak periods, as expected. The travel time on the MLs was almost 20% shorter than the average travel time on the GPLs during off peak hours. This difference was mainly due to the different speed limits for the two facilities.

Next, the average WTP for each of the previously selected distribution scenarios were calculated. To do so, the mid values of the WTP intervals in each scenario were multiplied by the percent of the population frequencies belonging to the respective intervals. The average WTP for each distribution scenario was then calculated by aggregating these values over all the intervals to obtain a weighted average. The scenario for which the weighted average WTP was within ±5% of the field average WTP was selected as the revealed WTP. During this process, at times, the distribution scenarios initially selected through the first condition did not meet the second required criterion. Therefore, it was required to conduct many more iterations of the values of WTP distribution scenarios and go through the simulation runs again. These trial and error attempts continued until both criteria were satisfied by one of the WTP distribution scenarios. This scenario was the one that best represented the NTE SOV drivers' average revealed WTP. Table 5-22 to 5-26 show the WTP weighted average estimated for WTP distribution scenarios, which were previously presented in Tables 5- 17 to 5-21.

Table 5-22 Samples of WTP Weighted Average Estimated for Different WTP Distribution Scenarios- AM Peak Periods

Number of Try													
4-40	4-41	4-43	4-47	4-52	4-136	4-142	4-143	4-144	4-145	4-156	4-157	4-165	4-169
ML Share (%) obtained through TPM Simulation Runs													
28.1	29.3	27.8	28.1	28.7	30.6	30.6	30.6	30.6	30.6	30.6	30.6	30.6	30.6
Weighted Average WTP ($/hr)													
123	104.7	109.8	102	95.4	113.4	114.6	115.5	116.4	116.7	117.8	118.2	118.8	118.2

Table 5-23 Samples of WTP Weighted Average Estimated for Different WTP Distribution Scenarios - PM Peak Periods

Number of Try													
3-40	3-43	3-47	3-52	3-58	3-136	3-143	3-144	3-147	3-153	3-156	3-168	3-171	3-179
ML Share (%) obtained through TPM Simulation Runs													
28.4	28.2	28.4	29.0	27.8	29.7	29.7	29.7	29.7	29.6	29.7	29.7	29.7	29.7
Weighted Average WTP ($/hr)													
87.3	85.3	79.5	86.5	78.75	94.5	96.5	97	97.5	96.25	98	98	100.9	101.1

Table 5-24 Samples of WTP Weighted Average Estimated for Different WTP Distribution Scenarios - AM Inter-Peak Periods

Number of Try													
2-70	2-74	2-78	2-83	2-85	2-97	2-100	2-184	2-191	2-200	2-210	2-215	2-221	2-222
ML Share (%) obtained through TPM Simulation Runs													
15.8	16.3	15.3	15.3	15.3	16.3	16.4	16.2	16.6	16.6	16.6	16.6	16.6	16.6
Weighted Average WTP ($/hr)													
53.8	53.4	53.2	54	54	54.6	54.6	57.2	61.6	63.6	66.6	68.4	70.8	71.2

Table 5-25 Samples of WTP Weighted Average Estimated for Different WTP Distribution Scenarios - PM Inter-Peak Periods

Number of Try													
2-200	2-204	2-210	2-216	2-220	2-222	2-225	2-229	2-230	2-231	2-232	2-235	2-236	2-237
ML Share (%) obtained through TPM Simulation Runs													
16.6	15.0	15.0	15.0	15.0	15.0	15.0	15.1	15.2	15.3	15.3	15.3	14.9	15.3
Weighted Average WTP ($/hr)													
63.6	64.8	66.6	68.8	70.4	71.2	72.4	74.1	74.6	75.1	74.8	73.3	72.1	74

Table 5-26 Samples of WTP Weighted Average Estimated for Different WTP Distribution Scenarios - Off Peak Periods

Number of Try													
1-40	1-41	1-43	1-45	1-52	1-53	1-238	1-239	1-240	1-241	1-242	1-243	1-244	1-245
ML Share (%) obtained through TPM Simulation Runs													
14.4	14.4	14.4	14.4	14.0	14.4	14.4	14.4	14.4	14.4	14.4	14.4	14.4	14.4
Weighted Average WTP ($/hr)													
58.8	61.55	57.45	56.55	58.15	57.1	57.2	57.9	58	58.3	58.5	59.25	59.1	59

5.2.4 Results and analysis of revealed WTP

The main objective of this study was to estimate the average revealed WTP values for the NTE ML drivers. As discussed, the WTP distribution scenarios that yielded the same split as the field were chosen for further analysis. To select the revealed WTP of the NTE drivers among these probable scenarios, the average WTP values estimated from the field data were used as the second selection criterion. In this way, the weighted average of the distribution scenario should have yielded the same value as the average WTP estimated from the field data. Thus, the attempt that satisfied both criteria was adopted as the revealed WTP distribution scenario for each respective time period.

The resulting average revealed WTP values for the NTE SOV drivers are presented in Table 5-27 for each time period. The table also shows the volume splits and WTP weighted average values yielded by running the selected scenarios through TPM as well as the actual values obtained from the field. As expected, the AM and PM peak WTP estimations were higher than non-peak periods. The average WTP values range was between $59 per hour for the off-peak period to $119 per hour for the AM peak period. The mean revealed WTP (all periods inclusive) was estimated to be $85 per hour for the NTE users.

The revealed average WTP estimates were intended to be used in the TPM for ML demand estimations during different times of day. This led to the development of a decision support system (DSS) tool for dynamic pricing of MLs, which was another objective of this study. The next chapter presents more details about the various modules and logic of this tool.

Table 5-27 The NTE Users' Revealed WTP Distributions for Different Time periods

AM Peak		PM Peak		AM Inter-peak		PM Inter-peak		Off Peak	
WTP Distribution Scenario									
WTP ($/hr.)	Frequency (%)	WTP Intervals ($/hr.)	Frequency (%)	WTP Intervals ($/hr.)	Frequency (%)	WTP Intervals ($/hr.)	Frequency (%)	WTP Intervals ($/hr.)	Frequency (%)
0-30	24.0	0-25	21.0	0-20	10.5	0-20	6.0	0-15	24.0
30-60	15.0	25-50	10.0	20-40	15.0	20-40	15.0	15-30	15.0
60-90	13.0	50-75	10.0	40-60	16.0	40-60	16.0	30-45	13.0
90-120	11.0	75-100	12.5	60-80	25.0	60-80	25.0	45-60	11.0
120-150	10.0	100-125	14.5	80-100	14.5	80-100	17.5	60-75	10.0
150-180	6.0	125-150	5.0	100-120	6.0	100-120	7.5	75-100	6.0
180-210	6.0	150-175	6.0	120-140	4.0	120-140	4.0	100-125	6.0
210-240	5.0	175-200	7.0	140-160	3.0	140-160	3.0	125-150	5.0
240-270	5.0	200-225	7.0	160-180	3.0	160-180	3.0	150-175	5.0
270+	5.0	225+	7.0	180+	3.0	180+	3.0	175+	5.0
Weighted Average WTP- TPM ($/hr)									
118.8		101.1		71.2		75.1		59	
Average WTP- Field ($/hr)									
123		106		71		75		59	
ML share- TPM (%)									
30.6		29.7		16.6		15.3		14.4	
ML Share- Field (%)									
29.2		29.2		15.9		14.6		13.9	

Chapter 6

Decision Support System for Dynamic Pricing

A key objective of this study was to develop a conceptual framework for a decision support system (DSS) to assist managed lane operators to assess alternative dynamic toll scenarios for an existing managed lane facility. The values of users' WTP play a role of utmost importance in ML dynamic pricing effectiveness. Therefore, it was critical in this study to evaluate the revealed average WTP of the NTE TEXpress travelers. These values were estimated through calibrating an existing toll pricing model (TPM 4.3) [6, 7] for data obtained from the field.

To develop a DSS tool, the model TPM 4.3 was updated and converted to a web-based dynamic toll pricing decision tool. Indeed, the model was modified and calibrated based on the corridor specific geometry and traffic characteristics to more accurately address the revealed WTP for the NTE users. In addition, for the purpose of this study, some changes to the current logic and algorithms of the model were made. Furthermore, the existing TPM model was written in an outdated Visual Basic programming language and was not very user-friendly. Therefore, the TPM codes were transferred to Java, which is a more modern, flexible and user-friendly programming language and would allow web-based access and execution of the program.

TPM was established based on a new paradigm in users' equilibrium condition [6,7]. Accordingly, the ML was assumed to reach equilibrium when the cost of traveling on the ML was higher than the travelers' WTP values [6,7]. The details of the model's concept were described earlier in Chapter 5. In this chapter, all components of the model and the process of converting the TPM to a DSS tool for dynamic toll pricing are discussed. The modifications made in order to update the previous version of TPM (4.3) to the latest version (TPM 5.0) are also described in this chapter.

The outline of this chapter is as follows. First, the model input modules are presented followed by explanations about the output modules. More details about the calculation and assignment processes are available in [6,7].

6.1 Input Variables

The first four screens of the DSS toll were designed to input the required information to model the corridor. The input variables are categorized as below:

- Facility Information
- User Information
- Willingness-to-Pay
- Objective

Each of these input modules is described in the following sections.

6.1.1 Facility information

First, data associated with the geometry and traffic flow characteristics of the corridor are required. The information for each facility (GPLs and MLs) includes the number and the length of the lanes. Here, users are required to first select the corridor's flow-density-speed relation from a drop-down menu. Based on the model selected, users are prompted to input the associated parameters for that specific model.

Figure 6-1 shows the TPM input data screen for facility information. In the following section, more details regarding the required parameters associated with traffic characteristics of the corridor are presented.

6.1.1.1 Corridor's geometric attributes

The required geometric attributes of the corridor include the total numbers of lanes per direction and the length of the corridor. As shown in

Figure 6-1, the model takes the information separately for each of the facilities (GPLs or MLs).

At the time of this study, both the GPLs and MLs facilities had two lanes in each direction and the length of the corridor was six miles. Since at the time, the access roads along the corridor were still incomplete and not continuous, they were not included in modeling the corridor. However, all the continuous existing lanes along the study corridor were considered to model the facility accurately.

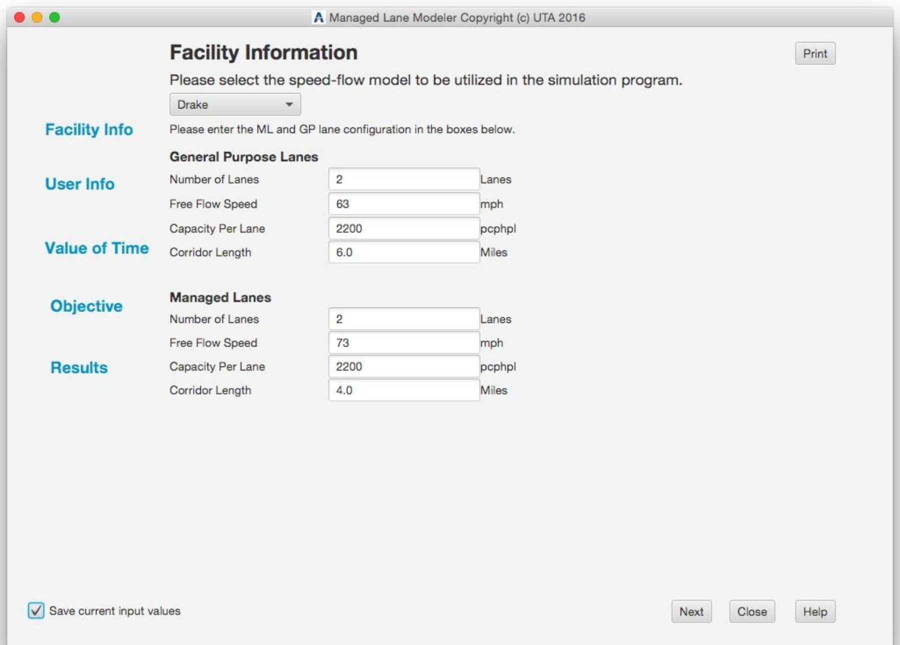


Figure 6-1 TPM 5.0 Data Input Screen- Facility Information

6.1.1.2 Corridor's traffic flow characteristics

The second series of data are associated with the traffic stream characteristics of the corridor under study. First, the relationship among the corridor's flow, density and speed is to be specified. The TPM gives the option to use one of three commonly-used macroscopic models, namely the Drake model [62], the Greenshields model and [75] the Underwood model [76]. The desired model can be selected from the drop-down menu provided in the input data screen. To determine the traffic flow model, which best represents the corridor characteristics, the models should be calibrated based on the data observed in the field. For the purpose of this study, based on the results of a former study [61], the Drake model was selected to characterize the corridor’s flow-density-speed relation. According to the model selected, other required parameters for using that model must be specified, as follows:

Free-Flow Speed

Free-flow speed is the average free-flow speed (in mph) for the study corridor. For the study section, free-flow speeds were measured in the field using a hand-held RADAR. They were determined to be 73 mph and 63 mph for the MLs and GPLs, respectively.

Capacity Per Lane

The capacity per lane is a maximum lane flow (in pcphpl) for freeway conditions. For this study, 2200 pcphpl was considered for corridor capacity.

Jam Density

Jam density is the concentration at which speeds approach zero (in pcpmpl). This is one of the required parameters for the Greenshields model.

6.1.2 User information

Figure 6-2 shows the TPM input data screen for user information and the essential data required to characterize the corridor users. For each vehicle class, the input data are as follows:

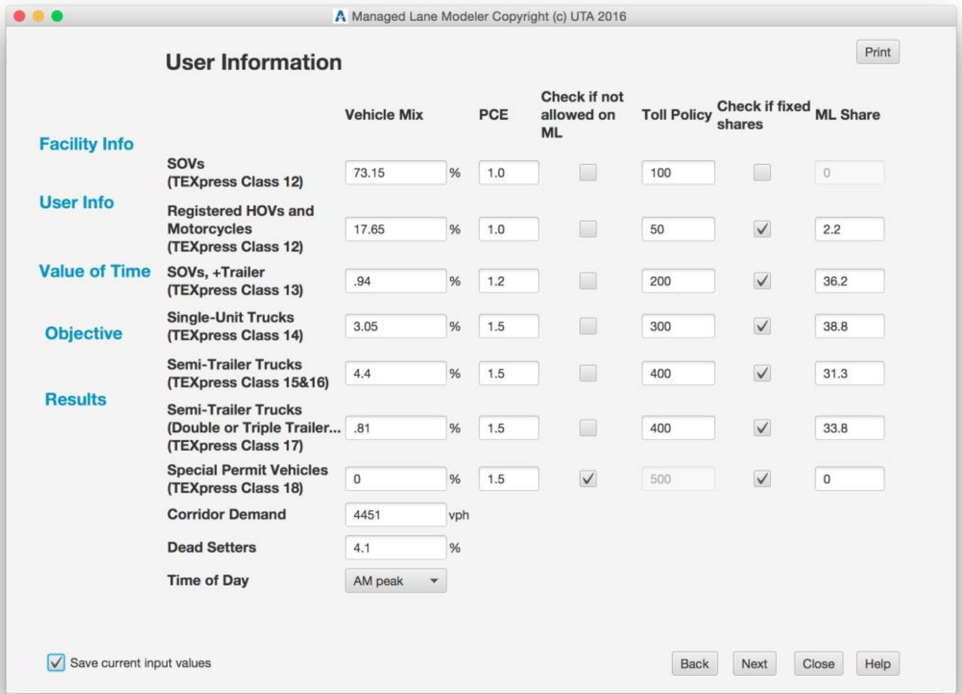


Figure 6-2 TPM 5.0 Data Input Screen- User Information

6.1.2.1 Vehicle mix

Vehicle mix is the percentage of each vehicle class in the study corridor (both MLs and GPLs). It presents the total number of vehicles in each class divided by the total vehicle counts in the corridor. The vehicle classes in TPM are defined as,

- Single Occupancy Vehicles (SOV)
- Registered High Occupancy Vehicles (HOV) and Motorcycles
- SOV +1 Trailers
- Single-unit Trucks
- Semi-trailer Trucks
- Semi-trailer Trucks, Double or Triple Trailers
- Special Vehicle or Special Permit Vehicles

6.1.2.2 Passenger Car Equivalent (PCE) factor

PCE is a multiplier applied to convert a mixed traffic stream into a homogenous stream in terms of passenger cars. The PCE factors used in this study were set based on the recommendations by the Highway Capacity Manual (HCM) 2010 [54].

6.1.2.3 Vehicles not permitted to use ML facility

Based on the different ML corridor's policies, some vehicle classes might not be allowed on ML facilities at all or during specific time periods. Through this option, the vehicle classes not allowed to enter the ML are specified and excluded from user equilibrium assignment by the model. However, according to the NTE policy, all vehicle classes are permitted to use the MLs.

6.1.2.4 Toll policy distribution

The toll amounts for each vehicle class are specified here. For each vehicle class, there may be different toll polices based on the number of axles and/or size of the vehicles. Toll policy scenarios are usually specified as a percent of the base toll scenario (SOV toll). Toll policy scenarios for the study corridor were obtained through the NTE website [51].

6.1.2.5 Fixed volume share

This option is one of the modifications applied to the previous version of the TPM to make it compatible with the objectives of this study. For this research, data associated with all vehicle classes were collected from the field. Although, the drivers of SOV class were the specific focus of this study, classes other than SOV were also considered so that their impacts on the corridor's traffic condition and consequently on SOV drivers' route choice decisions could be incorporated. To do so, the TPM was equipped with an additional option. The new option allowed the user to include (or exclude) any vehicle classes in the equilibrium assignment. Therefore, during the initial loading state in TPM, traffic counts associated with excluded classes were fixed and assigned to the respective MLs and

GPLs. Next, when a toll was charged, for the corridor to reach its equilibrium condition, only traffic counts associated with the remaining (included) vehicle classes were assigned between ML and GPLs. Eventually, the model included all the vehicles regardless of their class during re-estimating the corridor's cost of travel time savings (CTS), i.e. the toll charge converted to cost per minute of time savings. Thus, the traffic volumes associated with excluded vehicle classes were also considered as part of the corridor's flow in estimating the corridor's travel time. In simulating this study corridor, all vehicle classes except the SOVs were excluded from participating in the equilibrium process. This did not expect to impact the equilibrium results significantly since the percent of non-SOV classes in the mix were relatively low. Furthermore, their impacts on travel time in the ML were incorporated regardless.

6.1.2.6 ML Share Percentages

This option will be activated for all vehicle classes not included in user equilibrium as specified in the previous step (6.1.2.5 Fixed Volume Share). The actual ML shares as observed in the field for those classes are entered using this option. During the initial loading state, the model fixes and assigns the traffic counts for those classes to the associated facilities based on the percentages specified.

As discussed in the previous chapters, the ML share was one of the two criteria to determine the revealed WTP distribution scenario that best represented field conditions for the NTE ML users. In this study, all the vehicle classes except for SOV were fixed and assigned to the respective facilities. Therefore, the SOV was the only class that was included in the equilibrium assignment by the model. The results in terms of ML share percentages yielded through any of the trial WTP distribution scenarios were eventually compared to the actual ML share observed in the field.

6.1.2.7 Corridor demand

It shows the total number of vehicles in each direction in both MLs and GPLs in vehicles per hour.

6.1.2.8 Dead setters

Dead setters are defined as the percent of drivers in each vehicle class who will not use MLs if there is any charge at all. This could be due to their specific origin-destinations or other driver behavioral reasons. For this study, based on the previous studies [6,7], a 4.1% dead setters rule, which assumes that 4.1% of each vehicle class will not use the MLs if there is any charge.

6.1.2.9 Time period

The TPM was modified and converted to a DSS tool to dynamically set ML toll prices. This option provides the model with the users' WTP values estimated previously for different times of day and different vehicle classes. These values can be stored in the model and used as the default WTP values. The time periods can be selected from the drop-down menu. Based on the findings of this study, the default SOV drivers' WTP values are available for AM peak, PM peak, AM inter-peak, PM inter-peak, and off-peak periods. The WTP values for any other desirable times of day or vehicle classes can be estimated following the estimation process used in this study. By selecting any of the available time periods from the drop-down menu, the default values of WTP will automatically appear in the next screen (WTP input screen). The users have the option to change those as well as the WTP interval ranges and the frequency distributions.

6.1.3 WTP Values

The WTP distributions reveal how much the users are willing to pay to use any specific ML facility. The WTP distributions are entered separately for each vehicle class.

Figure 6-3 shows an example of the WTP input screen. This option shows one of the benefits of the TPM, which is its capability to integrate multiple vehicle classes in the new equilibrium concept. Indeed, different WTP distributions for different vehicle classes can be adjusted. This allows the model to utilize only one equilibrium algorithm by adjusting the percentages of population in each vehicle class. Moreover, TPM has the capability to convert the vehicles in all classes into passenger car equivalents.

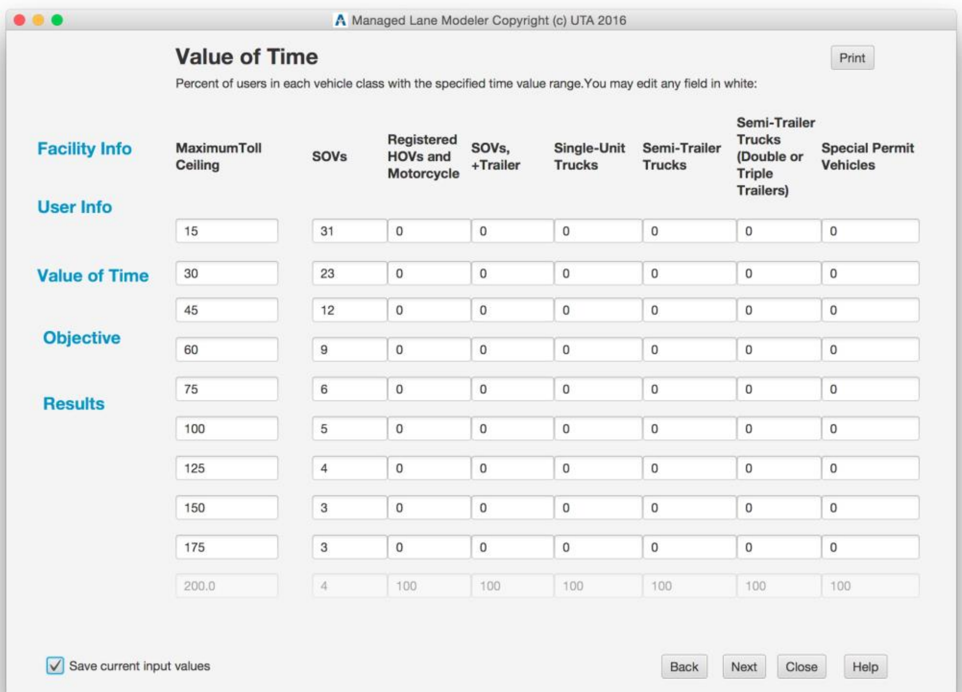


Figure 6-3 TPM 5.0 Data Input Screen- WTP

6.1.4 Objective

In this screen, the operator can specify one of two desired ML operational objectives (Figure 6-4). The first option is to specify an SOV toll amount to be charged. In this case, for a specified set of toll policies and demand, the model can predict the resulting volumes and speeds on MLs and GPLs. In the second option, users can specify a desired ML operating speed (Figure 6-4). In this case, the TPM estimates toll values that could result in maintaining the speed at or above the desired speed on the MLs [6,7]. For the NTE toll facility, the minimum speed can be set at 50 mph in compliance with the regional policy [4].

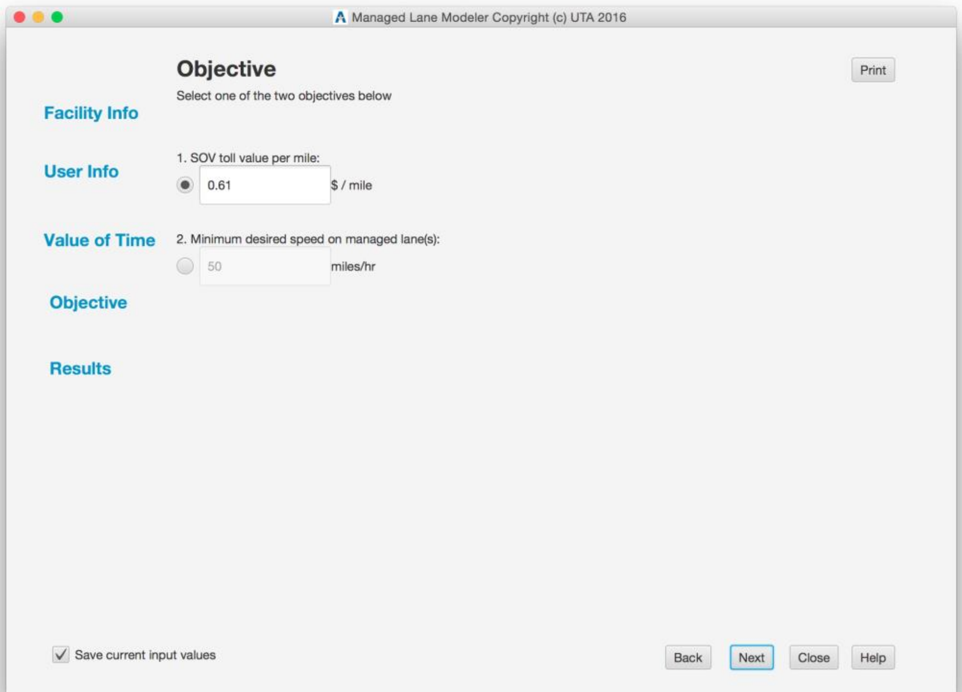


Figure 6-4 TPM 5.0 Data Input Screen- Objective

6.2 Output Variables

Figure 6-5 shows an example of the TPM 5.0 output screen. If toll values for each class of vehicles are specified, for a given total corridor demand the following key attributes are estimated:

- Managed Lane Volume and Speed
- Managed Lane Volumes by Vehicle Class

- General Purpose Lane Volume and Speed
- General Purpose Lane Volumes by Vehicle Class
- Total Toll Revenues

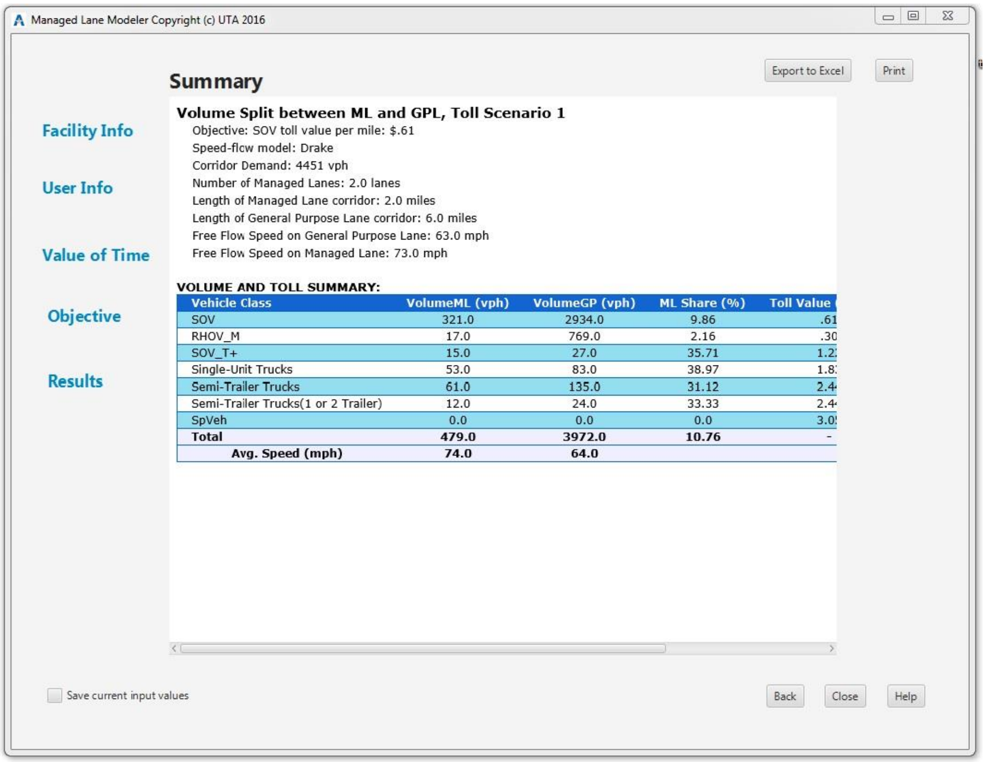


Figure 6-5 TPM 5.0 Output Screen

For a given corridor demand, if the objective of maintaining a desired speed in ML is specified, the output will include a recommended toll value for SOVs and for other classes of vehicles. Based on the calculated toll amount, the model then estimates the values of the above attributes. Outputs can be downloaded in a PDF format, as shown in Figure 6-6. The model outputs can also be exported into a Comma-Separated Value (CSV) file and be opened and saved in an Excel format.

In this chapter, the features of input and output of the Toll Pricing Model version 5.0 (TPM-5.0) are described. The various example input and output screens are also presented. The next chapter presents the study conclusions and recommendations for future studies.

Objective 1: SOV toll value per mile: 0.61
Speed-flow model: Drake
Number of Managed Lanes: 2.0 lanes
Number of General Purpose Lanes: 2.0 lanes
Length of Managed Lane corridor: 6.0 miles
Length of General Purpose Lane corridor: 6.0 miles
Corridor Demand: 4451.0 vph

VOLUME AND TOLL SUMMARY:

Vehicle Class	VolumeML(vph)	VolumeGP(vph)	ML Share (%)	Toll Value($/mile)	Total Revenue($/hr)
SOV	321	2934	9.86	0.61	1174.86
RHOV_M	17	769	2.16	0.3	30.60
SOV_T+	15	27	35.71	1.22	109.8
Single-Unit Trucks	53	83	38.97	1.83	581.94
Semi-Trailer Trucks	61	135	31.12	2.44	893.04
Semi-Trailer Trucks (1 or 2 Trailer)	12	24	33.33	2.44	175.68
SpVeh	0	0	0	3.05	0
Total	479	3972	10.76	-	2965.92

	ML	GPL
Total Volume (pc/hr)	545	4098.4
Avg. Speed (Mile/hr)	74	64

Figure 6-6 TPM 5.0 Output in CSV Format

Chapter 7

Conclusions and Recommendations

This study was mainly aimed at understanding the SOV drivers' behavior, particularly with respect to MLs. This goal was addressed by studying the revealed mode choice decisions made by the North Tarrant Expressway (NTE) users, which were captured by the camera records during different times of day. The data collection efforts for this study employed an alternative to the traditional data sources. The most common data collection efforts include stated preference survey data, and more recently loop detector, Global Positioning System (GPS), and dynamic toll data. For the purpose of this study, toll rates for various times of day in the study section were obtained from the NTE website [51]. The associated ML/GPL volume splits were obtained from video recordings.

In addition, while discrete choice models have been the most common method to analyze the WTP data, this research suggested an alternative approach in estimating the WTP values. The data were simulated through a modified version of an existing toll pricing model (TPM) [6,7] to estimate the average revealed WTP for the NTE travelers for different time periods. The model was established based on ML paradigm in users' equilibrium condition defined for the ML facilities [6,7]. The revealed average WTP values were estimated through the TPM by examining the revealed NTE drivers' mode choice decisions in response to the respective toll rates in effect.

Finally, the WTP values estimated for the NTE SOV drivers were used to modify the TPM. The model was also modified based on the geometry and traffic characteristics of the studied corridor. Besides, some changes to the algorithm of the previous version were also required. These modifications finally led to the development of a decision support system (DSS) tool for ML dynamic toll pricing.

This chapter presents the findings and contributions of this study, followed by discussions on the study limitations and potential future directions.

7.1 Research Findings

The analysis in this study was carried out in two phases. The first phase included an initial analysis to describe the drivers' general behavior with respect to the MLs usage. The second phase involved more in-depth analysis to estimate revealed WTP values. The results obtained from each analysis phase are summarized as follows.

7.1.1 Revealed propensity in using the NTE MLs

The data obtained for this study were initially evaluated to detect the prevailing tendency for the SOV drivers in the sample population. Indeed, travelers' decisions were studied with respect to their mode choice between MLs and GPLs under different tolls charged. The following results can be observed for the NTE drivers:

- Considerable percentages of SOV drivers using toll lanes (29.2% during AM and PM peaks, 15.9% during AM inter-peak, 14.6% during PM inter-peak, and 13.9% during off-peak periods).
- Low sensitivity for SOV drivers to toll values, especially during peak periods.
- No correlation between travel time savings and tolls paid during AM and PM peaks and the AM inter-peak period, underscoring the possibility of other potential reasons than VOT influencing the NTE travelers' mode choice decision (e.g. drivers' perception of more travel time reliability, safer geometry, and lax enforcement).
- No statistically significant relation between travel time savings and tolls during non-peak periods, again emphasizing the possibility of other potential reasons beside VOT affecting the NTE users' mode choice decision.
- Positive relation between tolls and corridor total volumes (expected)

- Positive relation between tolls and percentages of SOV drivers using toll lanes

7.1.2 Revealed Willingness-To-Pay Values

The method used in this study suggested a new approach to estimate the WTP values. This new method involved an existing toll pricing model (TPM) [6,7] to estimate the travelers' revealed WTP from their real-life decisions. Values of about $119, $101, $71, $75, and $59 per hours were estimated as the revealed average WTP for the NTE SOV drivers during the AM, PM, AM inter-, PM inter-, and off-peak periods, respectively. As the values show, the revealed WTP value during the AM peak is considerably higher than the PM peak value. This is most likely because during morning peak hours, the majority of trips are work trips. Therefore, the AM drivers are usually less sensitive to toll rates and are highly sensitive to travel time due to not wanting to be late to work. The PM peak travelers, on the other hand, are likely to have a higher variety of trip purposes with less critical late arrival penalties.

In addition, a value of $85 per hour was estimated for the mean revealed WTP (all periods inclusive) for the NTE SOV drivers. The WTP values estimated in this study showed higher WTP values compared with the former studies in the field. For example, in a study done for San Diego IH-15 in 2003 [58], the median WTP was estimated to be only $30 per hour, as determined through SP survey data. The authors pointed out the probability of biased results due to measuring only VOT and excluding drivers' other possible reasons for using toll lanes, such as the value of travel time reliability (VOR). Patil et al. evaluated the values of VOT and VOR for Katy Freeway users in Houston under urgent and ordinary situations [73]. Values of $8 to $47.50 per hour and $7.40 to $8.60 were estimated for urgent and ordinary situations, respectively. The results were based on the SP survey data conducted for Katy Freeway [34]. Another study was conducted for the same corridor [77], with the implied VOT estimated to be $22 per hour and the implied VOT and VOR together estimated as $59 per hour. These estimates were again based on SP survey data. Later, Huang analyzed the same dataset using advanced Prospect Theory (PT) models. He obtained relatively low WTP values ($8 to $14/hour) for Katy Freeway users [78]. In another study in 2011, dynamic toll data for IH-394 were used to estimated VOT [21]. A value of $78 per hour was estimated for morning peak hours. The main drawback of this study was mentioned to be excluding the VOR from WTP estimations [21]. To address this shortcoming, He et al. proposed a methodology to estimate VOT/VOR using the combination of dynamic toll data and loop detector data for IH-394. The results showed average values of $11.36/$25.45 per hour for VOT/VOR, respectively [20].

The studies mentioned here just present a sample of studies conducted in this area. The results clearly vary considerably for different studies. These variances in WTP values definitely could be caused by the differences in the studies' time periods and years and locations. For example, the WTP values are not expected to be the same for peak and non-peak periods or for drivers in Houston and Minneapolis. Another important point that should be considered is that the longer the new facilities have been introduced to the users, the more steady and predictable their behavior becomes. In addition, different sources of data can capture different aspects of users' behavior. For example, in some of these studies, the data source did not provide the travel time variabilities (reliabilities). In some others, the travelers' socio-demographic characteristics and/or trip attributes were not provided. Furthermore, different methodologies used in analyzing the data could result in different estimates. The more advanced discrete choice models could likely result in more accurate estimations. Different assumptions on the model's parameters, such as choice of distribution function for the random coefficient, could also result in different estimates. In addition to all the factors mentioned here, there would still be other reasons which could help explain the differences between the WTP values estimated in this study and the estimates from the previous studies.

However, this study applied camera images and TPM, a new and completely different data source and methodology, to estimate the WTP values. This could help explain the somewhat different results relative to those reported in the literature. First, the WTP values estimated in this study probably represent more than the values that travelers were willing to pay only for their travel time savings due to the data source and methodology used in this study. On the one hand, to obtain the desired results from trial and error attempts, one of the criteria used was the average WTP estimated from the field data. The value was estimated by dividing the average toll paid by the average time savings. In addition, through the TPM, the ML equilibrium condition was reached when the users' WTP values became less than the cost of traveling on the MLs. The cost was estimated based on the assumption that travelers paid a toll to only save their travel time. Therefore, it seems that the WTP estimated in this study involves only VOT.

On the other hand, the WTP distribution scenarios were obtained through trial and error attempts. Thus, their values were independent of other potentially influential factors such as travelers' socio-economic characteristics and/or trip attributes. Indeed, whether the travelers chose to pay a toll to drive on the MLs or not was known. However, why they chose to make such decisions was not identified in this study. It was presumed that the primary factor in paying a toll was saving travel time, i.e. the VOT. However, what was being observed was the WTP (not the VOT) to use MLs for a number of intertwined reasons and not just time savings. This could help enlighten why scatter plots of travel time savings versus toll for different times of day displayed no strong trend between the two variables. Indeed, during the AM and PM peaks and the AM inter-peak period, no trends were observed. During non-peak periods, the observed trends were more pronounced but still not statistically significant, with very low adjusted R-squared values. So, it can be concluded that the values paid by travelers likely should not be solely attributed to travel time savings. Furthermore, in dynamic toll pricing systems, drivers might infer current traffic conditions along the corridor through the amounts of toll being charged. From their point of view, the higher values of toll might indicate higher levels of congestion downstream, and consequently a higher probability to experience longer travel times on the GPLs. Accordingly, the WTP estimated in this study are likely to include the users' values of travel time reliability (VOR) and other values of intangible factors rather than only their VOT. These include, for example, the values users place on higher speed limits, safer facilities, more travel time reliability, a perception of lax enforcement, etc.

Further investigation to validate the results of this study can be beneficial in this regard. In addition, considering the possible sources of bias in the results of different studies can further help explain the differences. The possible sources of bias regarding the new data source and methodology used in this study are discussed further in the study limitations section later in this chapter.

7.2 Contributions

7.2.1 Innovative data source and analysis methods

This study suggested a number of unique approaches in estimating WTP values. The new approaches included a different revealed data source (camera images from the field) as well as an alternative analysis method (TPM) in WTP studies. The results of this new methodology may not directly address the questions about travelers' behavior in terms of their reasons to choose between the MLs and GPLs. However, these results can significantly contribute to decision making about transportation policies, in particular policies associated with dynamic congestion pricing for ML corridors.

While the revealed WTP values were estimated only for SOV drivers in this research, the model can easily be used to obtain the revealed WTP values for travelers' driving other vehicle classes by using a similar dataset. Furthermore, this method can also be employed to estimate the WTP values for travelers' driving other ML corridors in this or other regions.

7.2.2 Better understanding of travelers' behavior

As mentioned earlier, the ML is a relatively new concept in the nation's freeway system as well as the DFW highway network. In addition, the conventional toll pricing methods are being replaced by an emerging scheme called dynamic toll pricing. Since these new concepts are still in their early stages, the level of acceptance by users is not yet well specified. This study presents a procedure to better evaluate the travelers' behavior based on their revealed mode choice and with respect to different times of day and classes of vehicles. Also, the WTP estimates do not only represent the mean value of WTP, but also a frequency distribution of the sample population.

During peak periods, as previously shown, travel time savings might not have been the main reasons for paying toll for the NTE drivers. During non-peak periods, their motivations to pay tolls could be partially explained by travel time savings. It can be said that, other probable reasons such as more reliable travel time, safer geometry, higher speed limits, and a perception of lax speed enforcement might have been considered in their mode choice decisions. Further investigations would be beneficial to study the role of reasons other than time savings such as those mentioned above in using toll lanes.

Moreover, the results of this study showed relatively high WTP values and ML share percentages for the NTE drivers, indicating a high level of acceptance of MLs in the region.

7.2.3 Decision support system tool for ML dynamic toll pricing (TPM 5.0)

Using an existing toll pricing model (TPM-4.3) as a decision support system tool for dynamic toll pricing in ML facilities was another contribution of this study. This was achieved through calibrating and modifying the TPM [6,7] using the NTE revealed data. TPM 5.0 can be employed as a DSS tool to estimate the WTP values for drivers of any vehicle classes, on any ML corridors, and for any times of day. In addition, the model can be calibrated and modified for any ML facilities. Then, one of the two built-in objectives of the model can be invoked to predict the volume assignment on the facility for a given toll or to recommend a toll based on a desired ML average speed. TPM 5.0 can be accessed on the web and it is very user-friendly. The details on input modules of the DSS tool were presented in Chapter 6.

7.3 Study Limitations

The data used in this study were easy to collect. The camera images provided the information regarding the revealed mode choice decisions for travelers on both MLs and GPLs. Moreover, the volume and toll data for different times of day and different vehicle classes were easily reduced from the camera images, as well. Also, the analysis method employed only required the data associated with toll and traffic volume. Indeed, the process of WTP estimation was independent of travelers' socio-economic backgrounds or trip attributes.

On the other hand, the data analysis method was based on trial and error attempts of different WTP distribution scenarios through TPM. These new methods in data collection efforts and data analysis posed a number of advantages relative to the shortcomings associated with the existing methods in the field, as discussed in Chapter 2. However, there are some drawbacks and limitations associated with the data collection methodology used. These limitations are presented below.

7.3.1 Data limitation

Whereas the data used in this study had some advantages as discussed earlier in this chapter and in Chapter 2, there were a number of limitations which may introduce some bias in WTP estimates.

First, the traffic counts associated with Registered HOV and Motorcycle classes were not directly captured from the field and had to be estimated. This could affect the WTP estimates for these classes. In addition, in this study, only the GPLs and MLs of the NTE corridor were simulated through the TPM. The access roads were not considered since they were not continuous along the corridor at the time of the study. Including the frontage roads in the model, would definitely influence the WTP estimates.

In addition, the lack of information regarding the total length and cost of individual travelers' trips was another possible source of bias [18,32]. As shown in a previous study, travelers were more willing to pay tolls for shorter travel lengths [32]. It was also revealed by Li et al. that travelers' WTP varied due to their total trip cost. The WTP values were higher if the toll paid by travelers made up a small fraction of their overall trip cost [18]. For this study, the data were only collected from the first segment of the NTE ML corridor and the travel times and costs were not captured for an individual's entire trip. Therefore, the WTP estimated by this study were likely to have an upward bias.

Another potential source of bias was the manner in which travel times were estimated. First, the traffic flow model used in this study was selected based on the results from a previous study [61]. As mentioned, the corridor was not studied in detail to find the traffic flow model which best represented its characteristics. This could affect the accuracy of the travel time estimates. To obtain more precise results, a further study would be beneficial to calibrate the traffic flow models for the specific corridor. Moreover, due to the dynamic nature of ML corridors, it is unlikely to describe the stochastic behavior of travelers' by solely using deterministic traffic flow models. The deterministic single-regime speed-density traffic flow models characterize the average system behavior. So, more advanced models are required to capture the ML corridor's uncertainties [63]. Wang et al. proposed a stochastic speed-density relationship to overcome the shortcomings of deterministic models [63]. In another study, to more accurately estimate the freeway travel time, a (modified) dynamic traffic flow model was presented. The model used fixed-point detector data to describe and predict the corridor travel time under transition and congestion conditions [64]. In the concept of ML and dynamic toll pricing, further studies would be extremely useful to develop more accurate traffic flow models. A yet better alternative would be to directly measure travel times from field detectors such as Bluetooth readers or other such detectors.

Another source of bias was that the number of travelers on the GPLs might be misinterpreted. The camera images were recorded at the midway of the first ML segment. Along the first segment, for each direction, there are only one entry and one exit ramp on each end of the segment. The drivers on the MLs selected to enter the ML at the beginning of the corridor. Since there is no access ramp along the corridor, the same drivers exit the ML at the end of the corridor. However, this is not the case for the GPLs since there are multiple access ramps along the GPL facility. Therefore, the traffic volume captured by the camera might enter the GPLs after the MLs entry ramp. They might have entered the ML facility if they had access to it. The drivers captured by the camera located at the middle of the corridor might enter the corridor after the ML entrance and exit it before the end of the corridor. This problem cannot be solved by changing the camera location to the beginning of the corridor. The travelers do not choose to drive on the ML because they might need to exit the ML before the end of the corridor. But since there is no exit ramp along the corridor, they choose not to use the MLs. Finally, there was no information about origin-destination of the drivers on the GPLs. They might have entered and/or exited before and/or after the location of the camera. This problem could be somewhat mitigated by observing the field at the entrance of the ML corridor.

7.3.2 ML user equilibrium condition

The toll pricing model (TPM) used in this study was established based on the ML user equilibrium condition for MLs. Based on the new paradigm, the equilibrium condition was reached by ML corridor when the users' WTP values became lower than the cost of traveling on the MLs. The cost of switching to the ML was estimated based on the assumption that travelers paid toll to only save travel time. However, travel time savings may not be the only benefit perceived by drivers when choosing to use MLs. A Previous study has shown that the travelers' perceived travel time savings were more than what they really saved by switching to the MLs [70]. The purpose of trip (work commute) was also shown to significantly affect their perception of travel time savings [70]. If a percentage of the NTE travelers were assumed to overestimate the actual travel time savings, it could explain the relatively high values of average WTP estimates, especially during peak periods. In addition, one of the criteria which the results from the simulation runs required to meet was estimated based on the average WTP tolls to save a unit of travel time by travelers during each time period. Again, this approach makes no distinction between WTP and VOT.

7.3.3 Manually modifying trial and error WTP distribution scenarios

Another reason that might introduce bias in WTP values could be due to the process of trial and error attempts and their modifications for TPM being all done manually. Performing this process through developing computer programs would definitely optimize the results' accuracy as well as the analysis time. Also, the wide range of dispersion in the WTP intervals can be fixed through examining different trial and error distribution scenarios by these programs instead of performing the task manually. Moreover, figuring out the distribution shape of the travelers' WTP is another challenge of this method.

7.4 Future Directions

The field of travelers' willingness to pay toll is one of the most crucial fields in transportation policy. Although, existing literature has been substantially enhanced by various research efforts on this topic, further improvements in the field are still desired and possible. This research suggested a new practice in WTP studies. However, as discussed above, there are still a number of drawbacks associated with it. This section presents the direction for future studies in two sub-sections. First, based on the findings of the research and discussions in existing literature, a new paradigm in WTP estimations is suggested. Second, future studies to address some of the identified shortcomings in this research are recommended.

7.4.1 New paradigm in willingness-to-pay estimations

Despite significant progress made in the WTP studies, there is still room for further enhancements. There are various reasons that make the value of time analysis beneficial and desired. Among them, Small [11] mentioned three reasons. First, VOT is critical in decision making about transportation policy. Second, it contributes to better understanding of human behavior that is of interest for fields such as economics. Third, it is one of the important components in travel demand modeling [11]. Based on the findings of this research and the existing need for further improvements in this area, a new paradigm in WTP estimation studies is recommended. The new paradigm involves an alternative data source, an innovative analysis method, a new concept for WTP, and a relatively different definition for WTP values.

A new data source and analysis method were introduced through this study. In addition, as the third component of the new paradigm, a concept of real-time WTP values is suggested for dynamic toll pricing schemes. Indeed, for dynamic toll pricing systems, to set the real-time toll prices based on the real-time congestion levels on the corridor, it is recommended to measure travelers' real-time WTP values. For dynamic toll pricing, the real-time WTP estimates would replace the WTP values obtained for the average behavior of the population as observed in most existing literature. The major drawbacks associated with the existing approaches can be summarized as below.

First, the new concept relies thoroughly on the revealed behavior of the travelers. However, not all the data collection efforts measure the revealed travelers' behavior from their real-life mode choice experiences. This is due to the fact that some of the motivations that cause travelers to behave in a certain way are difficult to quantify or unknown to the researchers. Furthermore, the real-time WTP cannot be estimated only through studying the ML users' behavior, but also through studying the travelers' who choose to drive on the free adjacent lanes. This is another shortcoming with the current revealed data sources such as dynamic toll data. Such data only provide information on the ML users. In addition, the dynamic pricing of the MLs facilities intends to change the price based on the real dynamic traffic conditions on the corridor. All the existing data collection efforts fail to capture the wide variety of traffic conditions encountered in a corridor. For example, SP surveys just offer participants only a limited number of hypothetical scenarios. Although RP surveys investigate the revealed drivers' mode choice decisions, they still suffer from the restricted number of conditions under which the travelers' behavior can be studied. Other revealed data collection efforts capture a wider variety of conditions, but they are still limited to using historical datasets. However, the suggested method has the potential to capture the data and the associated travelers' behavior for any traffic conditions happening at the time.

Moreover, the concept of real-time WTP requires on-site data. SP or RP surveys are considerably time consuming to design, conduct, and reduce. The same problem is somewhat attributed to GPS data collection efforts. On the other hand, data provided by loop detectors or dynamic toll datasets are relatively fast-paced to access. However, there are still other drawbacks that make them somewhat unsuitable for use in dynamic toll pricing. For example, the dynamic toll data just cover the ML traffic counts, and data obtained from the loop detector cannot provide much information on travel time reliability. In addition, they both suffer from an absence of information on travelers' socio-economic backgrounds or trip attributes. However, this is another advantage of the suggested method that estimates the travelers' WTP values independent of their socio-economic characteristics and trips attributes.

Once again, regardless of data collection methods, estimating the WTP values through the discrete choice models is significantly time consuming. This problem gets more serious when to obtain more accurate data, more advanced models and/or more predictor variables in the models are used. In addition, discrete choice models mainly estimate the average behavior of the population studied. However, transportation systems, particular dynamic managed lane pricing, cannot merely rely on the average travelers' behavior. Indeed, it requires another gauge to efficiently address the dynamic nature of the ML corridors.

The new data source and analysis method suggested in this study can be employed as a platform to develop a tool in order to estimate the real-time WTP values. This method only requires the data associated with the actual toll lane usage and tolls paid. The traffic count data are simply available for different time periods and for both MLs and adjacent free lanes through camera records. Existing cameras located in the corridors can capture the required data, so there is no need to install new equipment. Moreover, the data can be obtained for different vehicle classes subject to different toll rates. This offers the opportunity for the ML operators to estimate the WTP for drivers of different vehicle classes by using the same dataset.

As discussed, the DSS tool developed in this study has the potential to be used by ML operators to measure the real-time WTP values for the ML users. However, the concept of WTP, data collection effort, and TPM all require further modifications and enhancements in order to develop an on-site DSS tool. Some of the possible and desired modifications and enhancements are discussed in the future studies section.

The last component in the new paradigm is a new definition for WTP values. The current literature defines the value of travel time savings (VTTS), also referred to as the value of time (VOT), to represent the travelers' willingness to pay to reduce their travel time [79]. Value of travel time reliability (VOR) presents the value travelers place on the reliability of estimated travel time [15]. VOR can essentially be thought of as the value the travelers place on reducing the variability of travel time by one unit [15]. ML facilities are intended to offer lower and more reliable travel times. Therefore, the travelers WTP are currently estimated as their willingness to pay to reduce travel time and/or variability of travel time in terms of a monetary unit per unit of time (usually in dollars per hour). In other words, the available literature mainly focuses on estimating WTP as a portion of users' WTP associated only with travel time (saving and/or reliability) through discrete choice models. However, other probable utilities offered by MLs for which they are also willing to pay are not addressed in those models. This could be explained due to the fact that these other probable influential factors are indeterminate, factors such as relative safety, higher speed limits, better geometry, etc.

On the other hand, the WTP values are frequently prone to change. The WTP values are different among regions, times, and individual travelers. They vary during different times and conditions even for an individual traveler. For example, a former study showed that risk-averse travelers had higher VOR and consecutively higher WTP compared with risk-taking travelers [70]. In another study, it was shown that drivers were considerably more willing to pay under urgent situations compared to ordinary situations [71]. Furthermore, different discrete choice models with different predictor variables and different assumptions would result in different WTP estimates.

The fundamental question asked in the current literature is how much drivers are willing to pay to save travel time or to have more reliable travel time. However, this study suggests studying the travelers' WTP values from another aspect. It is suggested to observe travelers' decisions in their real-life experiences without speculating on the reasons behind their decisions.

In this regard, it is suggested to instead ask how much drivers are willing to pay to drive one unit of length on the MLs. Therefore, the WTP value will be associated to the travelers' willingness to pay to drive one unit distance on toll lanes. As the toll is charged in terms of dollars per mile, the travelers' WTP are also estimated in terms of dollars per mile. The WTP values estimated through this new approach would not focus on the reasons behind the travelers' decision. However, they would significantly contribute to the transportation policy decisions, in particular for ML dynamic pricing schemes. This new paradigm has also the potential to overcome some of the drawbacks associated with data collection and the methodology employed in this study.

As mentioned, the new data collection and analysis methods employed in this study require further enhancements and modifications to be compatible with the new paradigm in WTP estimation discussed above. Moreover, future studies can investigate the possibility of developing a DSS tool based on the new paradigm in the WTP estimation, i.e. willingness to pay per mile rather than willingness to pay to save a minute of time.

7.4.2 Future studies

The future directions to improve the findings of this study are summarized as follows:

The decision support system tool developed for dynamic pricing of MLs can be applied for any ML corridors. To examine the accuracy of the results of this research, it would be useful to validate the model based on other ML corridors. Also, the focus of this study was only on the NTE SOV drivers' travel behavior. Further studies to investigate the drivers' travel behavior driving different classes of vehicles would provide a better understanding in this regard. Moreover, the data for this study were collected shortly (within a year) after opening the NTE TEXpress lanes. It is recommended to re-estimate WTP values based on data collected after the corridor has been operational for a few years so that users are more accustomed to the new ML corridors.

To mitigate the possible sources of bias associated with the data collection effort, it is suggested to employ a combination of other different data collection methods with the new data source used in this study. In addition, the ML corridor studied in this research represented a specific length of toll lane corridor. Investigating corridors with different lengths would provide a more comprehensive understanding of travelers' mode choice decisions. Furthermore, only the GPLs and MLs of the NTE corridor were simulated through the TPM. The access roads were not considered since they were not continuous along the corridor at the time of the study. Considering any continuous lanes along the corridor could improve the accuracy of the revealed WTP estimates. Additionally, to develop a more compatible DSS tool for measuring real-time WTP values, computer programs could perform the data reduction process from the camera records.

Regarding the potential bias caused by the data analysis method (TPM), the process of generating and modifying the different WTP distribution scenarios could be programed and done as part of the model. Therefore, instead of doing the whole process manually, it can be done automatically by the model. This could yield more accurate WTP estimates and minimize the wide range of the WTP intervals. Also, it would save significant amounts of estimation time. Moreover, the problems associated with the existing user equilibrium definition for MLs can be solved through adopting the new mile-based WTP concept offered by this study. The new measurement for WTP values could make the user equilibrium conditions easier to estimate. Indeed, the cost of traveling on the toll lanes is exactly equal to the amount of toll the travelers are willing to pay without the need to estimate an implicit per unit time toll values. So, the ML reaches the equilibrium condition when the travelers' WTP become lower than the tolls charged. This could also remove the problem associated with choosing the best traffic flow model for the corridor for estimating travel times.

Finally, in this study, the average revealed WTP values were estimated for the average data obtained for different times of day. However, to obtain more accurate results, the data are recommended to be simulated for every 5-minute interval (the time interval that real-time prices were re-calculated based on the level of congestion on the corridor [4]). It might require more time and more data points from the field. In addition to the average revealed WTP estimates for different times of day, attempts could also be made to obtain WTP estimates under different levels of congestion and if possible even for different trip purposes.

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