SIMULATION-BASED EVALUATION OF A FEEDBACK-BASED DYNAMIC CONGESTION PRICING STRATEGY FOR ALTERNATE FACILITIES - TRACKING IMPACTS OF VALUE OF RELIABILITY

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ABSTRACT

Dynamic congestion pricing is one of the most effective congestion management policies that is successfully implemented mainly in the form of High-Occupancy Toll (HOT) Lanes in the US. Evidence from previous research (Lam and Small, 2001) shows that driver behaviour in response to real-time changing tolls depends on both Value of Time (VOT) and Value of Reliability (VOR). Although VOT is usually included in the optimal toll calculations in the literature, VOR remains mainly unexplored as part of the congestion pricing concept. This paper presents a feedback-based dynamic congestion pricing algorithm for a portion of a highly congested urban network. The provided algorithm aims to reduce sharp fluctuations in toll rates within short time intervals by incorporating a feedback-based mechanism in the toll rate calculation process while incorporating VOT and VOR together to model user response in a more realistic way. The algorithm is tested on a network connecting New Jersey to New York City using a microscopic traffic simulation model

Keywords: Dynamic Pricing, Congestion Pricing, Value of Reliability, Value of Time

INTRODUCTION

Traffic congestion is one of the major problems of modern world and according to the 2011 Urban Mobility Report of Texas Transportation Institute the cost of congestion is more than $100 billion which is equivalent to $750 for every single commuter in the US. Projected numbers for 2015 and 2020 are even higher therefore immediate and effective solutions are necessary. Congestion pricing is considered as one of the most practical solutions which in principle aims to manipulate users' travel behaviours by charging them tolls depending on the congestion level. The two possible options for a driver who is using a facility under congestion tolls are either to change his/her departure time to avoid higher tolls during rush hours or using an alternative route to reach the desired destination within the same time period.

Several applications of congestion pricing are being operated in many different cities around the world (e.g. London, Stockholm, Singapore). Although the main idea is to charge users a fee for the traffic congestion they contribute by being a part of the congestion during rush hours, in practice most of the congestion pricing applications are based on pre-determined time-of-day toll schedules. Therefore a user traveling during rush hours does not actually pay the toll for the congestion he/she experiences for that single trip, instead pays an average amount depending on the historical traffic congestion data.

With the advances in intelligent transportation technology a vast majority of traffic data is now available real-time for both drivers and policy-makers. As a result of these developments congestion pricing policy is started to be implemented as real-time road pricing, in other words dynamic pricing. The idea of dynamic toll pricing is to make users pay a true time-dependent congestion charge, by determining the toll rates dependent on real-time traffic conditions. One of the major secondary benefits of dynamic pricing is the elimination of toll booths by collecting tolls with the help of electronic tag readers.

In the last two decades dynamic toll pricing has gained popularity and considered as a strong tool for congestion management evidenced by the successful implementations of several High Occupancy Toll (HOT) lane projects. Table 1 presents a summary of the current and proposed HOT projects in the United States.

Table I – Dynamic Pricing Implementations in the USA

Facilities with Dynamically Priced Lanes		
Facility	**Initiation Date**	**Agency/*Project website***
San Diego I-15, CA	April 1998	http://fastrak.511sd.com/san-diego-toll-roads/i-15-express-lanes
Minnesota I-394, MN	Spring 2005	http://www.mnpass.org/
I-15 Salt Lake City, UT	September 2006	www.udot.utah.gov/expresslanes
SR-167, WA	May 2008	http://www.wsdot.wa.gov/Tolling/SR167HotLanes/
I-95, FL	Summer 2008	http://www.95express.com/
I-680, Oakland, CA	September 2010	http://www.680expresslane.org/Home.asp
I-85, Atlanta	Fall 2011	http://www.peachpass.com/peach-pass-toll-facilities/about-i-85-express-lanes
SR-237, Silicon Valley, CA	March, 2012	http://www.vta.org/expresslanes/SR_237_project.html
I-495 Beltway, Northern Virginia	Fall 2012	https://www.495expresslanes.com/
I-110, Los Angeles, California	Fall 2012	http://www.metro.net/projects/expresslanes/
Future Projects		
SR-85, Silicon Valley, CA	2015	http://www.vta.org/expresslanes/
U.S. 101, Silicon Valley, CA	2016	http://www.vta.org/expresslanes/SR_101_project.html

Although HOT lanes are currently the only implementation for dynamic pricing, studies have been conducted to explore different possible tolled facilities such as crossings that are closely located to each other (Ozbay et al. (2011), Morgul and Ozbay(2011)). The findings of these studies show that when the connections between alternate facilities are sufficient for users to switch their routes, dynamic pricing can help to reduce peak period congestion.

Real-time tolls are calculated based on the real-time traffic conditions such as speed or occupancy (i.e. density). However tolling algorithms which cannot address the actual traffic conditions adequately can generate over-sensitive or under-sensitive toll rates which cause fluctuations in real-time toll rates within short time intervals. Efforts for developing tolling algorithms that can reflect the real time conditions in a more smooth way focus on the feedback-based approach (Zhang et al., (2008), Morgul and Ozbay (2011)) where the conditions from previous time intervals are included in the toll rate calculation and the rate of change in traffic conditions are taken into account.

For the simulation-based testing of feedback-based algorithms, driver behaviour in response to real time tolls is generally modelled by incorporating the Value of Time (VOT) component in the route decision of an individual. However Lam and Small (2001) showed that users of a dynamically priced facility (SR-91) value reliability as well as mean travel time. This means drivers are not only willing to pay for shortening their expected travel times but also for ensuring reliability to reach their destinations in their desired time window. Therefore the Value of Reliability (VOR) should also be included implicitly in the decision modelling.

The contribution of this paper is twofold: First, providing a feedback-based methodology, including both VOT and VOR in the driver decision process for the two tunnels connecting New Jersey and Manhattan within the context of a more complex transportation network with multiple decision points. Thus, this is a decentralized dynamic congestion pricing problem where a network-wide distribution of traffic is achieved as a result of individual decisions of travelers at these decision points. Second, we are proposing the use of realistic VOT and VOR functions estimated using New Jersey specific data. This will support the reliability of the simulation results and one of the first such attempts in the literature.

LITERATURE REVIEW

Dynamic pricing is a concept that has been explored in several different research fields such as communication networks (Gupta et al., 1995), inventory management (Elmaghraby and Keskinocak, 2003) and airline industry (Lin, 2006). Dynamic congestion pricing for roads is a relatively new area of study in traffic engineering and there are only a handful of real-world applications are present. Toll rates in dynamically priced facilities are based on several real-time measured traffic parameters for very short time intervals, including speed, occupancy, and traffic delay. Users are informed of the current toll rate with the help of variable message signs and allowed to make a route decision of either using the tolled road/lane to save time, or using an alternative road without paying a fee.

Earlier theoretical studies were generally conducted for dynamic toll rate determination based on network optimization for both fixed and variable demand including mode choice. Wie and Tobin (1998) provided two theoretical models for dynamic congestion pricing of general networks. The first model considered day-to-day learning of users with stable demands each day, while the second model considered the case of when users make independent decisions each day under fluctuating travel demand conditions. Joksimovic et al. (2005) presented a dynamic road pricing model with heterogeneous users for optimizing network performance. Wie (2007) considered dynamic congestion pricing and the optimal time-varying tolls with the Stackelberg game model. Friesz et al. (2007) considered the optimal dynamic toll problem with user equilibrium constraints and presented two algorithms with numerical examples. Xu (2009) provided a mathematical formulation to minimize the total travel time in a network and solve the problem for optimal time dependent tolls. The two levels of the problem include departure time and route choice decisions. Simulation-based models for dynamic pricing were also developed by some researchers. Mahmassani et al. (2005) conducted a study about variable toll pricing with heterogeneous users having different value of time preferences. They tested their models using the dynamic traffic assignment traffic simulator DYNASMART-P on three different real networks and the largest network they have consisted about 3000 links. Teodorovic and Edara (2007) proposed a real-time road pricing model on a simple two-node two-link parallel network. Their system made use of dynamic programming and neural networks. Karoonsoontawong et al. (2008) provided a simulation-based dynamic marginal cost pricing algorithm. They compared the dynamic and static scenarios in the simulation and obtained minor system benefits in the dynamic pricing case.

Feedback-based algorithms for dynamic pricing were also developed for practical applications. Yin and Lou (2007) proposed and simulated models for dynamic tolling using a feedback control-based method similar to ramp-metering. Zhang et al. (2008) developed a feedback-based dynamic tolling algorithm for HOT lane applications. Travel speeds and toll changing patterns were used as parameters in the model to calculate the optimal flow ratio for the HOT lanes, using feedback-based piecewise linear function. Then using a discrete route choice model they calculated the required toll rate by backward calculation. Zheng et al. (2012) developed a dynamic cordon pricing scheme using a linear feedback based toll rate calculation. The control parameter in their formulation is the network density for a confined region.

Route choice of users in response to dynamic tolls is often included in the tolling algorithm by the valuation of travel time savings and most of the above studies use values from earlier contributions. Efforts have also been done to include both VOT and VOR into the tolling scheme. Chung and Recker (2011) proposed a speed-based toll calculation scheme for HOT lanes to reflect both VOT and VOR. Assuming VOT and VOR parameters are independent of each other, toll rates for the managed lanes are determined by simply summing up the total savings obtained from those two parameters. Although the authors find VOR accounts for approximately 45% of the toll rates, independence assumption is weak and needs to be relaxed for a more realistic toll algorithm setup. Jang and Chung (2010) presented two dynamic pricing strategies for HOT lanes: revenue maximization and delay minimization. The toll strategy takes travelers' VOT distribution and a range for toll price is calculated by taking the inverse function of the cumulative distribution of VOT which is considered to be a function of toll rate.

All of the above studies consider dynamic pricing for either HOT lanes or cordon based pricing. Dynamic toll scheduling for alternate facilities such as closely located crossings are also addressed in previous studies. Ozbay et al. (2011) conducted a mesoscopic simulation-based study for New Jersey- New York tunnels where the tolls in both facilities are allowed to be dynamic. The results show that by only affecting route-choice decisions of the users similar to the HOT lanes such an implementation may provide benefits for overall performance of the facilities while creating more revenues. As implemented in many HOT lane facilities real-time road density-based step functions are used to calculate the toll rates. A more complicated feedback-based dynamic tolling algorithm is tested for the same network in a following study by Morgul and Ozbay (2011). Microsopic simulation-based results show that under dynamic pricing travel times experienced by the users in peak periods can be reduced compared to a base scenario where static tolls are employed.

METHODOLOGY

The idea of dynamic pricing suggests that toll rates that are dependent on the real-time traffic conditions can be used to regulate traffic congestion. Although performance reports from successful HOT lane implementations report improvements in traffic conditions in both tolled and free lanes, the toll-traffic relationship is not well established in the literature. Existing tolling algorithms in the literature mainly depend on VOT for modelling route choice, however it is also found that users for these dynamically priced facilities do not only count on travel time savings but also consider reliability as a determinant factor in their lane/route decisions (Lam and Small, 2001). In this section we present a feedback-based dynamic pricing scheme that employs VOT and VOR together for calculation of real-time toll rates.

Let's assume that there is an urban network which connects a suburb to a major city through two major connectors such as bridges of tunnels. Thus, although commuters might have a number of decision points in the suburban part of the network, their main decision comes to picking up one of the two connectors. First, we start with the definition of total cost of driving. We assume VOR as a direct parameter in the user utility function which was previously adopted by several studies following Jackson and Jucker (1982). Excluding operational and other costs we define the total cost of a user as:

$$TC_i = \tau_i + \alpha \times TT_i + \beta \times SD_i \tag{1}$$

Where, τ_i is the toll rate for for the i^{th} alternative, α is the value of time for the drivers, TT_i is the travel time, β is the value of reliability, SD_i is the schedule delay which is used as the indicator for reliability. Utility is assumed to be decreasing with increasing costs, therefore for the case of two alternatives, similar to the approach used in Zhang et al. (2008) utility function for selecting alternative 1 (U_1) and alternative 2 (U_2) can be simply found as follows:

$$U_1 = \frac{1}{TC_1} = \frac{1}{\tau_1 + \alpha \times TT_1 + \beta \times SD_1} \tag{2}$$

$$U_2 = \frac{1}{TC_2} = \frac{1}{\tau_2 + \alpha \times TT_2 + \beta \times SD_2} \tag{3}$$

A linear logit regression model is used to define the traffic distribution for each alternative using the following formula:

$$\begin{aligned} F_1 &= F_{TOTAL} \times P_1 = F_{TOTAL} \times \frac{\exp(U_1)}{\exp(U_1) + \exp(U_2)} \\ &= F_{TOTAL} \times f(\tau_1, \tau_2, SD_1, TT_1, SD_2, TT_2) \end{aligned} \tag{4}$$

where F_{TOTAL} is the total approaching flow from the main road, and P_1 is the probability of choosing alternative 1. The function $f()$ uses the independent variables $\tau_1, \tau_2, SD_1, TT_1, SD_2, TT_2$ and the dependent variable P_1. The toll rate for time stamp t $\tau_{i,t}$ can be calculated inversely from using the function $f^{-1}()$ as a result of transformation between SD_1 and P_1.

$$\tau_{1,t} = f^{-1}(\tau_{2,t-1}, P_{1,t}, TT_{1,t}, TT_{2,t-1}, SD_{1,t}, SD_{2,t-1}) \tag{5}$$

Therefore if F_1 is known, toll rate in alternative route 1 can be obtained by backward calculation. The flow ratio for alternative 1, F_1, is supposed to change depending on congestion levels. For example, if the average occupancy difference between the two alternatives is too high the ratio of vehicles using the less congested alternative should be higher. The two major assumptions for this formulation are that TT_1, TT_2, SD_1, SD_2 and F_{TOTAL} are real-time measurable with the available detector infrastructure and users have perfect information about the real-time changing tolls. Finally the derivation of the inverse function for $\tau_{1,t}$ is determined by the following equation:

$$\tau_{1,t} = \frac{1}{\dfrac{1}{\tau_{2,t-1} + \alpha \times TT_{2,t-1} + \beta \times SD_{2,t-1}} - \ln\left(\dfrac{1-P_{1,t}}{P_{1,t}}\right)} - \alpha \times TT_{1,t} - \beta \times SD_{1,t} \tag{6}$$

The toll rate for the second alternative route can be calculated simultaneously using the same method. Travel time parameters are measured by detectors, therefore the only two variables that have to be determined is the parameter α which is VOT and parameter β which is VOR. These two parameters should be estimated using SP or RP data of the facility users and the estimation procedure for our case study is explained in the following section.

Finally to avoid unrealistically low or high dynamic tolls, we assume that the set of possible toll rates are defined for strictly positive numbers and they are within an interval that limits them to a previously determined maximum toll value of $\tau_{\max}$ and to a minimum toll value of $\tau_{\min}$. According to this approach, if $\tau'_{n,t}$ is the value calculated from equation (6) for alternative *n* and for time interval *t*, our proposed tolling algorithm ensures that:

$$
\begin{aligned}
&\tau_{n,t} \in [\tau_{\min}, \tau_{\max}] \\
&0 < \tau_{\min} < \tau_{\max} \\
\\
&If \quad \tau_{\min} < \tau_{n,t}' < \tau_{\max} \\
&Then \quad \tau_{n,t} = \tau_{n,t}' \\
\\
&If \quad \tau_{n,t}' < \tau_{\min} \\
&Then \quad \tau_{n,t} = \tau_{\min} \\
\\
&If \quad \tau_{n,t}' > \tau_{\max} \\
&Then \quad \tau_{n,t} = \tau_{\max} \\
&n = 1, 2
\end{aligned}
\tag{7}
$$

CASE STUDY

Network

As mentioned above, the applicability of the tolling algorithm provided in the previous section requires two facilities, which can be regarded as alternative routes to each other. The Holland and Lincoln Tunnels are selected for the case study, since the location of the two crossings allows users to easily switch between the two as a result of dynamic tolling. In addition to their close locations, connecting roads between the two tunnel entrance points from the New Jersey side make it easier for drivers to switch from one alternative to the other. An evidence from observed traffic counts after the truck traffic prohibition in Holland Tunnel in 2001 show that the commercial vehicle traffic redirected to the Lincoln Tunnel as the closest alternative option (DOT Truck Study, 2006). Another finding from a stated preference survey that was conducted for the HOT lane feasibility study for Lincoln Tunnel shows that 41 percent of Lincoln Tunnel users consider Holland Tunnel as their next best alternative when traveling from New Jersey to New York (Wilbur Smith Associates, 2009). New Jersey Turnpike (NJTPK) is the major highway which gives exits to Holland and Lincoln Tunnels, with the difference in distance between the two exists approximately 5.5 miles (6 minutes in free flow conditions). Another alternative connecter road is Route 1-9, which is an arterial running through urban areas with traffic disturbed by signalized junctions. On the other side of the two tunnels, the distance between the two exit points inside Manhattan is approximately 3 miles. Three destination zones are provided in Manhattan.

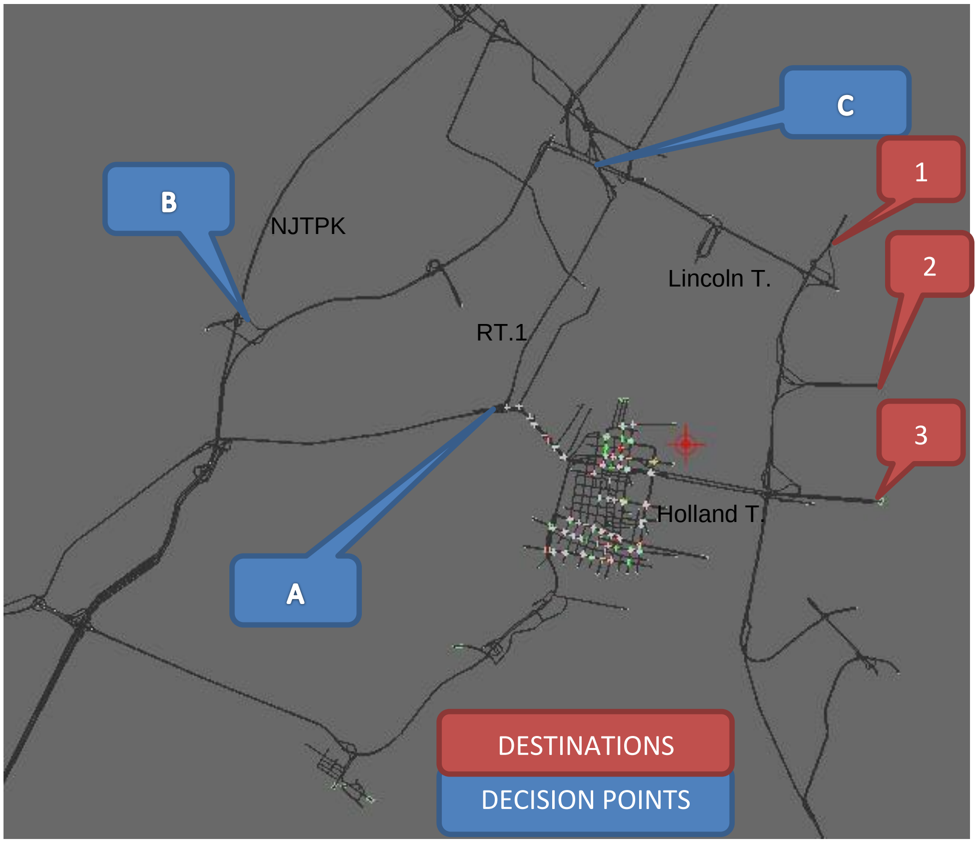

Figure 1 – Simulation Network

The micro-simulation network is constructed and calibrated in simulation software Paramics and shown in Figure 1. The network covers all the tunnels and bridges that connect New Jersey and New York and the major arterials with surrounding streets that feed the traffic that use these crossings. There exist 5072 links which reflect all the real-world traffic rules (i.e. stop, yield signs), signalizations which are calibrated according to real timings and prohibitions (bus, truck lanes). Network calibration is performed by minimizing the difference between observed volumes and simulated flows which are validated by several site visits and hourly traffic volumes and speeds obtained from different agencies (INRIX, TransCom, Jersey City DOT). In-built software parameters that control driver behavior are adjusted to obtain the most realistic flow and travel time results. Calibrated simulation volumes for the major intersections in the network and speeds for the major links and their differences with the observed values are given in Table 2 and Table 3. For further information about network development and calibration steps readers are referred to Regional Traffic Impact Study prepared by Rutgers Intelligent Transportation Systems Laboratory (RITS) in 2011.

Table 2 – Total Observed and Simulated Hourly Intersection Volumes after Network Calibration (RITS, 2011)

Volumes			
Intersection	**Observed (vph)**	**Simulated (vph)**	**Difference (%)**
Columbus & Marin	2,877	3,415	18.7
Columbus & Grove	2,542	2,947	15.9
Columbus & Barrow	2,106	2,392	13.6
Columbus & Jersey	3,075	3,146	2.3
Columbus & Varick	2,573	2,745	6.7
Columbus & Brunswick	3,109	3,164	1.8
Montgomery & Marin	2,507	2,732	9.0
Montgomery & Grove	2,005	2,475	23.4
Montgomery & Barrow	1,035	1,156	11.7
Montgomery & Jersey	1,771	2,076	17.2
Montgomery & Varick	1,571	1,871	19.1
Montgomery & Brunswick	1,705	1,728	1.3
14th & Marin	3,385	3,690	9.0
14th & Manila	4,285	4,501	5.0
14th & Erie	4,672	4,817	3.1
14th & Jersey	7,015	7,323	4.4

Table 3 – Total Observed and Simulated Link Speeds after Network Calibration (RITS, 2011)

Location	**Observed Speed (mph)**			**Simulated Speed (mph)**
	Average	**Max**	**Min**	
I-78 westbound	48.1	54.1	42.1	50.5
Route 139 westbound	31.3	39.6	22.9	32.4
14th Street	18.2	24.8	11.1	12.9
Route 495 westbound	41.8	49.0	34.6	42.1

Estimation of VOR and VOT parameters

VOT and VOR parameters (α and β respectively) for the cost function (1) are obtained from the NJTPK travel survey data which was conducted in 2004. The survey was originally designed to estimate VOT savings for the individuals who have used NJTPK on a regular basis. Since NJTPK is the main corridor that carries traffic to the selected tunnels, driver profiles in this case study are assumed to be similar. Each individual was asked for their most recent trips along with their schedule delays and their delay flexibilities (A detailed description of the survey is available in Ozbay et al. (2005)). Using the same dataset Ozbay and Yanmaz (2008) estimated the mean VOT in the range of $15-$20 per hour depending on departure time choice and trip purposes. In their analysis travel delays are considered as part of total travel duration and a single valuation (VOT) is estimated for total travel time. The idea behind this assumption is that value of savings from travel time and travel reliability can be combined which is similar to the concept of Variability Embedded Value of Travel Time Savings introduced by Hensher et al. (2011).

In this study we have adopted the classical value of reliability approach where it is assumed that value of mean travel time savings are different than value of reliability. A detailed summary of existing literature can be found in Carrion and Levinson (2012). In this approach several methods have been used to measure the reliability by previous studies such as standard deviation of travel time or observed schedule delays with respect to the desired arrival time. For our analysis we adopted the latter one and estimated the value of schedule delay as the reliability parameter.

The NJTPK travel survey includes stated preference questions for departure time choice and route choice. In this analysis we select the route choice as the dependent variable which is our major interest in this study and we employ a binary logit model depending on the route choice decision to estimate both VOT and VOR parameters. Independent parameters are travel cost, travel time and schedule delay for the reliability parameter.

Following Small (1982), we assume an reduced indirect utility of scheduling function depending on departure time (t_d) and preferred arrival time (PAT):

$$U(t_d;PAT) = \gamma_1 \text{Toll} + \gamma_2 \text{Travel Time} + \gamma_3 \text{ Schedule Delay} \tag{8}$$

In this linear function γ parameters needs to be estimated using discrete choice methods and expected to be negative. Then marginal rate of substitution can be calculated for VOT and Value of Schedule Delay (VSD) as follows:

$$\text{VOT}=\frac{\partial U / \partial \text{Travel Time}}{\partial U / \partial Toll} \tag{9}$$

Similarly, the willingness to pay for one unit schedule delay reduction, which we can assume as VOR if we measure the reliability in terms of schedule delay (early-late arrival):

$$\text{VSD}=\frac{\partial U / \partial \ Schedule\ Delay}{\partial U / \partial Toll} \tag{10}$$

Regression results for route choice decision are given in the Table 4:

Table 4 – Regression Results for Stated Preference for Route Choice

Number of Observations: 278 Wald Chi^2: 72.60 Log Likelihood: -122.46			
Parameter	**Coefficient**	**Standard Error**	**P> |z|**
Schedule Delay (min)	-0.135	0.009	0.151
Toll ($)	-0.844	0.653	0.196
Travel Time (min)	-0.256	0.004	0.000

All parameters are found to be significant at 90% confidence interval, therefore using equations (9) and (10), VOT and VSD are found to be $18.25/hour and $9.6/hour respectively. Reliability ratio which is defined as the ratio of VOR/VOT is found as 0.53 which is in an acceptable range compared to the empirical results in the literature (Hollander (2006), Carrion and Levinson (2011), Small et al. (2005)). Going back to Equation (1), final values for coefficients are selected for the realistic dollar values with the relationship $\beta = 0.53\alpha$.

Simulation

Traffic simulation for dynamic pricing is run for the afternoon peak period (between 3:00 PM and 6:00 PM). The first one hour is assumed to be the warm-up period therefore the results are shown for the two hours after 4:00 PM. A total of 250,902 trips are generated during the simulation period.

The dynamic tolling algorithm was applied by developing an API code which utilizes dynamic toll formulations and the driver behavior in response to the actual congestion dependent toll rates. The API code incorporates two main functions with the simulation. The first function is for the real-time toll rate calculation which utilizes Equation (6). This function accounts for the travel time to cross the tunnel in returning the toll rate, as well as the travel time to cross the alternative tunnel and the toll rate calculated for the alternative tunnel in the previous time step. Using these parameters as inputs it returns a toll rate which is used for route decision in the second stage of the API code (Figure 2).

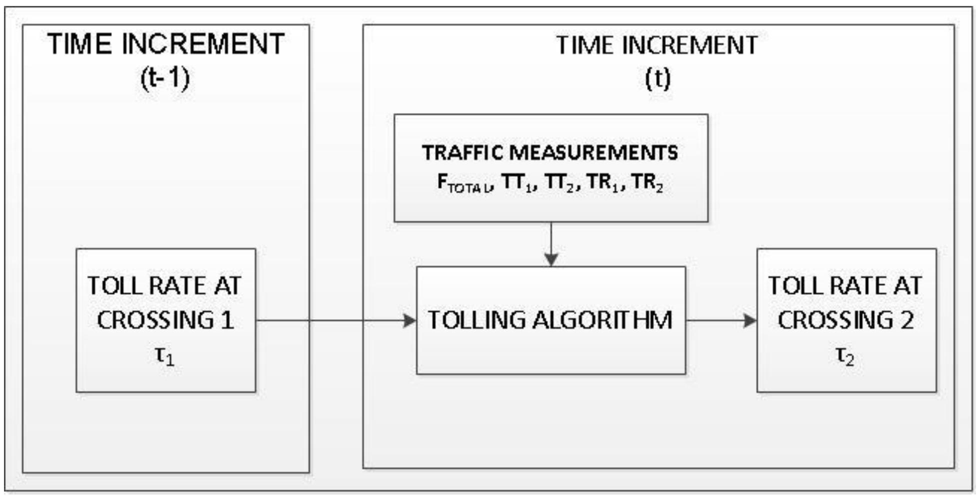

Figure 2 – Flowchart of the Paramics Implementation of the Dynamic Toll Pricing Algorithm

The second major function is concerned with the route choice, which is dependent on the toll rates calculated in real-time. According to this function, when a vehicle arrives at one of the decision points shown in Figure 1, two utility functions are defined for the two alternatives beyond the decision point, based on travel time and toll rate. Three decision points are defined where users are likely to switch to an alternative route. According to their respective utility function users consider the toll rates on either crossing and make a decision to use either one of them. There were also three destination points defined for users destined to different parts of Manhattan.

Schedule delay term which is used as the measure of travel reliability is calculated for each single trip as the difference of total travel time with the free flow travel time.

Results

The time-dependent change of toll rates throughout the simulation at the two crossings is shown in Figure 3. Three different demand loading levels are tested and as expected toll rates are increasing with higher demands. It can be observed that the Holland Tunnel starts to get congested earlier than Lincoln Tunnel, therefore the toll rate increases at the Holland Tunnel during the earlier stages of the simulation. Later, when some of the Holland Tunnel users start to switch their routes to the Lincoln Tunnel, toll rates at Lincoln Tunnel starts to increase while Holland Tunnel toll rates tend to be more stable. Through the end of the peak period, toll rates start to get lower for all demand levels in Lincoln Tunnel. However in Holland Tunnel diminishing toll rates can be seen only for 80% demand while it is expected that for lower demand levels recovery after peak periods is faster than higher demand levels.

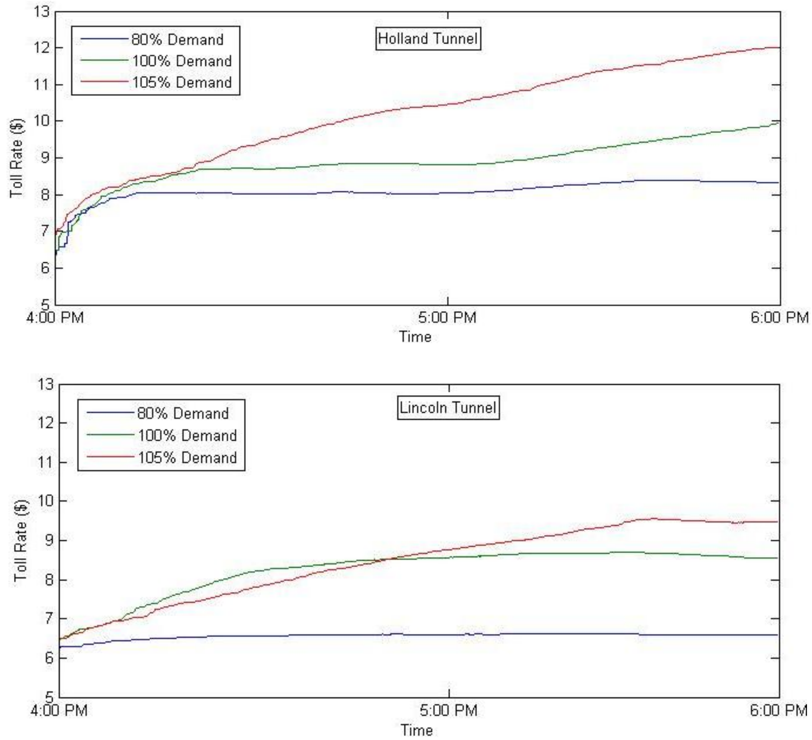

Figure 3– Dynamic Toll Rates in Holland and Lincoln Tunnels

Traffic conditions on tunnels under dynamic tolling are compared with base case in which static tolling is applied. As shown in Figure 4, 10-minute average travel speeds during the analysis period shows that dynamically priced toll rates can help to regulate the traffic better and higher average speeds are observed in both tunnels.

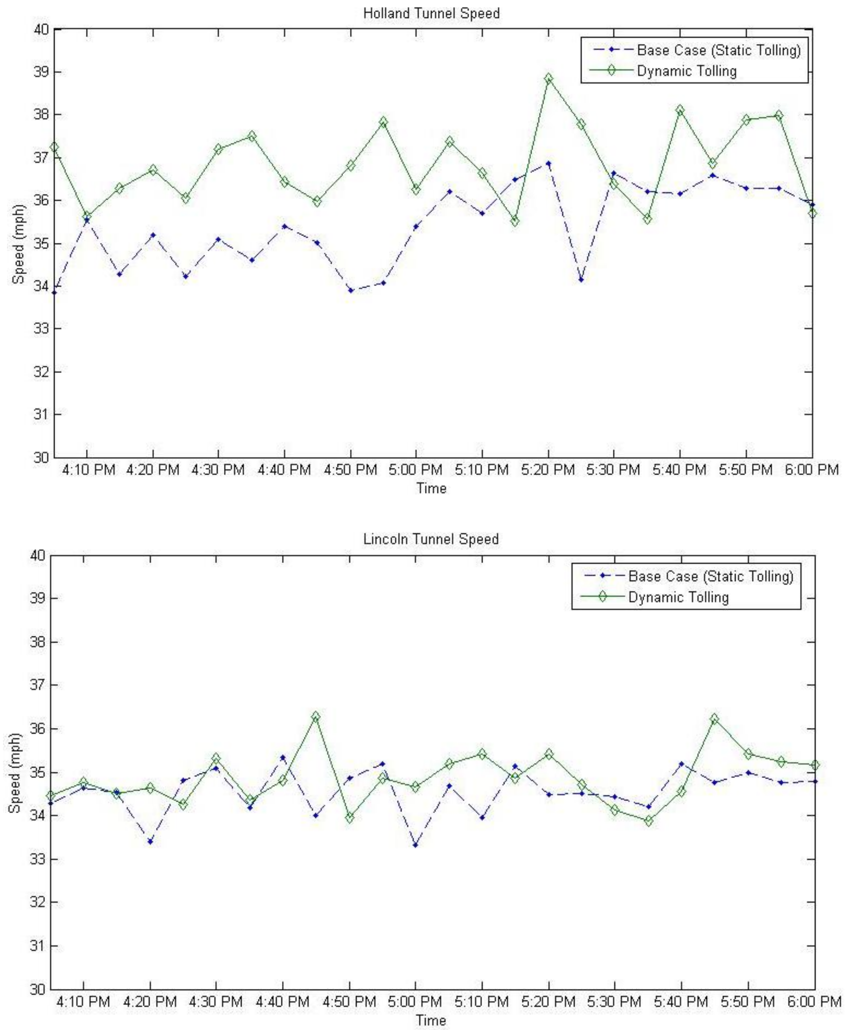

Figure4 – Travel Speeds in Holland and Lincoln Tunnels

In-tunnel traffic, however, is not the best representation of congested traffic conditions during the peak period since it shows the recovering traffic conditions after the bottleneck points. Figure 5 shows the average travel speeds observed for the traffic that are approaching the toll plazas which can be considered as the bottleneck points. Similar to the in-tunnel traffic, average speeds on the approaching points are higher for the dynamic tolling scenario compared to static tolling. The improved conditions can be interpreted as a result of toll rate determination based on real-time traffic conditions which makes drivers to switch between alternative routes in-advance to avoid higher tolls or longer travel times.

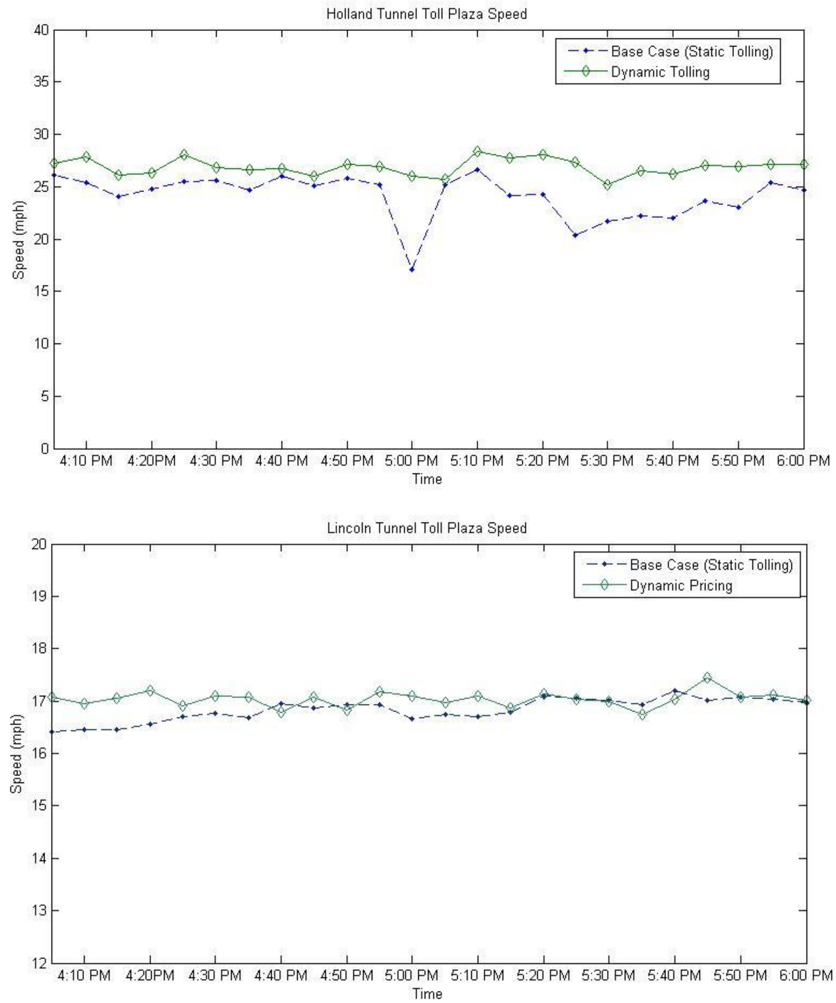

Figure 5 – Approaching (Bottleneck) Travel Speeds in Holland and Lincoln Tunnel Toll Plazas

One of the major objectives of this study is to analyse the effect of VOR in the utility function therefore simulations are also run for excluding VOR in the utility function that is only considering VOT as a determining factor for route choice. The difference in dynamic toll rates can be seen in Figure 6. For Holland Tunnel toll rates are slightly different in which in the first hour of the peak period toll rates determined by considering only VOT are lower while in the second hour the reverse is observed. However for Lincoln Tunnel toll rates when only VOT is included in the utility function is always lower than the case when VOR is included. These results are not solely enough to make a definitive conclusion however considering equation (6) it can be observed from the results of Lincoln Tunnel, increasing on-time arrivals which is considered as a higher reliability results in increasing toll rates for the peak period. As a result travellers which prefer to pay higher tolls enjoy both lower mean travel times and higher travel time reliability.

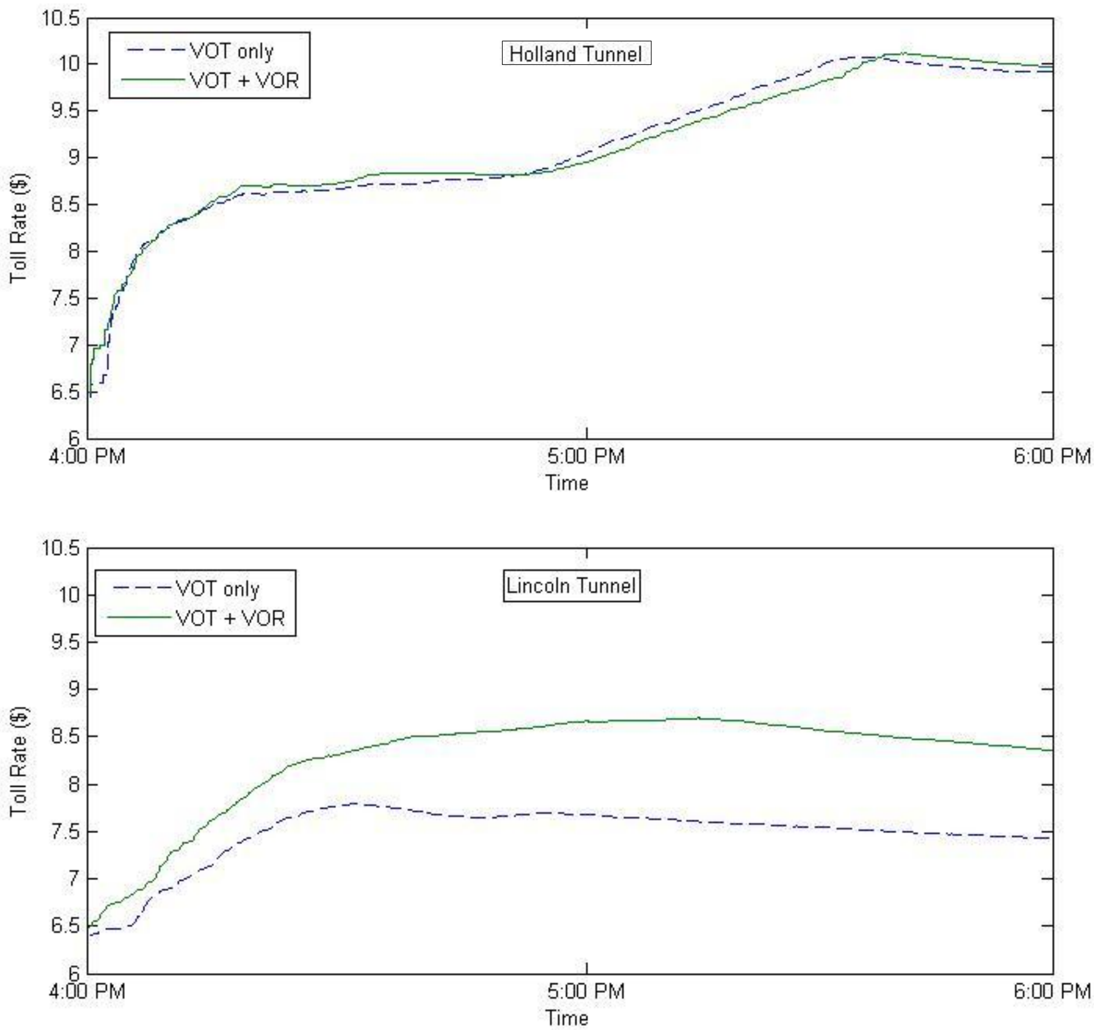

Figure 6 – Effect of including VOR in the Utility Function

CONCLUSION

Congestion pricing is one of the most effective peak-period congestion management tools that has been implemented successfully for many years in several different areas of the world. Dynamic pricing, or varying tolls depending on real-time traffic conditions, is a newer method that has been mainly used in the form of High Occupancy Toll (HOT) lanes in the United States. This paper proposes a methodology for an application of dynamic tolling to two neighboring tolled facilities. A feedback-based dynamic pricing algorithm is developed which addresses the problem of highly sensitive or less reactive tolling in dynamic pricing. The algorithm is tested on two tunnels between New Jersey and New York City with a microscopic traffic simulation of the traffic entering Manhattan. Observed traffic counts were used for simulating the travel demand.

The proposed model considers the effects on drivers' route choice behavior by incorporating VOT and VOR parameters together which is one of the first such attempts for a feedback-based setup in the literature. This is an important point for the validity of the simulation results since travelers route decision does not only depend on mean travel times but also reliability of the routes.

The micro-simulation results indicate that provided feedback-based dynamic tolling strategy performs effectively to manage peak period congestion. Travel speeds are found to be higher with dynamic pricing scheme compared to the static pricing which is a fixed pricing scenario in both in-tunnel traffic and approaching traffic measured for the bottlenecks before the toll plazas. The findings show that dynamic tolling scheme helps to mitigate peak period congestion by affecting users' route decision.

The applicability of the proposed methodology requires technology for real-time information conveying so that drivers can make the best choices among possible alternatives. Especially, the advances in the area of connected vehicles which will obviate the need for extensive deployment and maintenance of fixed infrastructure based sensors that will be needed for the deployment of a real-time dynamic pricing.

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