MESOSCOPIC SIMULATION EVALUATION OF DYNAMIC CONGESTION
PRICING STRATEGIES FOR NEW YORK CITY CROSSINGS

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ABSTRACT

Congestion pricing charges motorists during peak hours to encourage them to either switch their travel times or to use alternative routes. In recent years, with the help of technological developments such as electronic toll collection systems, pricing can be conducted dynamically; tolls can be changed in real-time according to measured traffic conditions. Dynamic pricing is currently deployed as High Occupancy Toll (HOT) lanes; however the time-dependent pricing idea can be extended to a setting where drivers make route choices that are relatively more complex.

In the case of New York City, many of the limited number of crossings to the island of Manhattan are tolled, and function as parallel alternatives. One of the key aspects of this study is the estimation of realistic values of time (VOT) for different classes of users, namely, commuters and commercial vehicles. New York region-specific VOT for commercial vehicles is estimated using a logit model of stated preference data. In this paper a simulation-based evaluation of dynamic congestion pricing on these crossings is conducted using a mesoscopic traffic simulation model with a simple step-wise tolling algorithm. The simulation results are analyzed to measure the change in volumes and toll revenues between potential dynamic pricing and static tolling currently in place.
INTRODUCTION

Congestion pricing can successfully manage traffic congestion by charging users for travel, particularly during peak hours, and can be implemented in static or dynamic form. Static pricing refers to a tolling system where toll rates remain fixed or are changed depending on the time of day, but the system toll rate schedule is not affected by the real-time traffic conditions. In dynamic congestion pricing, real-time traffic conditions are also considered. Several traffic parameters can be considered to determine the toll rate, including travel speed, occupancy, and traffic delays. These parameters are measured in real-time and toll rates are updated within short time intervals. Users are informed about the current toll rate with the help of variable message signs and they are allowed to choose between a tolled, faster, option, or a slower, free (or lower priced), option.

Dynamic pricing applications in the United States are limited to high occupancy toll lanes (HOT) where drivers may choose a less-congested tolled lane to save travel time. This paper aims to extend the idea of dynamic pricing to a network where drivers can choose from multiple alternative facilities to reach their destination. The New York metropolitan highway network is chosen for analysis, focusing on the bridges and tunnels crossing to Manhattan, which are some of the busiest tolled and non-tolled crossings in the country. A mesoscopic simulation network is created using Transmodeler and calibrated using real-world counts and other available traffic data. In the network users make route choices to cross to Manhattan depending on the dynamically varying tolls of the crossings. The goal is to observe the effects of dynamically priced tolls on traffic conditions using a similar tolling scheme being applied in current HOT-lane deployments.

This paper also considers varying behavior for different classes of vehicles through the use of realistic value of time (VOT) estimations. VOT is a significant input to pricing modeling as it determines the users’ route choice in response to both congestion and tolling. Passenger car and commercial vehicle values of time in the simulation network are different, with passenger car VOT taken from previous studies while commercial vehicle VOT is estimated in this paper using stated-preference data obtained from a 2004 region-specific study. The simulation output focuses on differences in traffic congestion parameters and total daily toll revenues for the dynamically priced network versus a simulation of the existing statically-tolled network. The output measures are analyzed in detail to determine the feasibility of dynamic pricing in this application.
LITERATURE REVIEW

Theoretical Dynamic Pricing Studies

The first studies of congestion pricing focused on static tolling, investigating the optimization of toll rates, toll plaza locations, or links to be tolled in a large network. The idea of tolling on roads has been an important topic of study for many decades. Pigou (1920) argued the idea of charging motorists for the first time in “Economics of Welfare” (1). Following Pigou’s argument, Walters (1961) gave the first comprehensive explanation of congestion pricing in his study about measuring private and social costs of highway congestion (2). Within the following years, Vickrey (1963) published a paper about road pricing in urban and suburban transport, Beckman (1965) studied the optimal tolls for highways, bridges, and tunnels, and Vickrey (1969) conducted another study about congestion theory. These studies constituted the fundamentals of modern congestion pricing theory (3, 4, 5).

Although dynamic congestion pricing studies are more recent, there are several theoretical studies available in the literature. Several authors conducted network optimization-based theoretical studies for dynamic pricing considering both fixed and variable demands, and even including different mode choices. Wie and Tobin (1998) provided two theoretical models for dynamic congestion pricing of general networks. The first model considered day-to-day learning of users with stable demands every day, and the second the case where users make independent decisions each day under fluctuating travel demand conditions (6). Joksimovic et al. (2005) presented a dynamic road pricing model with heterogeneous users for optimizing network performance (7). Wie (2007) considered dynamic congestion pricing and the optimal time-varying tolls with the Stackelberg game model (8).

Simulation-based models for dynamic pricing were also developed by some researchers. Mahmassani et al. (2005) conducted a study on variable toll pricing with heterogeneous users with different value of time preferences (9). Teodorovic and Edara (2007) proposed a real-time road pricing model on a simple two-link parallel network (10). Their system made use of dynamic programming and neural networks. Yin and Lou (2007) proposed and simulated two models for dynamic tolling. The first one is a feedback-control based method similar to the ALINEA concept in ramp-metering. The control logic for determining the toll rates is stated in Equation (1):
\[ r(t + 1) = r(t) + K(o(t) - o^*) \]  

where, \( r(t) \) and \( r(t+1) \) are the toll rates at time intervals \( t \) and \( t+1 \), respectively, \( o(t) \) is the measured occupancy, \( K \) is the regulator parameter and \( o^* \) is the desired occupancy for the tolled lane.

The second method is a reactive-self learning approach in which motorists’ willingness to pay can be learned gradually, and this data can be used to determine the toll rates (11). Lu et al. (2008) conducted a study on dynamic user equilibrium traffic assignment and provided a solution algorithm for dynamic road pricing. Their model considers traffic dynamics and heterogeneous user types with their responses to toll charges (12). Friesz et al. (2007) considered the dynamic optimal toll problem with user equilibrium constraints and presented two algorithms with numerical examples (13). Karoonsoontawong et al. (2008) provided a simulation-based dynamic marginal cost pricing algorithm. They compared the dynamic and static scenarios in simulation and obtained minor system benefits in dynamic case (14). Feedback-based algorithms for dynamic pricing were also developed for practical applications. Zhang et al. (2008) developed a feedback-based dynamic tolling algorithm for HOT (High Occupancy Toll) lane applications. In their model they used travel speed and toll changing patterns as parameters to calculate optimal flow ratio for the HOT lanes using feedback-based piecewise linear function. Then using the discrete route choice model they calculate the required toll rate by backward calculation (15).

Road Pricing Applications

Major road pricing applications in the United States and their tolling methods are listed in Table 1. Currently, dynamic pricing applications are limited to HOT lanes.

**Table 1: Major Value Pricing Applications in the United States**

<table>
<thead>
<tr>
<th>Facility</th>
<th>Initiation Date</th>
<th>Pricing Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facilities with Static Pricing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orange County SR-91, CA</td>
<td>December 1995</td>
<td>Pre-determined toll schedule (16)</td>
</tr>
<tr>
<td>Houston I-10, TX</td>
<td>January 1998</td>
<td>HOT lanes (17)</td>
</tr>
<tr>
<td>Lee County, FL</td>
<td>August 1998</td>
<td>Time-of-day pricing on bridges (18)</td>
</tr>
<tr>
<td>New Jersey Turnpike, NJ</td>
<td>Fall 2000</td>
<td>Time-of-day pricing (19)</td>
</tr>
<tr>
<td>Location</td>
<td>Date</td>
<td>Pricing Method</td>
</tr>
<tr>
<td>----------------------------------------------</td>
<td>--------------</td>
<td>---------------------------------------</td>
</tr>
<tr>
<td>Houston US 290, TX</td>
<td>November 2000</td>
<td>HOT lanes (20)</td>
</tr>
<tr>
<td>Port Authority of NY&amp;NJ Interstate Crossings</td>
<td>March 2001</td>
<td>Time-of-day pricing (21)</td>
</tr>
<tr>
<td>San Joaquin Hills Toll Road, Orange County, CA</td>
<td>February 2002</td>
<td>Time-of-day pricing (22)</td>
</tr>
<tr>
<td>Illinois Tollway, IL</td>
<td>Winter 2005</td>
<td>Time-of-day pricing (23)</td>
</tr>
</tbody>
</table>

**Facilities with Dynamic Pricing**

<table>
<thead>
<tr>
<th>Location</th>
<th>Date</th>
<th>Pricing Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>San Diego I-15, CA</td>
<td>April 1998</td>
<td>Dynamic pricing in HOT lanes (24)</td>
</tr>
<tr>
<td>Minnesota I-394, MN</td>
<td>Spring 2005</td>
<td>Dynamic pricing in HOT lanes (25)</td>
</tr>
<tr>
<td>WA167, WA</td>
<td>May 2008</td>
<td>Dynamic pricing in HOT lanes (26)</td>
</tr>
<tr>
<td>I-95, FL</td>
<td>Summer 2008</td>
<td>Dynamic pricing in HOT lanes (27)</td>
</tr>
</tbody>
</table>

**Value of Time**

Value of time (VOT) which is defined as the change in user’s willingness to pay for a unit change in travel time is one of the most important factors affecting driver behavior in response to congestion tolls. Blayac et al. (2001) proposed the idea of relaxing the constancy of marginal utilities and derived analytical functions to relate VOT, time, price, income level, and departure/arrival time restrictions (28). Following the same idea, Ozbay et al. (2008) improved the functions by adding departure time choices and used a nested logit model to estimate value of travel time of New Jersey Turnpike (NJTPK) users under the presence of a time-of-day pricing. Their findings showed that the value of time of NJTPK users was between $15-$20 (29).

Although there are many studies on commuter VOT there is a limited research on commercial vehicle VOT. One of the first studies on commercial vehicle VOT was published by Haning and McFarland (1963). Their analysis showed that commercial vehicle VOT should be greater than that of passenger cars, even if no cargo is being carried (30). Kawamura (1999) defined a commercial vehicle VOT using two different methods: switching point analysis and a random coefficient logit model. In his study, he analyzed the stated preference by conducting a survey on 77 trucking companies. His findings showed that commercial vehicle VOT has a mean of $23.4/hr and a standard deviation of $32/hr (31). Smalkoski and Levinson (2003) conducted a value of time determination for commercial vehicle operators in Minnesota. They fit a tobit
model to the data they obtained from the adapted stated preference survey. Fifty companies were interviewed and they found a VOT of $49.42/hr (32).

Most value of time estimation studies are based on stated preference user surveys. In these surveys, there are questions to get an idea about the traveler choice behavior under different circumstances. Vilain and Wolfram (2001) conducted a survey of truckers in the New York region and their study indicated that the response of truckers to congestion charges would be relatively modest (33). Holguin-Veras et al. (2005) state that 61.6% of commercial vehicles travel at the time they do because of customer requirements (34). This is an important finding showing that most of the truckers do not have schedule flexibility. In addition to stated preference, analysis of revealed preference data also gives an idea about possible trucker behavior. Ozbay et al. (2006) conducted an analysis of the impacts of time-of-day pricing application initiated in 2001 by the Port Authority of New York and New Jersey (PANYNJ), which operates the three crossings between Manhattan and New Jersey, as well as two other crossings in the region. The authors concluded that there is a decrease in truck traffic on peak shoulders but they also noted that there may be other factors affecting this decline, such as the economic recession that began in the New York region in 2001 (35).

Value of Time Estimation for NY-NJ Commercial Vehicles

In this section, an estimation of commercial vehicle value of time (VOT) using a binary logit model based on data obtained from the PANYNJ survey is presented, which is then used in dynamic pricing simulations. The statistical data analysis software STATA is used for the logit model construction and evaluation. A methodology was developed similar to Kawamura’s (1999) work on commercial vehicle value of time estimation using a logit model (31). A utility function for an individual or a firm $n$ choosing an alternative $i$ was assumed as in Equation (2):

$$U_{in} = \alpha C_{in} + \gamma T_{in} + \epsilon_{in}$$  \hspace{1cm} (2)

where $C_{in}$ is the monetary cost of travel and $T_{in}$ is the monetary cost of travel time for using alternative $i$ for an individual or firm $n$. The coefficients $\alpha$ and $\gamma$ are parameters and the random variable $\epsilon_{in}$ is the unobserved portion of the utility which is assumed identically and independently distributed (IID) with extreme value distribution. The unobserved portion of the
utility includes unobserved attributes, taste variations, measurement errors and imperfect information (31).

The standard logit formula is then used to calculate the probability $P_{in}$ of choosing alternative $i$ among $j$ alternatives, as in Equation (3):

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

where $V_{in}$ is the observable part of the utility (i.e. $\alpha C_{in} + \gamma T_{in}$). Coefficients $\alpha$ and $\gamma$ can be obtained by the maximum likelihood estimation method and the marginal utilities can be found by Equation (4) and Equation (5):

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

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

These ratios give the marginal effects of each parameter on the utility function and the value of time is simply calculated by the ratio of the two coefficients as in Equation (6):

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

The ratio in Equation (6) is how much an individual or a firm is willing to pay to reduce travel time by one unit. In a more simple way, this equation can be written as in Equation (7):

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

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

Independent variables used to define the cost related parameter $\alpha$ and time related parameter $\gamma$ are type of business and trip distance respectively. Levinson, et al. (2004) provided a detailed
study for per kilometer costs for different industries in Minnesota, depending on their trucker survey. The values they provided are for 2004 which is the same year of the PANYNJ survey. The regional consumer price indexes obtained from Bureau of Labor Statistics (BLS) are used for adjustment to the New York region, and per-mile operation costs are calculated for all data points.

In the PANYNJ survey, each respondent was asked for the origin and destination states of their regular trips. The time parameter is calculated for every data point by determining the average distance they travel. Analysis is conducted for different combinations of carrier types and origins (e.g. county or state) where the respondents’ trips originated. However there is a limited sample size for some regions.

The results showed that commercial vehicles that generate their trips from New York have a higher VOT compared to the commercial vehicles that generate trips from New Jersey. In addition when the shipment sizes are considered, less-than-truckload (LTL) type carriers have a higher VOT compared to the truckload (TL) type of carriers. Table 3 shows the estimation results obtained. When the data is not categorized a VOT of $33.62 is obtained for commercial vehicles. In a previous trucker interview that was conducted by PANYNJ for truckers, one respondent stated that if there was an exclusive truck lane he would prefer paying $5 or $6 toll for an extra ten minute time savings. This can be interpreted as a value of time between $30-$36 per hour, which agrees with the estimation (36).

**Table 2: Commercial Vehicle VOT Estimation and Estimations from Literature**

<table>
<thead>
<tr>
<th>Sample Group</th>
<th>Sample Size</th>
<th>Time coefficient, $\gamma$</th>
<th>Cost coefficient, $\alpha$</th>
<th>$Chi^2$</th>
<th>VOT ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin: New York</td>
<td>32</td>
<td>137.4</td>
<td>4.16</td>
<td>5.14</td>
<td>$32.99</td>
</tr>
<tr>
<td>Origin: New Jersey</td>
<td>152</td>
<td>79.48</td>
<td>4.01</td>
<td>4.21</td>
<td>$19.82</td>
</tr>
<tr>
<td>Origin: Middlesex, Union County</td>
<td>65</td>
<td>48.03</td>
<td>0.84</td>
<td>3.49</td>
<td>$56.72</td>
</tr>
<tr>
<td>Size: LTL</td>
<td>93</td>
<td>17.4</td>
<td>0.44</td>
<td>3.64</td>
<td>$38.9</td>
</tr>
<tr>
<td>Size: TL</td>
<td>52</td>
<td>29.8</td>
<td>2.2</td>
<td>3.74</td>
<td>$13.5</td>
</tr>
<tr>
<td>All samples</td>
<td>198</td>
<td>35.1</td>
<td>1.04</td>
<td>4.45</td>
<td>$33.62</td>
</tr>
</tbody>
</table>
### Results from Literature

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Region</th>
<th>VOT ($)(2004 values)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kawamura</td>
<td>1999</td>
<td>California, US</td>
<td>$31.37</td>
</tr>
<tr>
<td>Smalkoski &amp; Levinson</td>
<td>2003</td>
<td>Minnesota, US</td>
<td>$25.08-$51.43</td>
</tr>
</tbody>
</table>

**SIMULATION**

Both dynamic and static congestion pricing scenarios are studied in a mesoscopic simulation model of the Manhattan crossings, with a primary focus on charging tolls to enter Manhattan. The traffic simulation software TransModeler is used for simulating the dynamic pricing schemes at the mesoscopic level. Static pricing, which is currently applied at most of the crossings modeled, has fixed toll rates throughout the day (in some cases off-hour discounts exist). Traffic conditions do not affect the toll rates, as they would in a dynamic pricing case. A static pricing scenario is simulated for comparison to the dynamic case.

**Simulation Network**

The network used for pricing simulations is shown in Figure 1, compared to the real NY-area highway network. This network is a modified version of an extracted sub-network from the New York Best Practice Model, a regional travel demand model. Since pricing is expected to affect users’ route decisions, major connecting roads are included outside of Manhattan so that simulated drivers may select a different path to either save money due to different toll costs or travel times as a result of congestion. One of the major requirements in real world dynamic pricing implementations is the availability of an alternative route for travelers to select in case they are not willing to pay the toll. Dynamic pricing of High Occupancy Toll (HOT) lanes, where only one or two lanes of a free highway are tolled, allows users who prefer to avoid congestion in regular lanes to use HOT lanes by paying a dynamically priced toll. Travel speeds in HOT lanes are guaranteed to be higher than a previously set level of service by adjusting toll rates in accordance to the congestion level. Dynamic pricing application for Manhattan crossings
can be conducted when two or more crossings serve as the alternatives of each other. This
system allows users to select either cheapest or faster routes by comparing toll rates and selecting
the best possible alternative to enter Manhattan.

The major crossings to enter Manhattan currently consist of a mixture of free and tolled
alternatives with different toll rates. The crossings used in the simulation network are:

**Manhattan-Brooklyn/Queens Crossings (east of Manhattan)**

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

**Manhattan-New Jersey crossings (west of Manhattan)**

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

The network includes two connecting roads for Manhattan-New Jersey crossings for users
who want to use an alternative route to cross to Manhattan. These two routes are New Jersey
Turnpike (NJTPK), a major highway, and Route 1-9, an arterial, which increases the complexity
of the network since NJTPK is tolled and Route 1-9 is free. The crossings from New Jersey to
Manhattan are all tolled at a uniform rate. On the east side of Manhattan, I-278 (Brooklyn-
Queens Expressway) is provided to link the alternative crossings. These crossings are a mixture
of tolled and free routes.
Network Calibration

Network calibration is performed to ensure that traffic volumes are realistically distributed to the crossings. After several calibration trials all the crossings have at most a 10% error in traffic volume between the simulation volumes and real volume data, by modification of the link characteristics (e.g. free flow speed, speed limit, lane width etc.) (38). For dynamic pricing simulations the behavior of users in response to the dynamically priced tolls necessitates its own calibration. Driver values of time are adjusted to successfully implement the dynamic toll rate schedule, along with error factors defined in TransModeler which affect the perception of the shortest path of the user, such as how many links in advance users consider before doing a change in their route choice or gap acceptance models. These parameters were adjusted to ensure as realistic a simulation possible, however their true values are unknown since this application has not been field tested.

Toll Rates

In the static pricing scenario, toll rates given in Table 3 are held constant throughout the day, which is the current tolling application in all of the tolled crossings. Toll rates in static pricing are defined differently by vehicle class, but since not all vehicle classes are defined in the simulation, average values for each class are used. Truck tolls are calculated by taking the traffic...
volume percentages of truck classes by axle. The data obtained from static pricing simulations is used for comparison with dynamic pricing output data. The same demands are used in both simulations to compare the different volume distributions to the crossings and different toll revenues.

Table 3: Static Pricing Simulation Toll Rates

| MANHATTAN-NEW JERSEY CROSSINGS (George W. Bridge, Lincoln Tunnel, Holland Tunnel) |
|---------------------------------|------------------|
| Vehicle Class                  | Toll Rate        |
| Passenger Car                  | $8.00            |
| Trucks                          | $27.00           |
| Small Commercials              | $13.00           |

| MANHATTAN-BROOKLYN/QUEENS TOLLED CROSSINGS (Triborough Bridge, Queens-Midtown Tunnel, Brooklyn Battery Tunnel) |
|---------------------------------|------------------|
| Vehicle Class                  | Toll Rate        |
| Passenger Car                  | $5.50            |
| Trucks                          | $24.00           |
| Small Commercials              | $11.00           |

In the dynamic pricing scenario a robust tolling model is needed to meet driver satisfaction, by offering them acceptable toll rates to travel and to meet the minimum requirements for a previously set level of service for traffic. TransModeler enables dynamic pricing with two parameters, “minimum occupancy” and “maximum speed”. In this simulation study only average occupancy level was considered in determining the real-time toll rates.

Figure 2 shows the toll rate change in New Jersey-Manhattan and Brooklyn/Queens-Manhattan crossings compared with occupancy values. In the static pricing scenario an average occupancy rate of 11.6% is observed for New Jersey-Manhattan crossings, therefore the static pricing rates are set to 11% occupancy in the dynamic case. The Manhattan-Queens/Brooklyn Crossings have an average occupancy of 12% throughout the day. Therefore static toll rates are set to the minimum 12% occupancy interval in the dynamic pricing toll schedule. In the simulation, toll rates are updated every five minutes.
Figure 2: Toll Rate Change by Occupancy and Vehicle Class for a) NJ-Manhattan Crossings, and b) Brooklyn/Queens-Manhattan Crossings

MESOSCOPIC SIMULATION RESULTS

Both static pricing and dynamic pricing simulations are run for four separate periods (AM: 6–10am, MD: 10am–3pm, PM: 3–7pm, NT: 7pm–6am). Table 4 shows the simulation data obtained from the point sensors located in each crossing for each period, respectively, comparing the static and dynamic pricing cases. Sensors measure the traffic count within the simulation period and the average occupancies. Lower occupancy values indicate better flow conditions and higher speeds. The percent difference values indicate how different the dynamic case is from the static case.
Table 4: Time-of-day Comparison by Traffic Volumes and Occupancies

<table>
<thead>
<tr>
<th>Facility</th>
<th>AM VOL</th>
<th>AM OCC</th>
<th>MD VOL</th>
<th>MD OCC</th>
<th>PM VOL</th>
<th>PM OCC</th>
<th>NT VOL</th>
<th>NT OCC</th>
<th>% Diff.</th>
<th>% Diff.</th>
<th>% Diff.</th>
<th>% Diff.</th>
<th>% Diff.</th>
<th>% Diff.</th>
<th>% Diff.</th>
<th>% Diff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holland Tunnel</td>
<td>-4.5%</td>
<td>-1.1%</td>
<td>-11.0%</td>
<td>-2.0%</td>
<td>-0.5%</td>
<td>-2.0%</td>
<td>-8.2%</td>
<td>-1.1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lincoln Tunnel</td>
<td>-1.0%</td>
<td>7.3%</td>
<td>8.6%</td>
<td>-0.8%</td>
<td>-2.9%</td>
<td>-1.3%</td>
<td>8.4%</td>
<td>0.4%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>George Washington Bridge</td>
<td>0.4%</td>
<td>0.4%</td>
<td>-0.2%</td>
<td>0.0%</td>
<td>2.7%</td>
<td>1.3%</td>
<td>-0.1%</td>
<td>0.0%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manhattan Bridge</td>
<td>12.7%</td>
<td>0.8%</td>
<td>6.7%</td>
<td>0.1%</td>
<td>8.2%</td>
<td>0.4%</td>
<td>1.3%</td>
<td>0.5%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Queens-Midtown Tunnel</td>
<td>-26.1%</td>
<td>4.9%</td>
<td>-23.9%</td>
<td>-2.4%</td>
<td>-22.6%</td>
<td>-2.2%</td>
<td>-12.3%</td>
<td>-0.5%</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Williamsburg Bridge</td>
<td>17.3%</td>
<td>3.4%</td>
<td>14.3%</td>
<td>-0.9%</td>
<td>16.8%</td>
<td>0.7%</td>
<td>5.3%</td>
<td>0.2%</td>
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</tr>
<tr>
<td>Manhattan Bridge</td>
<td>4.3%</td>
<td>0.7%</td>
<td>1.9%</td>
<td>-0.2%</td>
<td>3.4%</td>
<td>0.1%</td>
<td>0.3%</td>
<td>0.0%</td>
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</tr>
<tr>
<td>Brooklyn Bridge</td>
<td>0.5%</td>
<td>0.0%</td>
<td>-0.3%</td>
<td>2.9%</td>
<td>4.3%</td>
<td>2.1%</td>
<td>0.3%</td>
<td>1.0%</td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td>Brooklyn Battery Tunnel</td>
<td>-3.6%</td>
<td>0.9%</td>
<td>-2.3%</td>
<td>-0.1%</td>
<td>-9.5%</td>
<td>-0.7%</td>
<td>-0.4%</td>
<td>0.0%</td>
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</tbody>
</table>

For the Brooklyn/Queens crossings, the tolled crossings (Triborough Bridge, Queens-Midtown Tunnel and Brooklyn Battery Tunnel) carry less traffic in dynamic pricing simulations than the free bridges. This is due to users avoiding higher tolls and using alternative routes in the peak periods, increasing the free crossings’ (Queensboro, Williamsburg, Manhattan and Brooklyn Bridges) traffic volumes. As expected, all of the free crossings’ average occupancies increased with the traffic shifted from tolled crossings. Similarly, traffic volumes increased for the free crossings and decreased or did not change for the tolled crossings. Average occupancies show that Brooklyn-Battery Tunnel and Queens-Midtown Tunnel had higher average toll rates compared to the static pricing and this fact further encouraged users to select one of the free alternative crossings. Significant changes are observed in traffic volumes for Queens-Midtown Tunnel, Williamsburg Bridge and Brooklyn Battery Tunnel.

On the NJ side, AM period results show that average occupancies of Holland Tunnel decrease as opposed to Lincoln Tunnel and George Washington Bridge, where average occupancies increased. Similar to the tolled Queens-Midtown Tunnel and free Williamsburg Bridge, a route shift can be also observed between Lincoln and Holland Tunnels. Traffic using George Washington Bridge is almost the same therefore it can be concluded that approximately 8% traffic was switched from Holland Tunnel to Lincoln Tunnel due to higher toll rates in the Holland Tunnel from high occupancy values.
Figure 3 shows the response of users of NJ-Manhattan crossings due to dynamic tolling. With an increasing number of vehicles in the system, higher toll rates are charged and the number of vehicles changing their routes increases, as expected. The total daily toll revenues calculated from the simulation network for both scenarios are given in Table 5. Results show that with the assumed toll schedules all NJ-Manhattan crossings collect higher revenues in the dynamic pricing scenario compared to the static pricing scenario. However on the Queens/Brooklyn-Manhattan side, the Queens-Midtown Tunnel generates far lower revenues due to the nearby free alternatives. Users must pay a toll in any route decision on the NJ-Manhattan side, therefore in the peak hours it is inevitable that they pay higher tolls compared to the static pricing case due to the network charging higher tolls to maintain the occupancy requirements in the crossings. Thus revenues increase throughout the network when dynamic pricing is deployed network-wide, even with a negative change in revenues from the Brooklyn/Queens-Manhattan crossings.

<table>
<thead>
<tr>
<th>Facility</th>
<th>Toll Revenues</th>
<th>Increase</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Static Pricing</td>
<td>Dynamic Pricing</td>
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<tr>
<td>Holland Tunnel</td>
<td>$482,520</td>
<td>$563,830</td>
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<td>Lincoln Tunnel</td>
<td>$594,110</td>
<td>$686,587</td>
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<td>George Washington Bridge</td>
<td>$1,437,000</td>
<td>$1,841,780</td>
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<td>Triborough Bridge</td>
<td>$358,717</td>
<td>$361,225</td>
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<td>Queens-Midtown Tunnel</td>
<td>$317,030</td>
<td>$228,048</td>
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<td>Brooklyn Battery Tunnel</td>
<td>$187,005</td>
<td>$222,435</td>
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<tr>
<td><strong>TOTAL</strong></td>
<td><strong>$3,376,382</strong></td>
<td><strong>$3,903,905</strong></td>
</tr>
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</table>
CONCLUSION

Two important issues in the deployment of successful dynamic congestion pricing are 1) the capability of changing toll rates in response to the changes in the network, and 2) the accurate estimation of value of time (VOT) for different classes of users. The former issue can be
addressed by using time-dependent toll rates while the latter requires estimation of VOT values using either revealed or stated preference data. One key issue is quantification of the advantages of dynamic tolling strategies before they can be deployed in real-world, which can be achieved through simulation. In this paper differences between dynamic and static pricing are analyzed using a real network through a mesoscopic simulation-based analysis. Driver behavior in response to real-time changing toll rates is incorporated into the simulation model by defining two different values of time for commuter and commercial vehicles.

Simulation results with realistic VOT values for different classes of users showed that dynamic pricing can achieve less congested conditions, especially at peak periods, when the occupancies at some of the tolled crossings are high. In addition, 16% higher toll revenues are collected in the hypothetical dynamic pricing scenario compared to the simulated static tolled scenario. Thus, it can be concluded that dynamic tolling strategies not only improve traffic conditions but increase revenues when applied to a large network similar to the one simulated. Further improvements can be made using an advanced dynamic tolling algorithm (e.g. feedback based) that gives more realistic toll rates in response to time-dependent changes in traffic conditions, a topic of research for another paper.

ACKNOWLEDGEMENTS

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REFERENCES


38. NYCDOT (2008), New York City Bridge Traffic Volumes, 2007, New York City Department of Transportation.