SIMULATION-BASED EVALUATION OF A FEEDBACK BASED DYNAMIC
CONGESTION PRICING STRATEGY ON ALTERNATE FACILITIES

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Abstract: 175 words
Word count: 4,747 Text + 9 Figures + 2 Tables = 7,497 words
Submission Date: August 1st, 2010
ABSTRACT

Congestion pricing is one of the most effective peak-period congestion management tools that has been implemented successfully 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 only used in the form of High Occupancy Toll (HOT) lanes in the United States. This paper proposes a methodology to extend the application of dynamic tolling to two neighboring tolled facilities. Current tolling algorithms being used for HOT lanes often result in highly fluctuating toll rates in short time intervals, creating an inconvenience for users. Following Zhang et al. (2008)’s study which addresses the problem of highly sensitive or less reactive tolling in dynamic pricing, a tolling algorithm is developed to calculate toll rates and define route decisions of users of two parallel routes. The algorithm is tested on two tunnels between New Jersey and New York City with a microscopic traffic simulation of the traffic entering Manhattan.
INTRODUCTION
In the last two decades dynamic pricing has gained popularity, evidenced by the successful implementations of High Occupancy Toll (HOT) lane projects. Currently there are four facilities in the United States that use dynamic pricing and several new projects have been proposed for future implementation. Table 1 presents a summary of the current and proposed HOT projects in the United States.

Table 1: Current and Forthcoming Dynamic Pricing Projects

<table>
<thead>
<tr>
<th>Facilities with Dynamic Pricing Lanes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facility</td>
</tr>
<tr>
<td>--------------------------------------</td>
</tr>
<tr>
<td>San Diego I-15, CA</td>
</tr>
<tr>
<td>Minnesota I-394, MN</td>
</tr>
<tr>
<td>WA167, WA</td>
</tr>
<tr>
<td>I-95, FL</td>
</tr>
</tbody>
</table>

Future Projects

<table>
<thead>
<tr>
<th>Facility</th>
<th>Initiation Date</th>
<th>Agency (Reference)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I-85, Atlanta</td>
<td>January 2011</td>
<td>Georgia Department of Transportation (5)</td>
</tr>
<tr>
<td>I-495 Beltway, Northern Virginia</td>
<td>To be determined</td>
<td>Virginia Department of Transportation (6)</td>
</tr>
<tr>
<td>I-110, Los Angeles, California</td>
<td>To be determined</td>
<td>Los Angeles County Metropolitan Transportation Authority (7)</td>
</tr>
</tbody>
</table>

One of the goals of dynamic pricing is to make users pay a true congestion charge, by determining the toll rates dependent on real-time traffic conditions. However, insufficiently developed tolling algorithms may generate toll rates that are either over-sensitive or under-sensitive to real-time traffic conditions (8). Figure 1 shows the toll rate changes in Minnesota’s I-394 HOT lanes during the morning peak period, where the highly fluctuating toll rate structure does not allow users to make optimal decisions of HOT usage. Thus there is a need for a better algorithm that generates smoother changes between consecutive time intervals.
Figure 2 shows the changes in traffic conditions and related toll rate changes on SR-167 HOT lanes in Washington. Although the toll rate changes are small they fluctuate. It might be possible to obtain smoother changes over time with a different algorithm.

Zhang et al. (2008) developed an algorithm that addresses the problem of generating over-sensitive or under-sensitive toll rates in HOT lane operations (8). This paper aims to provide a methodology to extend the algorithm proposed by Zhang et al. (2008) to dynamic pricing of two neighboring tolled facilities namely, the two tunnels connecting New Jersey and Manhattan. This application is suitable since the distance between the two crossings is close enough that users can easily switch between the two alternatives.
The algorithm is tested using the microscopic traffic simulator Paramics, where a network is constructed to include the two tunnels carrying traffic from New Jersey to Manhattan, Holland Tunnel and Lincoln Tunnel, and their two primary connecting roads on the New Jersey side, New Jersey Turnpike (NJTPK) and Route 1-9 (see Figure 3). Only inbound traffic is considered in the simulation since only the inbound direction is currently tolled. The results are compared with the static-priced tolls currently in place, and the feasibility of such an application is investigated.
LITERATURE REVIEW
Several aspects of congestion pricing have been studied for years by both economists and transportation researchers. Dynamic congestion pricing is a relatively new area of study in traffic engineering and there are only four applications currently in use in the world. Dynamic pricing uses several traffic parameters to determine toll rates, including speed, occupancy, and traffic delay. These parameters are measured in real-time and toll rates are updated within short time intervals. Users are informed of the current toll rate with the help of variable message signs and allowed to make a route choice decision of either using the tolled road to save time, or using an alternative road without a fee.

Theoretical studies for dynamic pricing are available in the literature which analyze the method in different ways. 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 each day, while the second model considered the case of when users make independent decisions each day under fluctuating travel demand conditions (11). Joksimovic et al. (2005) presented a dynamic road pricing model with heterogeneous users for optimizing network performance (12). Wie (2007) considered dynamic congestion pricing and the optimal time-varying tolls with the Stackelberg game model (13). 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 (14). Teodorovic and Edara (2007) proposed a real-time road pricing model on a simple two-link parallel network. Their system made use of dynamic programming and neural networks (15).

Yin and Lou (2007) proposed and simulated two models for dynamic tolling. The first was a feedback control-based method, similar to ALINEA concept in ramp-metering. The control logic borrowed from the ALINEA ramp metering control law proposed by Papgeorgiou et al. (1997) for determining the toll rates, stated in Equation (1).

\[ r(t+1) = r(t) + K(o(t) - o^*) \]  

(1)
where, \( r(t) \) and \( r(t+1) \) are the toll rates at time intervals \( t \) and \( t+1 \), respectively, \( o(t) \) is the measured occupancy, \( K \) is the regulator parameter, and \( o^* \) is the desired occupancy for the tolled lane. The second method was a reactive-self learning approach in which motorists’ willingness to pay can be learned gradually and the data used to determine toll rates (9).

Lu et al. (2008) conducted a study for dynamic user equilibrium traffic assignment and provided a solution algorithm for dynamic road pricing. Their model considered traffic dynamics and heterogeneous user types with their responses to toll charges (16). Friesz et al. (2007) considered the optimal dynamic toll problem with user equilibrium constraints and presented two algorithms with numerical examples (17). 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 case (18).

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 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 (1).

**METHODOLOGY**

**Feedback based dynamic Tolling Algorithm**

In practice, dynamic pricing is only applied for HOT lanes in which real-time traffic flow speeds are measured and toll rates are adjusted to obtain a Level of Service (LOS) of “C”, which refers to minimum speed of 45 mph. Zhang, et al. (2008) provided a feedback-based step-wise tolling model for HOT lane operations. The model they presented is easy to implement when the necessary infrastructure is present, and uses traffic flow speeds as the threshold parameter for the toll rate changes. The model contains two alternative lane options on one road: HOT lanes and general purpose lanes, as priced and free alternatives. Therefore the user decision is simply selecting to pay a toll to save travel time or using free lanes to save from toll cost but having lower travel speeds under congested conditions.

A similar model is developed for two alternative crossings in this paper. There are three main differences in the new model proposed in this paper:
1. Instead of HOT lanes where there is a free alternative on the same road, the model is considered for two tolled crossings which are alternatives to each other.

2. Instead of using traffic flow speed as the threshold parameter, average occupancies on the crossings are used in a step function. The reason for using occupancy is that it provides a better representation of congestion conditions in the crossings, since speed limits are lower than typical HOT lanes. The crossings are assumed to be close enough that time spent to switch to an alternative crossing is assumed to be zero.

3. The proposed model uses network-specific values of time, estimated using stated-preference data collected in a study conducted by Ozbay et al. (2006) (19). These realistic value of time estimations provide more realistic route choice behavior in response to changes in toll rates on the crossings.

The total cost for choosing one of the crossings is computed in Equation (2):

\[
TC_i = \alpha \times TT_i + TR_i
\]  

(2)

where \(TT_i\) is the average travel time for the \(i^{th}\) alternative, \(TR_i\) is the toll rate for the \(i^{th}\) alternative and \(\alpha\) is the coefficient to convert \(TT_i\) into cash value.

The utility function for selecting crossing 1 \(U_1\) and crossing 2 \(U_2\) are given in Equation (3) and Equation (4):

\[
U_1 = \frac{1}{TC_1} = \frac{1}{\alpha_1 \times TT_1 + \beta_1 \times TR_1}
\]

(3)

\[
U_2 = \frac{1}{TC_2} = \frac{1}{\alpha_2 \times TT_2 + \beta_2 \times TR_2}
\]

(4)

In these formulas calibration coefficient \(\beta\) is used for the toll rate parameter in the utility. A logit model is used to define the traffic assignment, show in Equation (5):

\[
F_1 = F_{TOTAL} \times P_1 = F_{TOTAL} \times \frac{\exp(U_1)}{\exp(U_1) + \exp(U_2)}
\]

\[
= F_{TOTAL} \times f(TR_1, TT_1, TR_2, TT_2)
\]

(5)

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

$$TR_1 = f^{-1}(F_1 / F_{TOTAL}, TT_1, TT_2, TR_2)$$  \hspace{1cm} (6)$$

$$TR_1 = f^{-1}(P_1, TT_1, TT_2, TR_2)$$  \hspace{1cm} (7)$$

It is assumed that $TT_1, TT_2$ and $F_{TOTAL}$ are measurable with the necessary detector infrastructure. Therefore if $F_1$ is known, toll rate in Crossing 1 can be obtained by backward calculation. The flow ratio for Crossing 1, $F_1$, is supposed to change depending on congestion levels. For example, if the average occupancy difference between the two crossings is too high the ratio of vehicles using the less congested alternative should be higher. Therefore a step-wise linear algorithm is defined to calculate $P_1$ for different congestion conditions. Zhang et al. (2008) used average speeds to define the threshold values, however as stated earlier, congestion level in the crossings is defined by average occupancy in the model proposed in this section. $\Delta P_1(t)$, the change in the rate of Crossing 1 users at time increment $t$, depending on the congestion level, can be defined in a step function. Desired occupancy levels are previously determined by the agencies operating the crossings, and the value changes depending on the number of lanes and lane widths. If the desired occupancy in Crossing 1 is assumed as 10%, a step-wise control mechanism can be formulated as:

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

$$\Delta P_1(t) = \begin{cases} 
    b_1 + k_1(O_1(t) - O_2(t)) & O_1 > 15 \\
    \text{sign} \times [b_2 + k_2(O_1(t) - O_2(t))] & 15 \geq O_1 > 10 \\
    k_3(O_1(t) - 10) & O_1 < 10 
\end{cases}$$  \hspace{1cm} (8)$$

where $P_1(t+1)$ and $P_1(t)$ are the flow ratios for traffic using Crossing 1 at time interval $t$ and $t+1$, $\Delta P_1(t)$ is the change increment, $b_1, b_2, k_1, k_2, k_3$ are parameters used for controlling the intensity of feedback increment, and sign is a variable representing:
\[
\text{sign} = \begin{cases} 
1 & P_i(t - 1) > P_i(t) \\
0 & P_i(t - 1) = P_i(t) \\
-1 & P_i(t - 1) < P_i(t) 
\end{cases}
\] (9)

Finally the derivation of the inverse function for \( TR_i \) is determined in Equation (10):

\[
TR_i = \frac{1}{\beta \times TR_2 + \alpha \times TT_2} - \ln \left( \frac{1 - P_i}{P_i} \right)
\] (10)

The toll rate formulation given in Equation (10) takes into account the toll rate of the alternative crossing, which is the main difference with the formula used by Zhang et al. (2008), where they have one tolled lane and alternative free lanes. The toll rate for the second crossing can be calculated using the same method. Travel time parameters are measured by detectors, therefore the only variable that has to be determined is the parameter \( \alpha \). Regarding Equation (1), this parameter refers to the value of time of drivers, which can be determined by surveys or past traffic data. Network specific values are obtained from Ozbay et al. (2006) for New Jersey Turnpike users, enabling realistic route choice behavior for simulated users. In their study, the authors defined a utility function for work related trips in peak hours:

\[
V_i = 0.05 R_i - 0.14 R_i t_i - 0.2 p_i - 0.24 p_i - 0.48 \tilde{t}_i - 0.18 t_{oi} - 0.11 \Delta_i^{early}
\] (11)

\[\text{early} = 0.16 p_i^2 - 0.44 \tilde{t}_i^2 - 0.11 d_i - 0.3 \tilde{t}_{oi}^i\]

In which the terms are defined as:

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

This utility formula includes the two parameters used in the algorithm of this paper, which are travel time and the cost of travel choice (simply, toll). The remaining terms are not considered in the scope of this study, therefore all other terms are zero. It can be observed that
the coefficient of travel time (0.48) is twice as the coefficient of toll rate (0.24) meaning that one unit increase in travel time (one hour in this case) decreases the utility function twice as much as one unit increase in the toll rate (one dollar) would (19). Following this conclusion based on peak period work related trips of New Jersey Turnpike users, the coefficient of travel time is set as twice the coefficient of travel time in the simulation utility function, defined using Paramics’ Application Programmer Interface (API). After defining the utilities for the alternatives, the probability of a user selecting one alternative is calculated by Equation (5). To avoid unrealistically high probabilities of selecting one alternative, maximum probabilities are defined for some of the decision points.

Network

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 Tunnel and Lincoln Tunnel are selected for 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. New Jersey Turnpike 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 connector 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. The map of the network constructed in Paramics is given in Figure 3.
Simulation

The tolling algorithms provided in the previous section were applied in the Paramics micro-simulation network by developing an API code which utilizes dynamic toll formulations and the driver behavior in response to 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 (10). 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.

The second major function is concerned with route choice, which is dependent on the toll rates calculated in real-time. According to this function, when a vehicle arrives to one of the decision points shown in Figure 3, two utility functions are defined for the two alternatives beyond the decision point, based on travel time and toll rate. Five decision points are defined where users are most likely to switch to the alternative route. According to the utility function users consider the toll rates on either crossing and make their decision to use one of them. There

Figure 3: Simulation Network
were also three destination points defined to obtain different travel times for users destined for different parts of Manhattan. Results are presented as the average of all trips.

The simulation is run for the morning peak hours when inbound traffic to Manhattan on the two tunnels is highest (20). The start time was set at 6:15 AM and the end time at 11:45 AM. The warm-up period is considered as the first 30 minutes, therefore the results are collected after the warm-up period concludes.

**Calibration**

Initially a base network with existing traffic conditions is constructed. This base network has static tolls at the two tunnels. Network calibration is performed by minimizing the difference between observed volumes and simulated flows, by varying the simulation parameters. In-built software parameters that control driver behavior are adjusted to match observed and simulated volumes, and obtain the most realistic flow and travel time results. Origin-Destination (OD) matrices are constructed using the NJTPK traffic data for each interchange point and hourly traffic counts for the Holland Tunnel and the Lincoln Tunnel (20). Additional links that are carrying traffic to the tunnels are loaded by the amount of traffic equal to the difference between the tunnel counts and users that are using the two tunnel exits from the NJTPK. Several trial-and-error runs are performed to match the traffic counts to simulated volumes until the differences are less than 10%. The errors between expected and simulated traffic volumes after final calibration are given in Table 2.

**Table 2: Error between Expected and Simulated Volumes after Final Calibration**

<table>
<thead>
<tr>
<th>Facility</th>
<th>ERROR</th>
</tr>
</thead>
<tbody>
<tr>
<td>NJTPK Exit 14C</td>
<td>1.1%</td>
</tr>
<tr>
<td>NJTPK Exit 15E</td>
<td>3.2%</td>
</tr>
<tr>
<td>NJTPK Exit 16E</td>
<td>2.4%</td>
</tr>
<tr>
<td>Holland Tunnel</td>
<td>-4.2%</td>
</tr>
<tr>
<td>Lincoln Tunnel</td>
<td>-8.4%</td>
</tr>
<tr>
<td><strong>TOTAL AVERAGE</strong></td>
<td><strong>-1.2%</strong></td>
</tr>
</tbody>
</table>
RESULTS

The time-dependent change of toll rates throughout the simulation at the two crossings is shown in Figure 4. It can be observed that the Lincoln Tunnel starts to get congested earlier than Holland Tunnel, therefore the toll rate increases at the Lincoln Tunnel during the earlier stages of the simulation. Later, when some of the Lincoln Tunnel users start to switch their routes to the Holland Tunnel, traffic conditions get better, and as a result toll rates decrease at the Lincoln Tunnel. In the later stages of the simulation the congestion level at the Holland Tunnel gets more severe relative to the Lincoln Tunnel and higher toll rates are observed at the Holland Tunnel. It is also observed that at peak period shoulders, the lowest toll rates are calculated, as expected.

Figure 4: Time-Dependent Toll Rates for Lincoln and Holland Tunnels

Driver behavior in response to dynamic toll rates is analyzed for every decision point. Probabilities of route choices at every decision point are given in Figure 5. The probability of New Jersey Turnpike users to choose the Holland Tunnel to cross to Manhattan is shown for Decision Point A, where it is observed that with the increased toll rates of the Holland Tunnel more users prefer to use the Lincoln Tunnel. Similar behavior can be observed at Decision Point B, which is the exit from New Jersey Turnpike to Route 1-9, and an additional alternative route to the Holland Tunnel. Thus, the Holland Tunnel toll rate controls the behavior at this decision point. Although there is another decision point on Pulaski Skyway (Decision Point D) which gives an option to switch the Lincoln Tunnel, it is observed that most NJTPK users destined for
the Lincoln Tunnel continue their trips on the NJTPK until the Lincoln Tunnel exit. The main reason of this behavior is the faster trips on New Jersey Turnpike, although they must also pay a higher toll ($3 higher for cars for cash tolls) to continue to the next exit.

At Decision Point C the number of users switching from the Lincoln Tunnel to the Holland Tunnel was limited to 20% to not get too far from the traffic counts for the NJTPK Lincoln Tunnel exit (Exit 16E). At Decision Point D, the probabilities are lower compared to the other decision points because the Holland Tunnel provides a shorter trip in free flow travel conditions to every destination point in Manhattan from this decision point. Finally the change in probability of users to switching to the Holland Tunnel at Decision Point E shows that when the Lincoln Tunnel toll rate increases, more users tend to switch their routes.
Sensitivity analysis of the coefficients of the two parameters in the route choice algorithm (Equation (5)) for Decision Point A is shown in Figure 6. This figure shows the change in the probability of selecting the Holland Tunnel with three different coefficient combinations. When the toll rate coefficient is two times the travel time coefficient, the route choice decision becomes more sensitive to the changes in travel conditions on the road.

The change in travel speeds and average occupancies at each tunnel are shown in Figure 7. The data is obtained from the simulation with detectors placed to measure upstream traffic.
It can be seen that the Holland Tunnel has higher travel speeds in the earlier stages of the simulation, but as conditions change users start to change their routes to the faster Lincoln Tunnel. Although there is a difference in travel speeds between the two crossings, it is also observed that travel speeds in both tunnels do not exceed 20 mph for most of the simulated period.

![Graph showing Speed and Occupancy Changes During the Simulation Period](image)

**Figure 7: Speed and Occupancy Changes During the Simulation Period**

As a better measure of congestion, occupancy values are also obtained from the detectors. Similar to the travel speed data, the Holland Tunnel performs better in terms of congestion during the first hour of the simulation period, while the Lincoln Tunnel has lower occupancy.
values and less congested traffic conditions for the later stages of the simulation. The change in travel times of the alternatives calculated in each decision point to the destination gives an idea about the effects of the tolling algorithm on route travel times, since travel time is one of the two parameters in the utility function that determines the users’ probability of choosing their routes.

Figure 8 shows the users’ average travel times to reach their destinations at each decision points using the two alternative routes. Generally, the proposed algorithm tries to keep the difference between the two alternative route travel times within a certain range and does not allow dramatically high differences between the two travel times. In other words, when the difference between the two travel times gets higher in a given time period, the algorithm tries to decrease the difference in the next time period. When analyzing each decision point, for example Decision Point A, it is observed that using the Lincoln Tunnel gives lower average travel times even though the distance to travel is lower via the Holland Tunnel to all three destination points. As expected, the Holland Tunnel offers lower average travel times towards the end of the simulation, when the congestion is mitigated. Similar behavior is observed for all decision points.
DISCUSSION

While this study simulates a feedback based dynamic pricing algorithm to optimize traffic conditions at Holland and Lincoln Tunnels, currently the facilities are statically priced. A comparison between dynamic and static tolls is also conducted. The network is simulated with static toll rates and the average occupancies and average travel speeds of the crossings are...
compared. The simulation uses the same demands for the same time period, and measurements are gathered with point sensors located at each crossing. For the Holland Tunnel, feedback based tolling algorithm is observed to be effective in decreasing the occupancy by 36%, as shown in Figure 9. On the other hand for the Lincoln Tunnel, occupancies are generally lower in the dynamic pricing scenario but there are some short time periods when the occupancies are lower in the case of the static pricing scenario. An average decrease of 11% in average occupancies is observed in the Lincoln Tunnel for the dynamic pricing case. A dynamic toll causes Holland Tunnel speeds to increase by 24% compared to the static toll case, and for the Lincoln Tunnel average speeds increase by 4% in dynamic pricing.
CONCLUSION

This paper presents a simulation-based study of a two-route feedback based dynamic tolling algorithm. The study network is developed and calibrated in Paramics for the Holland and Lincoln Tunnels, and their connecting routes (Figure 3). A modified version of the dynamic tolling algorithm proposed by Zhang et al. (2008) and a realistic route choice behavior model are implemented in Paramics by using its API capability. Observed volumes and other data from various sources are used as traffic demands and morning peak period is simulated with the dynamic feedback based tolling algorithm to compare it with the static tolling scheme similar to the one that is currently being used at these facilities.

It can be concluded that the dynamic feedback based algorithm performed effectively to manage peak period congestion. Route choice behavior of the users as a result of real-time toll rate changes is successfully simulated and logical route choices are observed at decision points where users are most likely to alter their route choice in terms of which crossing to use to enter Manhattan. Compared to the static tolling scenario, which is a representation of the current situation, the dynamic tolling scenario provides lower occupancies and higher speeds for both crossings. The simulation results showed that average occupancies decreased 36% for Holland Tunnel and 11% for Lincoln Tunnel, and average speeds increased by 24% and 4%, respectively, as a result of the dynamic pricing case compared with the static pricing case. Thus, it can be concluded that the proposed feedback based dynamic pricing algorithm for these two parallel facilities succeeds in improving the efficiency of the system. Future research can measure the effects on revenue and incorporate targets into the simulation, making dynamic pricing more attractive to agencies as well as users.
REFERENCES


