Title
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Authors
Jang, Kitae
Chung, Koohong

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A Dynamic Congestion Pricing Strategy for High-Occupancy Toll Lanes

Kitae Jang, Ph.D. Candidate (corresponding author)
Civil and Environmental Engineering
Institute of Transportation Studies
416 McLaughlin Hall,
University of California, Berkeley
California, 94720-1720, USA
TEL: 510-672-5404
FAX: 510-643-9922
E-mail: kitae_jang@berkeley.edu

Koohong Chung, Ph.D., P.E.
California Department of Transportation
Highway Operations Special Studies
111 Grand Ave., Oakland
California, 94623-0660, USA
TEL: 510-622-5429
FAX: 510-286-4561
E-mail: koohong_chung@dot.ca.gov

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ABSTRACT
High Occupancy Toll (HOT) lanes are emerging as a solution to address the underutilization of High Occupancy Vehicle (HOV) lanes and also means of generating revenue for state department of transportation. This paper proposes a method for dynamically determining the HOT toll price in response to the changes in traffic condition and documents procedures for estimating parameters needed for the proposed pricing strategies: revenue maximization and delay minimization. The proposed strategies have been applied to 14-miles of freeway segment in the San Francisco Bay Area, and the findings show that utilizing all the available HOV lane capacity (i.e. difference between HOV lane capacity and HOV demand) to serve the HOT demand does not result in maximizing the total revenue. There exists optimal level of HOV lane capacity that can be allowed for the use of HOT vehicle to maximize the revenue.
1. INTRODUCTION
High Occupancy Vehicle (HOV) lanes are special-use lanes that enable vehicles with a predetermined number of passengers to bypass congested traffic in general purpose (GP) lanes and have been widely installed along crowded urban freeways to improve overall mobility within metropolitan freeway systems. However, when HOV lanes are underutilized, they may nullify the benefits of HOV lanes (1, 2). To mitigate the inefficiency that arises from the underutilization and generate revenue, many state departments of transportation are considering High Occupancy Toll (HOT) lanes, which are HOV lanes that can be accessed by Low Occupancy Vehicles (LOV) at a fee, as a solution.

Several pricing strategies are currently employed by federal and regional transportation agencies. Some agencies use a deterministic pricing strategy by which the toll varies with respect to time of day without considering the level of congestion (3, 4, 5). Other agencies use a dynamic pricing strategy in which toll amount varies based on downstream traffic density (i.e. number of vehicles per mile) rather than expected traffic delays in GP lanes or travel time savings by using HOT lane (6, 7, 8). In addition, existing pricing strategies (9, 10) often do not consider the differences in travelers’ value of time (VOT) resulting in deterministic (and often unrealistic) mode choice behavior; fails to allow freeway users to choose different services according to their own preferences in the analysis. The heterogeneity of VOT has been identified (11, 12, 13) and the importance of incorporating the heterogeneity in determining the benefit of value pricing has been documented in previous studies (14, 15).

This study proposes a dynamic congestion pricing strategy that considers differences in individual’s VOT and real-time traffic delays in determining the toll price. The assumptions and the processes of estimating GP lane delay and HOV lane capacity that can be allocated to serve HOT demand are described in section 2 along with the detailed discussion of how the VOT distribution had been determined using mixed logit model in this study. Section 3 explains the proposed dynamic pricing strategy. The proposed strategy has been applied to data obtained from 14-mile corridor along the Interstate 680 in the San Francisco Bay Area. The findings from applying the pricing strategy are reported in section 4. This paper ends with summary of the findings and discussions of their implications in section 5.

2. GP LANE DELAY, HOV LANE UTILIZATION, AND VALUE OF TIME DISTRIBUTION

2.1. GP Lane Delay Estimation
Suppose that there exists a freeway and it has only a pair of ingress and egress points and HOV lane is separated from GP lanes as shown in Figure 1(a): for the facility that has multiple ingress and egress points, the delay can be estimated by applying queueing analysis on each of the consecutive ingress and egress point. The ingress and egress of the HOV lane in the Figure 1(a) span an active bottleneck which is marked by gray triangle. \( A(t) \) and \( E(t) \) in the Figure 1(b) show the cumulative numbers of vehicles arriving at upstream and downstream of the bottleneck by time \( t \). \( a(t) \) is the arrival rate at upstream (vehicles per unit time) and \( C \) is the capacity of the bottleneck. The arrival rate at the downstream of the bottleneck or discharge rate from the bottleneck can be expressed in terms of \( a(t) \) and \( C \) as the following.

\[
e(t) = \min \{ C, a(t) \}
\]

While the bottleneck is operating at its capacity, the delay of \( n^{th} \) vehicle entering the segment can be estimated when it enters the system by translating \( A(t) \) to the right by free flow travel time to the bottleneck. The horizontal displacement between the translated arrival curve, \( A(t) \), and \( E(t) \) in Figure 1(b) is the delay experienced by \( n^{th} \) vehicle leaving the system by time \( t \), \( d(t) \), and it can be expressed as shown in equation (2). Note that \( d(t) \), the amount of delay that \( n^{th} \) vehicle would have experienced if it were to use GP lane, is estimated when it enters the HOT lane at upstream. Thus, the expected delay can be used to determine the toll price for \( n^{th} \) vehicle as it enters the system.
The delay for all travelers, total delay can be estimated by integrating individual vehicles’ delay over the queued time period from \( t_0 \) to \( t_f \): total delay is the metric used to evaluate the performance of different HOT pricing strategies in section 4.4.

\[
d(t) = E^{-1}(n) - A_T^{-1}(n) \tag{2}
\]

Total delay = $D = \int_{t_0}^{t_f} (A_T(t) - E(t)) \, dt \tag{3}$

2.2. HOV Lane Utilization and Available Capacity for HOT Vehicles

When the existing HOV lane is to be converted to HOT lane, the HOV lane utilization rate can be directly measured from the site (e.g. using inductive loop detectors). When the existing route does not have HOV lane, its utilization rate can be estimated using equation (4). Equation (4) estimates the number of vehicles that would travel in the HOV lane by multiplying total traffic volume for the route by the proportion of vehicles eligible for HOVs. The proportion of vehicles for HOVs can be estimated by taking weighted average of travelers choosing HOVs by each mode’s average occupancy (i.e. converting the proportion of travelers to that of vehicles). The drawback of this equation is that the proportion of the GP lane traffic using the HOV lane is fixed over time. This assumption might not be realistic during the off-peak period. However, the estimated value can be used to forecast the time it takes for a facility to pay for itself when no other HOV utilization information is available. The observed HOV utilization rate
during the peak hour at the study route was comparable with $q_{HOV}(t)$ expected by equation (4) and the
survey data from the Bay Area Travel Survey (See section 4.2).

$$q_{HOV}(t) = a(t) \cdot \sum_{k} \frac{p_k}{o_k}$$  \hspace{1cm} (4)

$q_{HOV}(t)$: traffic volume in HOV lane at time $t$

$p_k$: proportion of travelers choosing transportation mode $k$ that is eligible to use HOV lane (i.e.,
HOV with 2 or more passenger and transit)

$o_k$: average number of passengers of transportation mode $k$

Figure 2 displays a triangular HOV lane flow-density relation with free-flow speed ($V_f$), the
capacity ($C_{HOV}$), and the jam density ($K_j$) \cite{16, 17}. While the flow in the HOV lane, $q_{HOV}(t)$, is sufficiently
lower than $C_{HOV}$, the traffic in the HOV lane will remain freely flowing. The remaining HOV lane
capacity, the difference between $C_{HOV}$ and $q_{HOV}(t)$, can be allocated to accommodate the LOVs who are
willing to pay a toll to travel in the free-flowing HOV lane to bypass the queued GP lanes. To avoid
delay in the HOV lane resulting from excessive LOVs’ migration, buffer term has been added in the right
side of equation (5). The effect of this buffer to the toll revenue and total delay are discussed in section
4.4.

$$C_{HOT}(t) \leq C_{HOV} - \delta - q_{HOV}(t)$$  \hspace{1cm} (5)

$C_{HOT}$: capacity of HOV lane, constant over time

$\delta$: buffer capacity to prevent delay in the HOV lane

$q_{HOV}(t)$: traffic volume in HOV lane at time $t$

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure2.png}
\caption{Fundamental Diagram for HOV Lane}
\end{figure}

2.3 Value of Time

The traveler’s value of time has been estimated using mixed logit. Equation (6) shows the explicit
expression of the utility of a traveler, $n$, choosing a transportation mode, $j$, used in this study. The travel
time and cost coefficients, $\beta_{n}^{time}$ and $\beta_{n}^{cost}$, are assumed to have log-normal distribution for the reasons that will be explained momentarily. The other remaining variables are control variables and their coefficients are assumed to be fixed. Variables in (a) of equation (6) are dummy variables representing transportation mode $j$ of $n^{th}$ traveler. The coefficients of variables in (a) reflect the travelers’ preference for each transportation mode while controlling other variables. The travelers’ preference to use public transit in Central Business District (CBD) is measured in the coefficient of CBD × transit in (b) of equation (6). The coefficient of Cost/Income in (c) of equation (6) reflects how travel costs influence travelers’ choice given their income levels. An example of estimated parameters is provided in section 4.3.

$$U_{nj} = \beta_{n}^{time} \cdot time_{nj} + \beta_{n}^{cost} \cdot cost_{nj} + \beta_{n}^{HOV2} \cdot HOV2_{nj} + \beta_{n}^{HOV3} \cdot HOV3_{nj} + \beta_{n}^{Transit} \cdot Transit_{nj}$$

(a)

$$= \beta_{n}^{CBDD} \cdot CBD_{nj} \cdot Transit_{nj} + \beta_{n}^{Cost/Income} \cdot Cost_{nj} \cdot Income_{nj} + \epsilon_{nj}$$

(b)

(c)

$$X_{nj}:$$ observed variables associated with the transportation mode $j$

$\beta_{n}:$ vector of coefficients of the variables for traveler $n$ representing traveler’s preference

$\epsilon_{nj}:$ independent and identically-distributed extreme value, independent of $\beta_{n}$ and $X_{nj}$

If $\beta_{n}$ were known and $\epsilon_{nj}$ follows independent and identically-distributed extreme value, the choice probability that traveler $n$ chooses transportation mode $j$ would be standard logit and can be expressed as shown equation (7).

$$L_{nj}(\beta_{n}) = \frac{e^{\beta_{n} \cdot X_{nj}}}{\sum_{i=1}^{J} e^{\beta_{i} \cdot X_{nj}}}$$

(7)

However, since $\beta_{n}$ are unknown and can be different for each traveler, they are assumed to be distributed among travelers with density $f(\beta_{n} | \Omega)$, where $\Omega$ indicates a set of parameters of the distribution representing $\beta_{n}$ in the population. Hence, the choice probability (i.e., mixed logit probability) is derived by integrating (7) over all possible values of $\beta_{n}$ weighted by the density, $f(\beta_{n} | \Omega)$.

$$P_{nj} = \int L_{nj}(\beta_{n}) \cdot f(\beta_{n} | \Omega) \cdot d\beta_{n}$$

(8)

In estimating the probability, the distribution for each coefficient is specified and the set of parameters, $\Omega$, of the distribution is estimated. Various distributions can be specified in order to properly represent the decision makers’ behavior (18, 19). The coefficients for both time and cost always have negative values for all travelers because traveler’s utility diminishes as time and cost increases. Thus, log-normal (single-tailed) distribution is suitable to represent those coefficients which are known to have values limited to one domain (negative in the current case) (20, 21). Since the integral in (7) does not have a closed form in general such that the probability cannot be calculated precisely, parameters for the distributions are approximated by simulation. Using values of $\beta_{n}$ drawn from its density function, $f(\beta_{n} | \Omega)$, the logit probability in (7), $L_{nj}(\beta_{n})$, is calculated. This process is repeated for many draws and the average of the resulting logit probability is taken as the simulated choice probability:
\[ P_{nj}^{S}(\Omega) = \frac{1}{R} \sum_{r=1,2,...,R} \beta_{n}^{r} \]  

(9)

- \( P_{nj}^{S}(\Omega) \): the simulated choice probability for any given set of parameters, \( \Omega \)
- \( R \): the number of iterations
- \( \beta_{n}^{r} \): \( r \)th draw from the density function, \( f(\beta_{n}|\Omega) \)

The simulated choice probability in (9) is then used to compute simulated log-likelihood, \( LL^{S} = \sum_{n=1}^{N} \sum_{j=1}^{J} 1_{nj} \cdot \ln\left\{ P_{nj}^{S}(\Omega) \right\} \), where \( 1_{nj} \) is an indicator function that returns one if traveler, \( n \), chooses a transportation mode, \( j \), and zero otherwise. The maximum simulated likelihood estimators are the values of parameters, \( \Omega \), which maximize \( LL^{S} \). The distribution of value of time (VOT) can then be estimated by dividing randomly drawn \( \beta_{n}^{time} \) and \( \beta_{n}^{cost} \) from and log-normal distributions via simulation. An example of the approximated distribution of VOT and cumulative distribution, \( F_{VOT}(\theta) \), is shown in section 5 of this paper.

### 3. PRICING STRATEGY

Pricing the toll too low can result in excessive LOV migration from GP lanes leading to deterioration of traffic condition in the HOT lane while high toll price cannot effectively address the issues that arise from under utilization of the facility. To promote the diversion of the proper number of LOVs from GP lanes to HOV lanes, the proposed pricing strategy estimates the number of travelers who are willing to pay the toll to avoid the delay in the GP lanes based on the cumulative distribution function of VOT, \( F_{VOT}(\theta) \). Subsequently, the number of HOT vehicles, \( q_{HOT}(t) \), can be estimated by multiplying total number of LOVs in GP lanes by the proportion of LOV drivers’ VOT is greater than the unit toll price at time \( t \). The number of HOT vehicles, \( q_{HOT}(t) \), should be less than the allocated capacity for the HOT vehicles, \( C_{HOT}(t) \), to avoid delay in the HOV lane.

\[ C_{HOT}(t) \geq q_{HOT}(t) = \left\{ 1 - F_{VOT}(\theta) \right\} \cdot q_{GP}(t) \]  

(10)

- \( C_{HOT}(t) \): HOV lane that can be allocated to serve HOT demand at time, \( t \)
- \( q_{HOT}(t) \): the number of HOT vehicles determined by the pricing strategy
- \( q_{GP}(t) \): the number of LOVs on GP lanes at time, \( t \)
- \( F_{VOT}(\theta) \): cumulative distribution function of VOT
- \( \theta \): toll price ($ per unit time) at time, \( t \)

Given the constraints in (5) and (10), thus, the range of \( \theta \) is continuously derived from the distribution of VOT at time, \( t \).

\[ \theta_{i} \geq F^{-1}\left\{ 1 - \frac{C_{HOT} - \delta - q_{HOT}(t)}{q_{GP}(t)} \right\} \]  

(11)

The lower bound of \( \theta_{i} \), \( \theta_{i}^{L} \) is a threshold of VOT that differentiates travelers who are willing to pay the toll according to the travel time saved by using the HOV lane at a particular time, \( t \), from those who does not. Therefore, the toll, \( \pi(t) \), at time, \( t \), is determined as a product of delay in GP lanes and threshold of VOT, \( \theta^{L} \).
\[
\pi(t) = d(t) \cdot \theta_t^L
\] 

(12)

4. CASE STUDY

4.1. Study Site and Data Description

The proposed dynamic pricing strategy has been applied to a 14-mile segment of Interstate 680 southbound, located in the San Francisco Bay Area. The site currently has a HOV lane (and three GP lanes) and California Department of Transportation (Caltrans) is planning to convert it to a HOT lane with dynamic congestion pricing in near future. Currently, vehicles with two or more passengers are permitted to use the HOV lane. Under the planned system, the toll price will be posted on Changeable Message Signs (CMS) upstream from the entrance to the 14-mile segment. The toll price will change to reflect the status of traffic at five-minute intervals, and will be automatically collected by an electronic toll collection system. During the morning peak hours, this freeway segment becomes congested in GP lanes while the existing HOV lane often remains underutilized (22).

A dataset available to the public, the Bay Area Travel Survey (BATS)\(^1\), conducted by the Metropolitan Transportation Commission in 1990, was used, focusing on work trip data for the present analysis. Although the monetary values reported in the survey might require update, it does not affect the proposed strategy. The survey respondents were asked to provide their income level and location of work place information, then to choose a transportation mode based on travel time, cost and distance of the alternatives. Those alternatives were categorized into four different modes: LOV, HOV (2 occupants), HOV (3 or more occupants) and Transit. The survey data include all the values needed to estimate the parameters required by the proposed dynamic toll pricing strategy. The result of the survey is shown in Table 1.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time (min.)</td>
<td>32.6</td>
<td>18.1</td>
</tr>
<tr>
<td>Travel cost ($)</td>
<td>1.7</td>
<td>1.6</td>
</tr>
<tr>
<td>Travel distance (mile)</td>
<td>14.4</td>
<td>7.8</td>
</tr>
<tr>
<td>Household income (thousands of dollars)</td>
<td>60</td>
<td>32.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Modes</th>
<th>Fraction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;LOV&quot;</td>
<td>72.0</td>
</tr>
<tr>
<td>HOV (two passengers)</td>
<td>9.8</td>
</tr>
<tr>
<td>HOV (three or more passengers)</td>
<td>4.0</td>
</tr>
<tr>
<td>Transit</td>
<td>14.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Work location</th>
<th>Fraction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central Business Districts (CBD)</td>
<td>19.6</td>
</tr>
</tbody>
</table>

\(^1\) LOV: In the current case study, vehicles with one passenger (i.e., Single Occupancy Vehicle (SOV)) are LOVs.

4.2. Delay Estimation

The delay in GP lanes are estimated by following the method described in section 2.1. The capacity of a GP lane was specified as 2,000 vehicles per hour per lane (vphpl) while the capacity of an HOT lane was specified as 1,600 vphpl. Both values are based on the empirical study conducted on California freeways with buffer-separated HOV lanes, which had geometric and operational conditions comparable to the planned HOT lane on Interstate 680 (23). Traffic flow data from the inductive loop detector located

\(^1\) ftp://ftp.abag.ca.gov/pub/mtc/planning/BATS/BATS90/
closest to the entrance of the planned HOT segment during weekdays were acquired from the California Freeway Performance Measurement System (24) and averaged over a one-month period. Since there was no rail transit service parallel to the planned HOT segment, transportation modes other than LOV were considered eligible for the HOV lane.

Figure 3 shows the measurement of average traffic flow over the weekdays in April, 2008 from the loop detector data located closest to the entrance of the planned HOT segment. In the current HOV lane of the study site, HOVs can enter and exit at anywhere along the HOV lane (i.e. continuous access HOV facility), and, thus, it is difficult to consistently estimate the HOV lane demand over time. In this case study, the data were measured across four GP lanes at upstream of where HOV lane starts and traffic volume in the HOV lane, $q_{HOV}(t)$, was estimated using equation (4). The estimated $q_{HOV}(t)$ during morning peak hours (5 a.m. to 9 a.m.) was 780 vphpl, comparable to the actual observation of 711 vphpl (25) at downstream HOV lane.

![Figure 3 Measurement of Traffic Flow at the Entrance of Planned HOT Segment (April 2008)](image)

The queueing diagram shown in Figure 4 was constructed using the capacities and traffic volume mentioned in the preceding section. The figure shows the formation of the queue at 7:10 a.m. and its dissipation about two hours later. The total delay, estimated by equation (3), was approximately 2,580 vehicle-hours.

![Figure 4 Queueing Diagram under Current Situation](image)
4.3. Parameter Estimation for VOT
The coefficients in equation (6) have been estimated and the results are shown in Table 2. The first and second columns in Table 2(a) show that the description of variables and their distribution. The estimated coefficients and their standard deviation are shown in third and fourth columns. The standard errors of these estimates are shown in the parentheses adjacent to them. Most estimates were statistically significant and within reasonable values. Table 2(b) shows fixed coefficients shown in (a), (b) and (c) of equation (6). The estimated coefficients for mode choices are relative values with respect to LOVs; negative value indicates that LOVs were most preferred by travelers. The coefficient for CBD × transit indicates that travelers tend to use public transit more when workplaces are located within a CBD. Better accessibility and connectivity of the transit service in a CBD may explain this pattern. The ratio of cost to income coefficient has a negative value, indicating that travelers are less inclined to use a particular mode of transportation when its travel cost is high relative to their income.

Table 2 (a) Parameter Estimates of Random Variables in Mixed Logit Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Distribution type</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel cost ($)</td>
<td>Log-normal</td>
<td>-0.6274 (0.2051)</td>
<td>0.5160 (0.2212)</td>
</tr>
<tr>
<td>Travel time (hour)</td>
<td>Log-normal</td>
<td>-1.2452 (0.1716)</td>
<td>1.0005 (0.2205)</td>
</tr>
</tbody>
</table>

Table 2 (b) Parameter Estimates of Fixed Variables in Mixed Logit Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOV (two passengers)</td>
<td>0.1372</td>
</tr>
<tr>
<td>HOV (three or more passengers)</td>
<td>0.2485</td>
</tr>
<tr>
<td>Transit</td>
<td>0.2587</td>
</tr>
<tr>
<td>CBD × transit</td>
<td>0.2846</td>
</tr>
<tr>
<td>Cost ($) per income (ten thousands of dollars)</td>
<td>0.0114</td>
</tr>
</tbody>
</table>

The cumulative distribution function of VOT has been constructed via simulation performed using one million random draws from each distribution of time and cost coefficient. The distribution of VOT derived by simulation had mean of $8.74/hour, median of $8.30/hour, and standard deviation of $2.85/hour. The mean and median values were compared with those estimated from discrete choice models in the literature. The estimated parameters of VOT were within a reasonable range of VOT (26). Histogram and cumulative distribution function are shown in Figure 5(a) and (b), respectively.

Figure 5 (a) Counts of Value of Time, and (b) Cumulative Distribution of Value of Time
4.4. Results

The toll price was reset every five-minute intervals under the proposed dynamic pricing strategy and this time interval is comparable to what has been used in the demonstration project in Southern California (22). Figure 6(a) and (b) shows the changes in total revenue and total delay during a morning peak-hour with respect to the changes in buffer level, \( \delta \) (see Figure 2). As \( \delta \) decreases, \( C_{\text{HOT}}(t) \) will increase while \( \theta_l^L \) decreases. Then, more LOVs will use HOT lane and it will affect \( d(t) \) during the next time interval. As the buffer level increases, \( C_{\text{HOT}}(t) \) will decrease while \( \theta_l^L \) increases. Less LOVs will use HOT lane and it will also affect \( d(t) \) during the next time interval.

Daily total revenue from operating HOT lane is shown in Figure 6(a) and they are calculated by summing \( q_{\text{HOT}}(t) \times \pi(t) \) over the congested time period. The figure shows that the revenue increases until the amount of buffer capacity, \( \delta \), reaches to 275 vehicles per hour, and the revenue diminishes thereafter. The total delay during the same morning peak period shown in Figure 6(b) was computed by equation (4). The Figure 6(b) indicates that the delay monotonically increases as \( \delta \) increases. When \( \delta \) is zero, the total delay in the GP lanes reaches its minimum at the cost of increasing the chance of HOV lane being overcrowded. These figures indicate that the proposed pricing strategy can specify to achieve different objectives (i.e., delay minimization, revenue maximization, or any combination of delay and revenue) by controlling parameter of \( \delta \).

Figure 6 (a) total revenue vs. buffer capacity, \( \delta \), and (b) total delay vs. buffer capacity, \( \delta \)
The dark bold and light grey lines in Figure 7 show how the three key parameters, $q_{HOT}(t)$, $\theta^L_t$, and $\pi(t)$, change in revenue maximization and delay minimization cases. Compared with revenue maximization, delay minimization case has greater value $C_{HOT}(t)$ due to the absence of $\delta$, lower $\theta^L_t$ and $\pi(t)$ (see the grey line in Figure 7 (b) and (c)). The lower $\theta^L_t$ resulted in diverting more vehicles from GP lanes, $q_{HOT}(t)$ (see the grey line in Figure 7 (a)). Consequently, the reduced demand for GP lanes resulted in the minimum total delay and shorter queue duration.
Figure 7 (a) variations of the number of HOT vehicles, \(q_{HOT}(t)\), over time; (b) variations of threshold value of VOT, \(\theta_L\), over time, over time; and (c) variations of toll price, \(\pi(t)\)

5. SUMMARY AND DISCUSSION

This study examined dynamic toll pricing strategy that considers the difference in travelers’ VOT and changes in expected travel time savings. Section 2 of this paper discussed how the parameters needed for the strategy can be estimated. The delay that \(n^{th}\) travelers would experience by staying in the GP lane to exit the system was estimated by queueing analysis such that toll price for the traveler can be posted in advance based on expected travel time saving. The distribution of value of time has been estimated by mixed logit model. The findings from applying the proposed strategy revealed that the pricing strategy is mainly controlled by \(\delta\).

The underutilization of the HOV lane has not been compared to \(\delta\), but it has been noted that \(\delta\) should always be less than the existing underutilization level. Otherwise, it will exacerbate the issues that HOT facility attempts to address.

Decreasing \(\delta\) resulted in increase in \(C_{HOT}(t)\) and decrease in \(\theta_L\). Consequently, it attracted more LOV to use HOT lane and it decreased \(d(t)\) during the next time interval. Increase in \(\delta\) leads to decrease in \(C_{HOT}(t)\) and increase in \(\theta_L\). Although \(d(t)\) in this case was monotonically increasing function of \(\delta\), since \(\delta\) is assumed to be less than underutilization level of HOV lane, the system wide delay under HOT system is still less than the delay without HOT system. The findings shown in Figure 7 indicated that there exists optimal value of \(\delta\) that maximizes the total revenue.

6. REFERENCES


24. Freeway Performance Measurement System (PeMS), (2008) (accessed 05.05.08) <http://pems.eecs.berkeley.edu>
