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Highway agencies strive to provide the highest possible level of service (LOS) to their users. Traffic density, the main factor affecting the freeway, is determined by converting a mixed traffic stream to an equivalent passenger car stream using passenger car equivalencies (PCEs). Traditionally, equivalent delay and microscopic simulation have been used to estimate PCE values. This study presents an alternative methodology to estimate PCEs on the basis of lagging headways derived from video-recorded traffic data. This methodology allows for site-specific PCE values to be calculated based on prevailing traffic characteristics. In addition, the methodology provides separate PCE values for single-unit trucks (SUTs) and combination trucks (CTs). Compared to the single value provided in the Highway Capacity Manual (HCM), defining two separate truck PCEs provides a more robust description of the equivalent traffic stream.

Lagging headway, defined as the distance from the rear bumper of a leading vehicle to the rear bumper of the following vehicle, is the actual space a vehicle consumes while in the traffic stream. This research used three-stage-least-squares (3SLS) regression to generate a model that predicts lagging headways for three vehicle classes; passenger cars (PC), SUT, and CT. The headways are influenced by prevailing traffic flow characteristics of a freeway segment. The 3SLS model was then expanded to predict lagging headways for each of the nine vehicle-following combinations, which were used to calculate class-average lagging headways. The PCE values were calculated as the ratio of the lagging headway of each truck class to that of PC. Forecasting accuracy comparisons showed that the two models provide reliable predictions of vehicle class lagging headways and hence lead to reliable PCE values for SUT and CT.
Introduction
A typical traffic stream is composed of passenger cars (PC), single-unit trucks (SUT), combination trucks (CT), buses, and recreational vehicles, and the distribution among these classes is heavily influenced by location and time. Heavy vehicles have different physical and operational characteristics compared to passenger cars. These differences, which include size and acceleration/deceleration abilities, result in different traffic behavior by different vehicle classes. Heavy vehicles also have a physical impact on other vehicles and a psychological impact on drivers in adjacent lanes due to their larger size and maneuvering difficulties (Al-Kaisy et al., 2002; Krammes and Crowley, 1986).

Level of service (LOS) is a qualitative measure of a traveler’s trip quality under prevailing roadway and traffic conditions. The current *Highway Capacity Manual* (HCM) provides a density-based LOS graduation: There are six levels from A (free-flow conditions) to F (complete congestion) (HCM, 2010). For basic freeway segments, density is the dominating factor in the LOS calculation. Since density is expressed in PC per mile per lane, there is a need to convert a mixed traffic stream into pure passenger car flow. The HCM methodology utilizes passenger car equivalency (PCE) to convert a mixed traffic stream into an equivalent passenger car stream. Spatial lagging headway (see Figure 1 for a description) provides a suitable alternative approach to density, and thus for determining PCEs. Vehicles in a traffic stream consume different amounts of space depending on a number of traffic factors; therefore, by measuring lagging headway, one can determine the average amount of

Figure 1: Schematic headway diagrams (a) CT following any vehicle (b) SUT following any vehicle (c) PC following any vehicle.
space consumed by each class of vehicle. The ratio of each truck lagging headway to the passenger
space consumed by each class of vehicle. The ratio of each truck lagging headway to the passenger
car lagging headways will provide actual PCEs (VanBoxel et al., 2010).

The present methodology used by the HCM for developing PCEs utilizes traffic simulations instead
of real field observations (Van Boxel et al., 2010; Elefteriadou et al., 1997; Sumner et al., 1984). Also,
the present version of HCM provides a single PCE value for all truck types. The proposed procedure
seeks to develop separate PCE values for SUT and CT on the basis of lagging headways measured
from real traffic data.

Review of Past Research

In the 1950 edition of the Highway Capacity Manual (HCM), trucks were arbitrarily considered
equivalent to two cars and the term “passenger car equivalent” was not used. It was not until 1965
that the term “passenger car equivalent” was formally introduced in HCM and was defined as “the
number of passenger cars displaced in the traffic flow by a truck or a bus, under the prevailing
roadway and traffic conditions” (HRB, 1950; HRB, 1965). The 1985 version of the HCM adopted
the volume to capacity (v/c) ratio approach, developed by Linzer et al. (1979) for calculating PCEs.
In the 2000 version of the HCM, heavy vehicles were converted into a passenger car equivalent using
a passenger car equivalency factor (PCE). PCE was defined as “the number of passenger cars that
are displaced by a single heavy vehicle of a particular type under prevailing roadway, traffic, and
control conditions” (HCM, 2000). Both the 2000 and 2010 versions of the HCM provide different
PCE values depending on the percentage of heavy vehicles, different grades, and grade length for
freeways and multilane highways but a single value for both CT and SUT. In previous studies, various
methodologies have been used to calculate the PCEs for different types of facilities. The dominant
criteria for PCE determination include headway (Werner and Morrall, 1976; Seigun et al., 1982),
speed (Hu and Johnson, 1981), delay (Cunagin and Messer, 1983), volume/capacity ratio (Linzer
et al., 1979), density (Webster and Elefteriadous, 1999), platoon formation (Van Aerde and Yagar,
1984), travel time (Keller and Saklas, 1984), and queue discharge flow (Al-Kaisy et al., 2002).

Huber (1982) used simulations to derive PCE equations using three different criteria; speed and the
density of base (passenger car only) and mixed steams, and the passenger car speed in base and mixed
streams. Huber equated a base-stream flow rate, \( q_B \), to a mixed-stream flow rate, \( q_M \), having same
impedance to flow (Huber, 1982; Demarchi and Setti, 2003). The Huber equation is:

\[
PCE = \frac{1}{\Delta p} \left[ \frac{q_B}{q_M} - 1 \right] + 1
\]

where \( \Delta p \) is the proportion of trucks in mixed traffic stream.

The Huber procedure is for only one type of heavy vehicle. Sumner et al. (1984) used microscopic
simulations to expand this procedure to obtain the PCE of each type of subject vehicle in a mixed
traffic stream by accounting for different trucks types in addition to PC, as presented in Equation 2:

\[
PCE_s = \frac{1}{\Delta p} \left[ \frac{q_s}{q_M} - \frac{q_B}{q_M} \right] + 1
\]

Where \( q_s \) is the flow rate of the subject vehicle type “s”. The traffic stream in the first simulation
was composed of the base flow (\( q_B \)) (PC only), the second simulation was a mixed stream (\( q_M \)) (PC and
other vehicles), and the third simulation (\( q_s \)) consisted of a mixed stream in which \( \Delta p \)% of vehicles
of interest replaced the PC. For the three simulation models, the delay in vehicle-hours was plotted
against flow. Determining the values for \( q_B \), \( q_M \), and \( q_s \) that correspond to the same impedance level
and using Equation 2, the PCE for the subject vehicle type can be calculated.
Webster and Elefteriadou (1999) expanded the work of Sumner et al. (1984) by including a wide range of freeway conditions. The PCE tables in the current version of the HCM (HCM, 2000) are derived from the work of Elefteriadou et al. (1997). Also, a number of past studies have estimated the PCEs for freeway sections using different methodologies (Webster and Elefteriadou, 1999; Rakha et al., 2007). The lagging headway concept is more suited to freeways where density is the primary determinant of LOS. However, the concept of using headway ratio for determining PCE was first applied by Werner and Morrall (1976), who derived the relationship for determining PCE for level terrain as follows:

\[ PCE = \left( \frac{H_m - P_{PC}}{P_T} \right) / P_T \]  

where \( H_m \) is the average headway for the entire traffic stream, \( H_{PC} \) is the passenger car headway, and \( P_{PC} \) and \( P_T \) are the proportion of PC and trucks, respectively, in the traffic stream. The study results by Werner and Morrall provided generalized PCEs for trucks, buses, and recreational vehicles on two-lane highways.

Cunagin and Chang (1983), using time headway as the performance measure, determined the impact of heavy vehicles on traffic flow for freeway sections on the basis of measured headways for seven different combinations of a certain vehicle class “m” following vehicle class “k” and demonstrated that the presence of trucks resulted in higher average headways. Also, Seguin et al. (1982) used the concept of spatial headway for calculating PCEs.

The relative amount of space consumed by a vehicle has been suggested as the basis for estimating PCEs (Elefteriadou et al., 1997). Assuming that lagging headway depends on the size of the following vehicle, the PCE was formulated as in the following equation (Elefteriadou et al., 1997):

\[ PCE_{ij} = \frac{H_{ij}}{H_{PC_j}} \]

Where \( H_{ij} \) is the total lagging headway of the following vehicle class under condition \( j \), \( H_{PC_j} \) is the passenger car lagging headway, and \( PCE_{ij} \) indicates the PCE value for vehicle class \( i \) under roadway conditions \( j \).

More recently, Van Boxel et al. (2010) carried out an exploratory study using data from a single microloop detector to derive PCEs using spatial lagging headway. In a subsequent buildup from that research endeavor, the current study seeks to develop PCEs for freeway sections using spatial lagging headway based on a comprehensive data set from multiple freeway segments over a longer time horizon.

**Study Methodology**

The current study uses a statistical approach for estimating the spatial lagging headway for three vehicle classes: PC, SUT, and CT. The lagging headway values for each vehicle class are the dependent variables in the model. Since the dependent variables are considered endogenous, meaning they influence each other, the three equations were modeled simultaneously using a three-stage-least-squares (3SLS) regression. In other words, the lagging headway of vehicles in a vehicle class directly influences the lagging headway of the vehicles in the other vehicle classes. Had the study used a single-equation estimation of the endogenous variables, such as ordinary least squares regression, the resulting parameter estimates would have been biased due to a correlation between the random error terms and the randomly correlated variables (Washington et al., 2011). Since lagging headways are always a positive value, the models were set-up to predict the natural logarithm of the lagging headways, thus always predicting positive values. Mathematically, the system of regression models can be represented as follows:
\[ \ln(H_{pc}) = \alpha_1 + \beta_{pc}X_{pc} + \lambda \ln(H_{st}) + \tau \ln(H_{st}) + \varepsilon_{pc} \]  \hspace{1cm} (5)

\[ \ln(H_{st}) = \alpha_2 + \beta_{st}X_{st} + \delta \ln(H_{pc}) + \alpha \ln(H_{ct}) + \varepsilon_{st} \]  \hspace{1cm} (6)

\[ \ln(H_{ct}) = \alpha_3 + \beta_{ct}X_{ct} + \varphi \ln(H_{pc}) + \xi \ln(H_{st}) + \varepsilon_{ct} \]  \hspace{1cm} (7)

where \( \ln(H) \) is the natural logarithm of the average lagging headway of vehicle type \( i \), \( \beta_i \) is a vector of estimable parameters, \( X \) is a vector of known traffic data (such as speed of different vehicle classes, total vehicle flow, vehicle flow for individual vehicle classes, and percent car and trucks), \( \lambda, \tau, \delta, \alpha, \xi, \) and \( \varphi \) are estimable scalars, and \( \varepsilon_i \) is the disturbance term.

The choice of the system equation method depends on the nature of the relationship between the dependent variables. In this case \( \ln(H_{pc}), \ln(H_{st}), \) and \( \ln(H_{ct}) \) are endogenous variables, meaning \( \ln(H_{pc}) \) belongs to the set of independent variables of \( \ln(H_{st}) \) and \( \ln(H_{ct}) \). Similarly \( \ln(H_{st}) \) and \( \ln(H_{ct}) \) belong to the set of influential factors of \( \ln(H_{pc}) \) and so on. Since the dependent variables are endogenous and the error terms are correlated, the 3SLS method is appropriate to estimate the parameters of the equations simultaneously (Anastasopoulos, 2009).

In the second phase of this study, the average spatial lagging headways are estimated on the basis of type of vehicle leading and following. It is assumed that headways are expected to differ by the type of vehicle that is following or leading. A passenger car following another passenger car may generally prefer a different lagging headway than one following an SUT or CT. This study develops a nine-equation 3SLS model for average spatial lagging headway and then ultimately finds the average lagging headway for each vehicle class. The average lagging headways on the basis of type of vehicle leading and following are estimated using the following system of equations:

\[ \ln(H_{pc-pc}) = \beta_{pc-pc}X_{pc-pc} + \lambda H_{pc-cf} + \tau H_{st-pc} + \varphi H_{ct-pc} + \varepsilon_{pc-pc} \]  \hspace{1cm} (8)

\[ \ln(H_{pc-st}) = \beta_{pc-st}X_{pc-st} + \varphi H_{ct-st} + \varepsilon_{pc-st} \]  \hspace{1cm} (9)

\[ \ln(H_{pc-ct}) = \beta_{pc-ct}X_{pc-ct} + \lambda H_{pc-st} + \varepsilon_{pc-ct} \]  \hspace{1cm} (10)

\[ \ln(H_{st-pc}) = \beta_{st-pc}X_{st-pc} + \varphi H_{ct-st} + \varphi H_{ct-st} + \varepsilon_{st-pc} \]  \hspace{1cm} (11)

\[ \ln(H_{st-st}) = \beta_{st-st}X_{st-st} + \tau H_{st-st} + \varepsilon_{st-st} \]  \hspace{1cm} (12)

\[ \ln(H_{st-ct}) = \beta_{st-ct}X_{st-ct} + \varphi H_{ct-st} + \varepsilon_{st-ct} \]  \hspace{1cm} (13)

\[ \ln(H_{ct-pc}) = \beta_{ct-pc}X_{ct-pc} + \tau H_{st-st} + \varepsilon_{ct-pc} \]  \hspace{1cm} (14)

\[ \ln(H_{ct-st}) = \beta_{ct-st}X_{ct-st} + \tau H_{st-st} + \varphi H_{ct-pc} + \varepsilon_{ct-st} \]  \hspace{1cm} (15)
\[ \ln(H_{m-k}) = \beta_{m-k} \cdot X_{m-k} + \varphi \cdot H_{m-k} + \varepsilon_{m-k} \]  

(16)

where \( \ln(H_{m-k}) \) is the natural logarithm of average lagging headway of vehicle type \( m \) when following a vehicle type \( k \), \( \beta_{m-k} \) is a vector of estimable parameters, \( X_{m-k} \) is a vector of known traffic data (such as speed of different vehicle classes, total vehicle flow, and vehicle flow for individual vehicle classes), \( \lambda, \tau, \) and \( \phi \) are estimable scalars, and \( \varepsilon_{m-k} \) is the disturbance term. Having estimated the individual headways, the class average headway can be estimated as follows:

\[ \overline{H}_{pc} = p_{pc-pc}H_{pc-pc} + p_{pc-sut}H_{pc-sut} + p_{pc-ct}H_{pc-ct} \]  

(17)

\[ \overline{H}_{sut} = p_{sut-pc}H_{sut-pc} + p_{sut-sut}H_{sut-sut} + p_{sut-ct}H_{sut-ct} \]  

(18)

\[ \overline{H}_{ct} = p_{ct-pc}H_{ct-pc} + p_{ct-sut}H_{ct-sut} + p_{ct-ct}H_{ct-ct} \]  

(19)

where \( \overline{H}_{mp} \) is the class average lagging headway for class \( m \), \( p_{m-k} \) is the percentage of vehicles of class \( m \) following class \( k \) vehicles, and \( H_{m-k} \) is the average lagging headway of vehicle class \( m \) following vehicle class \( k \).

**Data Collection and Preparation**

**Data Requirements**

A calculation of spatial lagging headway requires a dataset that provides both a time stamp of when a vehicle crosses a reference point, and the speed of the individual vehicle. With this data the spatial leading headway can be calculated as follows:

\[ LH_i = 1.4667V_i(t_i - t_{i-1}) \]  

(20)

Where \( t_i \) is the time stamp of vehicle \( i \) in seconds, \( V \) is the speed in miles per hour (mph), \( t_{i-1} \) is the timestamp of the previous vehicle, and \( LH_i * \) is the spatial leading headway (in feet) of vehicle \( i \). The leading headway can be converted to lagging headway by subtracting the leading vehicle length and adding the following vehicle length as shown in equation (4):

\[ LH_i = LH_i^* - L_{i-1} + L_i \]  

(21)

where \( L_{i-1} \) is the length of the leading vehicle, \( L_i \) is the length of vehicle \( i \), and \( LH_i \) is the lagging headway of vehicle \( i \) (Figure 1).

The Federal Highway Administration (FHWA) utilizes a 13-class vehicle-classification system. However, as is often the case, the data sources do not contain enough information to be this specific. Consequently, a limited number of classes are established based on vehicle length. The present study classifies vehicles into three classes: PC, SUT, and CT. Therefore, we are interested in determining the lagging headway of each of these three vehicle classes so that PCE values can be established separately of SUT and CT.
This study makes use of video-recorded data. The data were collected using a mobile traffic laboratory (cargo van) fitted with cameras and a recording system. A telescopic mast raises a pair of video cameras to a height of 50 feet above ground level. Each camera is then adjusted so that it captures the vehicles as they approach the van from both directions. Working in unison, the pair of cameras provides a comprehensive record of the traffic experienced at a particular location covering all the traffic lanes. For this study, four sites were selected along Interstate-465 near Indianapolis, Indiana, USA: Two sites were located south and two sites were located north of the city center. The sites had minimal grade and represented a typical freeway section as specified by the HCM. A total of 2,100 lane-hours of data from these locations were collected during the months of October 2009 to March 2010.

**Data Preparation**

The recorded video clips were processed and the data were split into 15-minute clips for each lane. Each clip was analyzed separately. The extracted data include the speed, lagging headway, and vehicle class of each individual vehicle, as well as the total number of vehicles in each vehicle class. For an individual vehicle $i$, the lagging headway, $LH_i$, is lower bounded by the vehicle length (total congestion) and is upper bounded by the sum of the vehicle length and the stopping sight distance ($SSD_i$). A vehicle with lagging headway that exceeds stopping sight distance is not considered to be “following” another vehicle in the traffic stream (in essence, they have “open road” in front of them). While it is physically possible for lagging headway to exceed this upper bound, such conditions suggest that low traffic does not affect the vehicle’s headway. The data were extracted using the software package Traffic Tracker. Table 1 presents the summary of the extracted data from the videos.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average PC lagging headway</td>
<td>ft.</td>
<td>213.062</td>
<td>42.459</td>
</tr>
<tr>
<td>Average SUT lagging headway</td>
<td>ft.</td>
<td>302.550</td>
<td>127.446</td>
</tr>
<tr>
<td>Average CT lagging headway</td>
<td>ft.</td>
<td>347.672</td>
<td>101.701</td>
</tr>
<tr>
<td>PC Flow</td>
<td>PC/15min.</td>
<td>218.646</td>
<td>74.452</td>
</tr>
<tr>
<td>SUT Flow</td>
<td>SUT/15 min.</td>
<td>13.066</td>
<td>7.370</td>
</tr>
<tr>
<td>CT Flow</td>
<td>CT/15min</td>
<td>28.162</td>
<td>16.259</td>
</tr>
<tr>
<td>Traffic Volume</td>
<td>Vehicles in 15 minutes</td>
<td>259.874</td>
<td>77.791</td>
</tr>
<tr>
<td>Average PC Speed</td>
<td>mph</td>
<td>61.241</td>
<td>7.314</td>
</tr>
<tr>
<td>Average SUT Speed</td>
<td>mph</td>
<td>60.599</td>
<td>8.810</td>
</tr>
<tr>
<td>Average CT Speed</td>
<td>mph</td>
<td>59.939</td>
<td>7.993</td>
</tr>
<tr>
<td>Percent PC</td>
<td>Percentage</td>
<td>83.742</td>
<td>9.200</td>
</tr>
<tr>
<td>Percent SUT</td>
<td>Percentage</td>
<td>5.184</td>
<td>3.200</td>
</tr>
<tr>
<td>Percent CT</td>
<td>Percentage</td>
<td>11.074</td>
<td>6.895</td>
</tr>
</tbody>
</table>

*Note: 1 foot = 0.305 meters; 1mph = 1.609 kph*
Modeling Results

This study developed two sets of models. The first set consists of a three-equation 3SLS model that was developed using 452 observations (average values extracted from each 15-minute video clip constitutes one observation). The 452 observations constitute only those observations where all three lagging headways were observed. The second set consists of a nine-equation 3SLS model with a total of 142 observations. This data set is limited due to the limited number of observations that had instances of all nine combinations of vehicle following pairs (car following car, car following SUT, car following a CT, SUT following car, SUT following SUT, SUT following CT, CT following car, CT following SUT, and CT following CT).

3SLS Model 1: Lagging Headway for Three Vehicle Following Combinations

Table 2 displays the results of the three-equation 3SLS estimation for lagging headways along Interstate-465 (urban interstate) using 452 observations.

**PC Lagging Headway**

The negative sign for the variables PC flow (PC/15 minutes) and SUT flow (SUT/15 minutes) indicates that an increase in PC or SUT flow rate decreases the predicted lagging headway of PC. This is an intuitive result; as more vehicles are added to the traffic stream, the spatial constraints increase, resulting in a decrease in headway. Average passenger car speed is a significant variable that increases passenger car headway. This is also intuitive as a larger stopping distance is required at higher speeds; thus, drivers are more likely to increase space between their vehicle and the vehicle ahead of them. Conversely, as SUT speed increases, passenger car headway decreases. This suggests that PCs may be more comfortable with faster-moving SUTs. Both endogenous variables have a significant positive relationship, meaning an increase in lagging headway of SUT or CT increases passenger car lagging headway. This may be due to certain unaccounted similarities between the travel behaviors of these three vehicle classes. The SUT coefficient, which is slightly higher than that of the CT, suggests that the PC headway is more influenced by SUT than CT.

**SUT Lagging Headway**

The number of SUT in the traffic stream is much lower than the number of PC (on average SUT are 5 percent of the overall traffic stream). Both the speed of the PC and the SUT have significant correlation with the SUT lagging headway. However, an increase in the PC speed decreases the SUT lagging headway, while an increase in the SUT speed increases the SUT lagging headway. This suggests that when SUT increase their speed, they exercise caution and keep more space between themselves and the leading vehicle, while an increase in passenger car speed actually makes the SUT more comfortable thus decreasing their headway. Both of the endogenous variables are positive and significant. An increase in PC and CT lagging headway is associated with an increase in SUT lagging headway.

**CT Lagging Headway**

The CT equation has a comparable fit to the SUT equation. The equation has an adjusted R² of 0.2435, indicating that some of the variance in lagging headway data is explained, but not as much as in the PC equation. The results also suggest that the SUT flow is an important variable affecting the lagging headway of the CT. An increase in the SUT flow results in an increase in the lagging headway of CT. This suggests that in the presence of SUT, CT exercise caution by keeping greater distance from the leading vehicle. In addition, as the CT increase their speed, they increase their headways. This indicates that at higher speeds, CT tend to provide themselves with greater room because they need a greater distance for braking if the need arises. Lastly, as was the case for the PC and SUT equations, the results suggest that there is a positive significant relationship between the
lagging headway of each vehicle class. This shows the direct positive relationship between the three headways; if vehicles of a given class increase their headway in a traffic stream, then vehicles of the other two classes increase their headway accordingly.

3SLS Model 2: Lagging Headway for 9 Vehicle Following Combinations

Table 3 displays the results of the nine-equation 3SLS model estimated for urban Interstate-465 using 142 observations. Nine model equations are estimated, three each for PC, SUT, and CT. The system-weighted adjusted $R^2$ value of this model is 0.6403. The discussions for different model equations are presented in the following sections.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Average PC Lagging Headway) (ft.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.259</td>
<td>20.231</td>
</tr>
<tr>
<td>PC Flow (PC/15min.)</td>
<td>-0.001</td>
<td>-9.464</td>
</tr>
<tr>
<td>SUT Flow (SUT/15 min.)</td>
<td>-0.003</td>
<td>-4.319</td>
</tr>
<tr>
<td>Average PC Speed (mph)</td>
<td>0.017</td>
<td>14.877</td>
</tr>
<tr>
<td>Average SUT Speed (mph)</td>
<td>-0.002</td>
<td>-2.403</td>
</tr>
<tr>
<td>ln(Average SUT lagging headway (ft.))</td>
<td>0.142</td>
<td>6.748</td>
</tr>
<tr>
<td>ln(Average CT lagging headway (ft.))</td>
<td>0.096</td>
<td>3.386</td>
</tr>
<tr>
<td>Adjusted R$^2$</td>
<td>0.6543</td>
<td></td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>2.0647</td>
<td></td>
</tr>
<tr>
<td>ln(Average SUT Lagging Headway) (ft.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-1.696</td>
<td>-3.725</td>
</tr>
<tr>
<td>Average PC Speed (mph)</td>
<td>-0.015</td>
<td>-4.720</td>
</tr>
<tr>
<td>Average SUT Speed (mph)</td>
<td>0.009</td>
<td>4.434</td>
</tr>
<tr>
<td>ln(Average PC lagging headway (ft.))</td>
<td>0.733</td>
<td>7.750</td>
</tr>
<tr>
<td>ln(Average CT lagging headway (ft.))</td>
<td>0.644</td>
<td>10.340</td>
</tr>
<tr>
<td>Adjusted R$^2$</td>
<td>0.2605</td>
<td></td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>1.7968</td>
<td></td>
</tr>
<tr>
<td>ln(Average CT Lagging Headway) (ft.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.254</td>
<td>8.056</td>
</tr>
<tr>
<td>SUT Flow (SUT/15 min.)</td>
<td>0.003</td>
<td>2.033</td>
</tr>
<tr>
<td>Average CT Speed (mph)</td>
<td>0.004</td>
<td>2.653</td>
</tr>
<tr>
<td>ln(Average PC lagging headway (ft.))</td>
<td>0.248</td>
<td>4.153</td>
</tr>
<tr>
<td>ln(Average SUT lagging headway (ft.))</td>
<td>0.352</td>
<td>10.465</td>
</tr>
<tr>
<td>Adjusted R$^2$</td>
<td>0.2435</td>
<td></td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>1.9911</td>
<td></td>
</tr>
</tbody>
</table>

*Note: 1 foot = 0.305 meters; 1 mph = 1.609 kph*
Table 3: Model 2: Estimated 9-equation 3SLS results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-stat</th>
<th>Variable</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Average PC-PC Lagging Headway) (ft.)</td>
<td></td>
<td></td>
<td>ln(Average PC-SUT Lagging Headway) (ft.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed of PCs</td>
<td>0.0101</td>
<td>5.863</td>
<td>Percentage of PCs</td>
<td>0.063</td>
<td>21.233</td>
</tr>
<tr>
<td>Percentage of PCs</td>
<td>0.05</td>
<td>36.716</td>
<td>Percentage of SUTs</td>
<td>0.0306</td>
<td>3.291</td>
</tr>
<tr>
<td>Percentage of SUTs</td>
<td>0.0991</td>
<td>9.309</td>
<td>Headway PC-CT</td>
<td>0.002</td>
<td>5.494</td>
</tr>
<tr>
<td>Headway PC-CT</td>
<td>0.0017</td>
<td>6.842</td>
<td>No. of PCs</td>
<td>-0.0015</td>
<td>-7.723</td>
</tr>
<tr>
<td>Headway SUT-PC</td>
<td>-0.0002</td>
<td>-1.852</td>
<td>No. of CTs</td>
<td>0.0043</td>
<td>8.659</td>
</tr>
<tr>
<td>Headway CT-PC</td>
<td>0.0006</td>
<td>3.353</td>
<td>Adjusted R-square</td>
<td>0.765</td>
<td></td>
</tr>
<tr>
<td>No. of PCs</td>
<td>-0.0006</td>
<td>-6.105</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of SUTs</td>
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<td>-5.187</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of CTs</td>
<td>0.0041</td>
<td>22.545</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Adjusted R-square</td>
<td>0.6405</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Average PC-CT Lagging Headway) (ft.)</td>
<td></td>
<td></td>
<td>ln(Average SUT-PC Lagging Headway) (ft.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed of SUTs</td>
<td>0.0079</td>
<td>2.77</td>
<td>Percentage of PCs</td>
<td>0.068</td>
<td>2.599</td>
</tr>
<tr>
<td>Percentage of PCs</td>
<td>0.0442</td>
<td>21.266</td>
<td>Percentage of PCs</td>
<td>0.0539</td>
<td>20.358</td>
</tr>
<tr>
<td>Percentage of SUTs</td>
<td>0.0812</td>
<td>4.945</td>
<td>Percentage of SUTs</td>
<td>0.1156</td>
<td>5.662</td>
</tr>
<tr>
<td>Headway PC-PC</td>
<td>0.0037</td>
<td>7.261</td>
<td>Headway CT-PC</td>
<td>0.0007</td>
<td>2.222</td>
</tr>
<tr>
<td>No. of PCs</td>
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<td>-3.037</td>
<td>Headway CT-SUT</td>
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<td>5.211</td>
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<tr>
<td>No. of SUTs</td>
<td>-0.0045</td>
<td>-2.489</td>
<td>No. of PCs</td>
<td>-0.0005</td>
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<tr>
<td>No. of CTs</td>
<td>0.0041</td>
<td>14.216</td>
<td>No. of SUTs</td>
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</tr>
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<td>Adjusted R-square</td>
<td>0.4758</td>
<td></td>
<td>Adjusted R-square</td>
<td>0.871</td>
<td></td>
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<tr>
<td>ln(Average SUT-SUT Lagging Headway) (ft.)</td>
<td></td>
<td></td>
<td>ln(Average SUT-CT Lagging Headway) (ft.)</td>
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<td></td>
</tr>
<tr>
<td>Speed of SUTs</td>
<td>0.0224</td>
<td>2.516</td>
<td>Speed of SUTs</td>
<td>0.0131</td>
<td>2.792</td>
</tr>
<tr>
<td>Speed of CTs</td>
<td>-0.0209</td>
<td>-2.501</td>
<td>Percentage of PCs</td>
<td>0.0511</td>
<td>10.928</td>
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<tr>
<td>Percentage of PCs</td>
<td>0.0467</td>
<td>12.39</td>
<td>Percentage of SUTs</td>
<td>0.0757</td>
<td>6.34</td>
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<tr>
<td>Percentage of SUTs</td>
<td>0.0865</td>
<td>5.917</td>
<td>Headway CT-SUT</td>
<td>0.001</td>
<td>3.532</td>
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<tr>
<td>Headway SUT-PC</td>
<td>0.0021</td>
<td>3.041</td>
<td>No. of PCs</td>
<td>-0.0011</td>
<td>4.527</td>
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<tr>
<td>No. of CTs</td>
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<td>3.426</td>
<td>No. of SUTs</td>
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<td>7.086</td>
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<tr>
<td>Adjusted R-square</td>
<td>0.4549</td>
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<td>Adjusted R-square</td>
<td>0.5715</td>
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<tr>
<td>ln(Average CT-PC Lagging Headway) (ft.)</td>
<td></td>
<td></td>
<td>ln(Average CT-CT Lagging Headway) (ft.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed of PC</td>
<td>0.0259</td>
<td>7.621</td>
<td>Speed of PCs</td>
<td>-0.0193</td>
<td>-3.601</td>
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<tr>
<td>Percentage of CTs</td>
<td>0.2168</td>
<td>15.463</td>
<td>Percentage of PCs</td>
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<td>Headway SUT-PC</td>
<td>0.0012</td>
<td>3.361</td>
<td>Headway SUT-PC</td>
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<td>No. of PCs</td>
<td>0.0034</td>
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<td>3.796</td>
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<td>No. of SUTs</td>
<td>0.004</td>
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<td>Headway CT-PC</td>
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<td>2.913</td>
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<tr>
<td>No. of CTs</td>
<td>-0.0167</td>
<td>-11.166</td>
<td>No. of PCs</td>
<td>-0.0013</td>
<td>-5.495</td>
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<td>Adjusted R-square</td>
<td>0.6891</td>
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<td>No. of SUTs</td>
<td>0.0059</td>
<td>4.442</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>No. of SUTs</td>
<td>0.0055</td>
<td>8.315</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>No. of CTs</td>
<td>0.5305</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>142</td>
<td></td>
<td>Number of Observations</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R-square</td>
<td>0.7993</td>
<td></td>
<td>System Weighted Adjusted R-squared</td>
<td>0.6403</td>
<td></td>
</tr>
</tbody>
</table>

*Note: Dependent Variable = Natural Log of (Average Lagging Headway of vehicle m following vehicle k) in feet
PC Following

Each of the first three equations (Equations 8–10) estimates the passenger car following headway for one of the three vehicle classes (PC following PC, PC following SUT, PC following CT). The three equations have a good statistical fit with adjusted $R^2$ values of 0.6405, 0.7650, and 0.4758, respectively. The percentages of PC and SUT have a positive sign in all three model equations, meaning an increase in either would result in an increase in passenger car lagging headway, regardless of the class of vehicle it follows. The developed model also suggests that the passenger car headway increases with increasing passenger car speed. This is potentially due to the requirement of larger stopping sight distance at higher speeds. The variables representing the number of PC, SUT, and CT are all significant in one or more of the car following equations, albeit with different magnitudes (Table 3). Endogenous variables appear in all three equations and either increase or decrease the headway depending upon the nature of interaction between the two vehicles involved.

SUT Following

Equations 11-13 provide the three cases in which SUT follow other vehicles. The three equations have a good statistical fit, with adjusted $R^2$ values of 0.8710, 0.4549, and 0.5715, respectively. The percentages of PC and SUT are significant variables with a positive influence in all three equations. This suggests that increasing the percentage of cars and SUT is associated with an increase in SUT lagging headway, regardless of what vehicle type is being followed; however, the magnitude of influence differs according to the class of vehicle being followed. The developed model reveals that with increasing speed, the SUT headway increases. This may be due to the propensity of drivers to maintain a larger stopping sight distance at higher speeds to avoid rear-end crashes. The number of PC, SUT, and CT are three variables that are all significant in these equations. The addition of PC or SUT is observed to be associated with a reduction in available space, thus reducing the headway. On the other hand, the addition of CT increases the headway as SUT maintain a longer distance, potentially for safety. This is also shown in the passenger car following Equations 8–10, thus demonstrating the similarity in the behavior of these classes of vehicles in the traffic stream. The endogenous variables are statistically significant in all three equations, and they are found to increase the headway in all types of vehicle interactions involved.

CT Following

Equations 14–16 represent the three cases where CT follow other vehicles. The three equations have a good fit, with adjusted $R^2$ values of 0.6891, 0.5305, and 0.7993, respectively. The number of PC, SUT, and CT are three variables that are statistically significant in all three equations. An increase in SUT or CT affects the lagging headway of CT differently depending on the class of vehicle being followed by the CT (Table 3). Furthermore, when the percentage of passenger cars or CT increases, the lagging headway of CT increases, indicating that when these vehicles make up a larger portion of the traffic stream, CT exercise more caution. The speed of passenger cars is another significant variable that increases headway when CT are following passenger cars but reduces headway when CT are following SUT. In the former case, it appears that passenger cars “pull away” from CT, leading to larger headways, while an increase in passenger car speed may relegate CT to the travel lane only, where they fall closely in line with SUT. The endogenous variables appear in all three equations, which always increase the headway in all types of vehicle interaction involved (Table 3).
Evaluation of the Modeling Schemes

To evaluate the predictive accuracy of the developed models, the mean absolute percent error (MAPE) is estimated as follows (Washington et al., 2011):

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{PE_i}{X_i} \right|$$  \hspace{1cm} (22)

Where $PE_i = 100 \cdot (X_i - F_i)/X_i$ is the percentage error for observation $i$ of the actual and predicted headway $X_i$ and $F_i$, respectively. The resulting MAPE for the two modeling schemes (three-equation and nine-equation 3SLS models by vehicle class) are presented in Table 4. Values closer to zero signify a higher predictive accuracy. For example, a MAPE of 0.087 (as in the PC average headway of the three-equation 3SLS model) suggests that on average, the forecasts underestimate or overestimate the true values by 8.7 percent.

Finally, Figure 2 presents the predicted over the actual values of the headways by vehicle class and model type and graphically illustrates the statistically superior predictive accuracy of the nine-equation 3SLS models compared to the three-equation counterparts.

Calculating PCE Values Based on Model Results

PCE values have the potential to allow appropriate and accurate conversion of a mixed traffic stream into pure passenger car flow. Different methodologies can result in different PCE estimates leading to different traffic densities and ultimately different levels of service. Table 5 presents the comparison of actual observed headways and observation-based predicted headways estimated using a three-equation 3SLS model and a nine-equation 3SLS model. The three-equation 3SLS model directly predicts the lagging headway for each vehicle class using Equations 5–7. The nine-equation 3SLS model predicts nine lagging headways (three for each vehicle class) using equations 8–16, then the average class lagging headway is calculated using Equations 17–19. The ratio of SUT or CT lagging headway is used to calculate the PCE for each vehicle class.

Table 4: MAPE values by vehicle class and model type.

<table>
<thead>
<tr>
<th></th>
<th>3-Equation 3SLS Model</th>
<th>9-Equation 3SLS Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC Average Headway</td>
<td>0.087</td>
<td>0.060*</td>
</tr>
<tr>
<td>PC-PC Average Headway</td>
<td>0.061</td>
<td></td>
</tr>
<tr>
<td>PC-SUT Average Headway</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>PC-CT Average Headway</td>
<td>0.066</td>
<td></td>
</tr>
<tr>
<td>SUT Average Headway</td>
<td>0.210</td>
<td>0.146†</td>
</tr>
<tr>
<td>SUT-SUT Average Headway</td>
<td>0.128</td>
<td></td>
</tr>
<tr>
<td>SUT-PC Average Headway</td>
<td>0.160</td>
<td></td>
</tr>
<tr>
<td>SUT-CT Average Headway</td>
<td>0.149</td>
<td></td>
</tr>
<tr>
<td>CT Average Headway</td>
<td>0.046</td>
<td>0.032‡</td>
</tr>
<tr>
<td>CT-CT Average Headway</td>
<td>0.033</td>
<td></td>
</tr>
<tr>
<td>CT-PC Average Headway</td>
<td>0.028</td>
<td></td>
</tr>
<tr>
<td>CT-SUT Average Headway</td>
<td>0.035</td>
<td></td>
</tr>
</tbody>
</table>

* 9-Equation 3SLS predicted headway averaged by PC (comparable to 3-Equation 3SLS predicted headway).
† 9-Equation 3SLS predicted headway averaged by SUT (comparable to 3-Equation 3SLS predicted headway).
‡ 9-Equation 3SLS predicted headway averaged by CT (comparable to 3-Equation 3SLS predicted headway).
headway to PC lagging headway provides a PCE value for each truck class for each model. Table 5 compares these observation-based PCE values to those provided in the current version of the HCM. The PCE values provided by both the three-equation 3SLS model and the nine-equation 3SLS model are similar, but they differ from the single PCE value provided by the HCM for both SUT and CT. As is evident from the table, the HCM and the predicted PCE values based on real observations vary between 8.5 percent and 9.5 percent for the four locations where data were collected. Applying these equations and the headway ratio methodology to data collected at other similar urban freeways segments would provide a highway agency with site-specific PCE values for both SUT and CT.

While the current study provided results that varied by less than 10 percent, other locations with higher traffic volumes and greater CT flow may experience a greater disparity between the PCEs based on actual traffic observations and the HCM single PCE values.
The present study presents a statistical approach for determining the PCE values for SUT and CT using the well-established concept of “spatial lagging headways.” Two sets of 3SLS models were developed as functions of a number of traffic variables. The first is a three-equation 3SLS model that predicts the lagging headway of each vehicle class. The second is a nine-equation 3SLS model that predicts the class average lagging headways, where headways were separated on the basis of class of vehicle leading in a traffic stream. Video data were collected using a mobile traffic laboratory at four locations along Interstate-465 in Indianapolis between the months of October 2009 to March 2010. The analyses showed that the predicted headways based on field data allow for reliable calculation of PCE values for two truck classes. The results support the assertion that separate PCE values for SUT and CT provide a more robust description of the equivalent traffic stream. The average observed lagging headways for PC, SUT, and CT across all four study locations were 213, 303, and 348 feet, respectively. Both models predict the PC and CT lagging headways within 1 percent and predict the SUT lagging headways within 4.2 percent of the true field observations. Interestingly, using a large data set covering multiple locations over an extended period of time allowed us to model headways and estimate PCEs rather reliably.

The models can be applied to data collected at similar interstate segments to provide site-specific lagging headways for the three vehicle classes. Then, utilizing the headway ratio methodology, a highway agency can calculate the site-specific PCEs for both SUT and CT and thus provide a more robust description of the traffic stream in terms of an equivalent passenger car flow.

This study utilized data from four different locations at an urban interstate. An expansion of the data to include additional highway segments and more information per segment, such as climatic conditions and highway geometric characteristics, would allow for a more robust model. The final result of this study is a pair of models that predict lagging headways of each of three vehicle classes based on traffic stream characteristics and hence allows estimation of separate PCE values for SUT and CT. This is a valuable tool for roadway management and evaluation, because such information allows for determination of location-specific PCE values for different classes of trucks.

Table 5: Comparison of headways and PCEs by vehicle class.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measured (average across all locations)</th>
<th>HCM Method</th>
<th>3 SLS Predicted (Present Study)</th>
<th>3-Equation (% deviation)*</th>
<th>9-Equation (% deviation)*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average PC–Lagging Headway (ft.)</td>
<td>213.063</td>
<td></td>
<td>211.729</td>
<td>212.335</td>
<td>(-0.63%)</td>
</tr>
<tr>
<td>Average SUT–Lagging Headway (ft.)</td>
<td>302.55</td>
<td></td>
<td>289.828</td>
<td>293.614</td>
<td>(-4.20%)</td>
</tr>
<tr>
<td>Average CT–Lagging Headway (ft.)</td>
<td>347.672</td>
<td></td>
<td>350.368</td>
<td>349.132</td>
<td>(-0.78%)</td>
</tr>
<tr>
<td>PCE – SUT 1.5</td>
<td></td>
<td></td>
<td>1.3689</td>
<td>1.3828</td>
<td>(-9.58%)</td>
</tr>
<tr>
<td>PCE – CT 1.5</td>
<td></td>
<td></td>
<td>1.6548</td>
<td>1.6443</td>
<td>(9.35%)</td>
</tr>
</tbody>
</table>

* Percent deviation (shown in parenthesis) is with respect to the actual or HCM values.

**Note: 1 foot = 0.305 meters; 1mph = 1.609 kph

Conclusion

The present study presents a statistical approach for determining the PCE values for SUT and CT using the well-established concept of “spatial lagging headways.” Two sets of 3SLS models were developed as functions of a number of traffic variables. The first is a three-equation 3SLS model that predicts the lagging headway of each vehicle class. The second is a nine-equation 3SLS model that predicts the class average lagging headways, where headways were separated on the basis of class of vehicle leading in a traffic stream. Video data were collected using a mobile traffic laboratory at four locations along Interstate-465 in Indianapolis between the months of October 2009 to March 2010.

The analyses showed that the predicted headways based on field data allow for reliable calculation of PCE values for two truck classes. The results support the assertion that separate PCE values for SUT and CT provide a more robust description of the equivalent traffic stream. The average observed lagging headways for PC, SUT, and CT across all four study locations were 213, 303, and 348 feet, respectively. Both models predict the PC and CT lagging headways within 1 percent and predict the SUT lagging headways within 4.2 percent of the true field observations. Interestingly, using a large data set covering multiple locations over an extended period of time allowed us to model headways and estimate PCEs rather reliably.

The models can be applied to data collected at similar interstate segments to provide site-specific lagging headways for the three vehicle classes. Then, utilizing the headway ratio methodology, a highway agency can calculate the site-specific PCEs for both SUT and CT and thus provide a more robust description of the traffic stream in terms of an equivalent passenger car flow.

This study utilized data from four different locations at an urban interstate. An expansion of the data to include additional highway segments and more information per segment, such as climatic conditions and highway geometric characteristics, would allow for a more robust model. The final result of this study is a pair of models that predict lagging headways of each of three vehicle classes based on traffic stream characteristics and hence allows estimation of separate PCE values for SUT and CT. This is a valuable tool for roadway management and evaluation, because such information allows for determination of location-specific PCE values for different classes of trucks.
Acknowledgments

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References


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Optimizing HOT Lane Performance Using Congestion Pricing Algorithms

By Piyali Chaudhuri, Cameron Kergaye, Peter T. Martin, and Xuesong Zhou

High-occupancy toll (HOT) lane operations have been implemented in several urban areas in the United States and are considered an effective measure to mitigate demand through congestion pricing. However, literature indicates a lack of predeployment evaluation of congestion pricing algorithms (CPAs) and traffic optimization due to the complexity of dynamic HOT strategies. This paper presents a tool that can predict the potential of a CPA to manage a HOT lane operation in an urban freeway. We develop a practically operational feedback-control that not only recognizes drivers’ lane-switching behavioral responses to dynamically changing tolls and traffic conditions but also dynamically optimizes HOT lane operation under a CPA. This would enable forecasting expected HOT lane performance prior to project implementation. Results show that the HOT lane effectively utilizes excess capacities of the HOV lane under the CPA. HOT lane demand nearly doubles while general-purpose lane speeds increase by 25 percent during peak periods, showing an overall improvement in traffic mobility along the freeway. Overall, the developed tool performed reasonably well in optimizing traffic operations of the HOT lane system under various traffic conditions. Further, a sensitivity analysis was conducted by systematically changing model input parameters to determine the effects of such changes on the model predictions.

Introduction

Federal and state governments have begun promoting use of high-occupancy vehicle (HOV) lanes in diverse ways to better manage and efficiently utilize existing facilities. States have already demonstrated the effectiveness of adding HOV lanes to their transportation networks. However,
HOV lanes have not influenced the majority of single-occupancy vehicle (SOV) drivers to carpool or use transit, and remain underutilized. High-occupancy toll (HOT) lanes offer a way to better utilize excess HOV lane capacities in order to offset congestion. Many states are thus considering converting their HOV lanes to HOT lanes to make better use of unoccupied capacity and generate needed revenue. Therefore, HOT lanes have been increasingly recognized in research and practice as a viable measure to improve traffic operation.

The HOT concept was first proposed by Gordon J. Fielding and Daniel B. Klein as an HOV freeway facility available to SOV drivers willing to pay a toll. In 1995, the first HOT lane project was implemented on SR-91 in Orange County, California, USA, followed by others in Texas, Minnesota, and Colorado. Although many studies have focused on HOT lane evaluations from policy-making, feasibility, attitudinal or equity perspectives, few of them focused on the congestion pricing algorithm (CPA) and resulting traffic optimization due to tolling strategies. Therefore, an efficient feedback-control tolling algorithm aimed at overall HOT lane operation optimization is needed.

The goal of the paper is to present a tool that can systematically evaluate the potential of a CPA to manage a HOT lane operation in an urban freeway. We develop a practical feedback control that (1) recognizes drivers’ behavioral responses to lane-switching based on changing tolls and traffic conditions and (2) dynamically optimizes HOT lane operation under a CPA. Currently, these HOV lanes have been underutilized, averaging less than half their potential capacity. By permitting SOV drivers to purchase use of the available capacity, mobility across all lanes should improve. The CPA was designed to dynamically regulate HOT lane performance using a congestion-sensitive scheme. In reality, motorists will decide whether to pay for using HOT lanes based on toll rate and traffic conditions in HOT and general purpose (GP) lanes (and switch their lanes accordingly). This paper implements such decision-making processes by integrating a driver’s dynamic lane-switching behavior into the CPA. This would enable forecasting expected HOT lane performance prior to project implementation. Using this tool, state agencies could assess effectiveness and performance of their HOT lanes in advance. Identifying key issues and incorporating them into an evaluation tool are anticipated to be of benefit to the myriad regions considering HOV to HOT lane conversion. The goal is supported by the following objectives:

- Perform parametric sensitivity analysis; and
- Study demand elasticity of SOV drivers.

**Literature Review**

HOV lanes have been introduced in many cities in the United States and abroad in order to encourage commuters to carpool and ease traffic congestion. According to an analysis by the US Census Bureau, 12.2 percent of commuters carpooled in 2000 while 77 percent drove alone and 4.7 percent used public transit. In locations where HOV drivers have an HOV lane, however, SOV drivers often notice underused capacity. Within transportation research, ineffective use of HOV lanes during periods of general congestion is also documented. Employing a dynamic queuing model with discrete choices, Dahlgren argues that adding a regular lane to existing lanes is more effective in reducing delay costs than adding an HOV lane in most cases. Safirova et al. demonstrated a case of extreme underutilization of HOV lanes: In 1998, New Jersey converted 31 miles of HOV lanes on I-287 and I-80 to GP lanes. Pointing out that 43 percent of carpoolers are members of the same household, Fielding and Klein proposed converting HOV to HOT lanes that are not only for carpoolers but also for solo drivers willing to pay tolls. Safirova et al. showed that the biggest advantage of a HOT lane over an HOV lane is that it provides a self-regulating mechanism: when congestion in regular lanes is high, solo drivers find it more desirable to pay a toll to use the freely moving lane. In theory, the toll
could fluctuate throughout the day to keep the traffic in the HOT lane flowing smoothly at all times. Thus, a HOT lane is essentially a hybrid congestion-pricing HOV lane.

Various congestion pricing models have been developed during the last four decades. Some of them have already been implemented. The widely known implementations are in Singapore, Hong Kong, and London. Following the pioneering work of Vickrey, many researchers studied various aspects of congestion pricing problems. Literature shows that there are many studies on dynamic pricing models, however, existing research on CPA for HOT lane operations is very limited. For I-15 HOT lanes in San Diego, California, USA, the base price varies from $0.50 to $4.00 depending on time of day. Tolls are adjusted based on real-time traffic conditions, where the maximum toll is $8.00 for heavily congested conditions. A similar pricing scheme was implemented for I-394 MnPass Express Lane in Minnesota. The tolls are adjusted such that the traffic flow is maintained at 50–55 miles per hour (mph). Traffic density is applied as a detection input and the update interval for tolling is specified as three minutes. Tolls may range from $0.25 to $8.00, although $1.00 to $4.00 is typical during peak hours. Although these tolling approaches approximate traffic response-based toll adjustment, minimal use of traffic flow theory makes it difficult to quantitatively achieve optimal system performance.

Further review of the literature indicates an absence of systematic approaches for dynamically adjusting HOT lane tolls. Chu et al. proposed a priority-based operation framework for HOV lane use based on vehicle occupancy, type, and toll rate. But no further investigations were conducted on dynamic tolling strategies. Yin and Lou proposed two approaches for dynamic toll determination. The first was to use a ramp metering control algorithm, ALINEA, by converting metering rates to toll rates. The second approach was to use a route choice model (i.e., the logit model) for toll determination. Their major research work was focused on parameter estimation and model calibration by using real-time traffic counts measured from both HOT and general purpose lanes. Recently, Zhang et al. proposed a feedback-based tolling algorithm to optimize the HOT-lane operations. On the basis of traffic speeds, the dynamic toll rates were back-estimated using the logit model. Although literature shows usage of ramp metering control and logit models, the unique characteristics of HOT lane operations cannot be adequately accommodated by simply transplanting another control method to model HOT lane operations. Hence, a more efficient feedback-based tolling algorithm aimed at overall HOT lane optimization is needed.

This paper develops a tool that can predict the potential of a CPA to dynamically optimize HOT lane operation. We develop a feedback-control mechanism that recognizes drivers’ behavioral responses to a lane-switching mechanism. When placed in a feedback loop with the CPA, the process converges to produce estimates of travel times, costs, and flows on the freeway. Based on these results, various measures of toll road success (such as travel speeds and revenue generation) can be obtained. Further, a sensitivity analysis was included by systematically changing input parameters in the model to determine the effects of such changes on the model/tool outputs. This would ensure the robustness of the model predictions and identify parameters to which the overall HOT lane operation is most sensitive.

**Experimental Design**

The I-15 express lane is a single HOV lane running in each direction from Exit 269 in Orem to Exit 309 in north Salt Lake City in Utah, USA. The HOV lane is separated from the GP lane by double white lines with transitions to access points indicated by dashed lines. The existing HOV lanes are open 24 hours to vehicles with two or more occupants, motorcycles, emergency vehicles, buses, and clean-fuel vehicles as well as to SOV drivers displaying appropriate decals on their windshields. The new express lane’s pricing mechanism was implemented in the fall of 2010.
Figure 1 illustrates the geographical limits of the testbed. The 41-mile testbed is composed of two noncontiguous sections. A 35-mile southern section (with 22 interchanges spaced 1–2 miles apart) starts at Exit 278 in American Fork and extends northward to Exit 313 in North Salt Lake. A six-mile northern section (with two interchanges) starts at Exit 322 in Farmington and ends at Exit 328 in South Layton. The testbed is longer than any other HOT corridors in the Unites States. The testbed has approximately 30 access points in each direction, which renders it more complex than other HOT corridors in San Diego, Minnesota, or Seattle. Further, the testbed runs through an urban center, rather than to or from one.

Methodology

Concept of Zone Tolling

The CPA utilizes a zone tolling approach. The testbed is divided into six zones, typically five to 10 miles in length. Shorter zones are located in more dense, urban areas, while longer zones are located in suburban areas. Major interchanges designate most of the zone boundaries. The zones are further subdivided into segments that are portions of testbed lying between two successive access points to the HOT lane.

The CPA operates under the following assumptions:

- All vehicles entering a zone in a particular direction pay the same toll;
- Tolls within a zone are differentiated by direction. A vehicle entering access point #2 in the northbound (NB) direction may pay a different toll than one entering the same access point but in the southbound (SB) direction;
- Each zone calculates its own toll for each direction of travel; and
- Access points that lie adjacent to zone boundaries are treated as follows: A vehicle is entering the HOT lane in NB direction at access point #3. The CPA assumes that this vehicle will not be charged for traveling in zone #1. Rather, it will be charged for travel in zone #2, once it crosses the zone boundary. This assumption eliminates the possibility that a driver is charged twice for two zones when making a trip between successive access points.

Data Collection

Historic loop data were collected for 2009 using Utah Department of Transportation’s (UDOT’s) Freeway Performance Measurement System (PeMS). PeMS is a real-time archive data management system for transportation operations. It collects raw detector data in real-time, stores and processes this data, and reports this data online. Transportation agencies can utilize PeMS to analyze freeway
performance. The loop data consists of 20-second counts averaged separately for HOV and GP lane segments within the zones along the testbed. Toll calculations are based on speeds and volumes in the HOT and GP lanes, which vary throughout the day, and static parameters of predetermined available HOT capacity and pricing limitations. PeMS is available online and provides data via a manual extraction process. Due to the large quantity of data needed for this paper, an automated method to access and retrieve the data was developed. Figure 2 provides the pseudo code summarizing the steps involved.

**Congestion Pricing Algorithm**

The CPA was adapted from the dynamic pricing algorithm utilized for the I-15 managed lane in San Diego by HNTB Corporation. The algorithm determines toll rates for using the HOT lane per zone in each direction. Toll rates are calculated per three-minute aggregation intervals. The important variables and default values required in CPA are defined as follows:

- **toll\_min** — Minimum toll (25¢) charged to vehicles
- **toll\_max** — Maximum toll ($1) charged to vehicles
- **Cap** — Functional capacity (1675 veh/hr) of the HOV lane
- **toll\_inc** — Incremental toll rate (25¢)
- **S\_(GP)\_min** — Minimum desired speed (53 mph) in GP lanes
- **S\_(HOT)\_min** — Minimum desired speed (55 mph) in HOT lane
- **D\_(HOT)\_max** — Maximum allowable density (26 veh/hr) of HOT lane
- **Z\_base** — Base value ($250) for maintaining free-flowing conditions on HOT lane
- **Z\_inc** — Incremental increase ($10) to Z\_base
- **Z\_max** — Maximum zone value (twice Z\_base)

---

**Figure 2: Pseudo code depicting the steps involved in data extraction.**

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Login to PeMS (tdot.pems.traffic.com)</td>
</tr>
<tr>
<td>2</td>
<td>Go to ‘detector health’ and look for required stations and their detectors from list</td>
</tr>
<tr>
<td>3</td>
<td><strong>Initialization:</strong> ( i = 0, ) current traffic monitoring station</td>
</tr>
<tr>
<td></td>
<td>( d = 0, ) current detector</td>
</tr>
<tr>
<td></td>
<td>( TMS, ) total number of traffic monitoring stations</td>
</tr>
<tr>
<td></td>
<td>( D_i, ) total number of detectors at station ( i )</td>
</tr>
<tr>
<td>4</td>
<td><strong>Step 4:</strong> for (start_time in-range 0:00:00 Jan 1, 2009 to 0:00:00 Dec 31, 2009)</td>
</tr>
<tr>
<td></td>
<td>define end_time = start_time + 23:59:40</td>
</tr>
<tr>
<td></td>
<td>for ( i = i + 1 )</td>
</tr>
<tr>
<td></td>
<td>for ( d = d + 1 )</td>
</tr>
<tr>
<td></td>
<td>find ( data ) where ( data ) is data measured by TMS detector ( d ) of station ( i )</td>
</tr>
<tr>
<td>5</td>
<td><strong>Step 5:</strong> IF ( i &lt; TMS )</td>
</tr>
<tr>
<td></td>
<td>IF ( d &lt; D_i )</td>
</tr>
<tr>
<td></td>
<td>GO TO Step 7</td>
</tr>
</tbody>
</table>
Figure 3 illustrates the computational steps of the CPA. Codes were developed to address the conditional clauses and increments within the algorithm. The following is an explanation of each step in the figure:

**Step 1:** If the time is midnight, then baseline parameters are reset. Otherwise, the interval increments are by one.

**Step 2:** During each time interval, the detection system (loop detectors) needs to record speed and volume data in the HOT lane as well as speed data in the GP lanes for every segment of the zone.

**Step 3:** Once the time interval is complete, the detection system needs to calculate average speed on each segment of the HOT and GP lanes and volume on each segment of the HOT lane.

**Step 4:** The detection system needs to identify the maximum flow rate out of all HOT segments and lowest average speed of all GP and HOT segments.

**Step 5:** Calculate remaining capacity for critical HOT segment.

**Step 6:** Check for conditions. First, check whether there is any remaining capacity in the HOT lane. If yes, check if HOT speeds exceed 55 mph. If yes, calculate toll. If no, close HOT lane to SOVs. Second, if there is remaining HOT capacity, check if HOT speeds are less than 55 mph. If yes, check whether HOT density is greater than 26 vehicles/hour. If yes, close the HOT lane to SOVs. Otherwise, calculate toll. Third, check if toll is within the maximum-minimum range. Finally, check whether GP speeds are greater than 53 mph. If yes, increment zone value; otherwise, decrement zone value for the next iteration.

Once all calculations are complete, the time is advanced by three minutes ($t = t+3$). This process is repeated until midnight of the next day, at which point the timer is reset.

**Feedback-Control Mechanism**

A feedback-control mechanism based on driver’s dynamic lane-switching behavior was developed and integrated into the CPA to project traffic conditions in HOT and GP lanes. The technique used to resemble driver’s lane-switching behavior is analogous to the method of successive averages introduced by Robbins and Monro for general fixed-point problems ($f(x) = x$). Here, for each iteration ($k$), the current solution ($x^k$) is averaged with an auxiliary solution ($y^k = F(x^k)$) generated by the algorithm. The current solution in the next iteration is an average of these two solutions,

$$x^{k+1} = (1 - \lambda^k)x^k + \lambda^ky^k$$

(1)

Literature shows no evidence of any particular methodology that accounts for drivers’ dynamic lane-switching behavior based on changing tolls. Therefore, the lane switching mechanism developed in this paper employs the general methodology of “day-to-day” route-swapping process or route-choice adjustment process based on projected dynamical systems. These methods are often used in iterative algorithms for solving various mathematical problems in general and travel forecasting models in particular. Depending on the needs of this problem, we have developed a behaviorally sound method to realistically estimate traffic conditions in response to dynamic tolls.

The entire methodology of CPA with integrated feedback-control based on driver’s dynamic lane-switching behavior is illustrated in Figure 4. The first step is to assign initial time-dependent flows along the HOT and GP lanes. In step 2, the time-dependent flows are fed into the drivers’ dynamic lane-switching method. We consider SOV drivers to switch between lane types based on changing tolls. Inserting the percentage of HOV, the number of SOV drivers along the HOT lane is determined. Next, the driver’s dynamic lane-switching method calculates the generalized travel times for HOT and GP lanes using the Bureau of Public Roads (BPR) function as shown in Equations 2 and 3 respectively:
\[ GT_{(HOT)} = \text{FFTT}_{HOT} \left[ 1 + \alpha \left( \frac{V_{\tau(HOT)}}{C_{HOT}} \right)^\beta \right] + \frac{\text{Dollar Value of HOT Charge (}\tau\text{)}}{VOT} \] (2)

\[ GT_{(GP)} = \text{FFTT}_{GP} \left[ 1 + \alpha \left( \frac{V_{\tau(GP)}}{C_{GP}} \right)^\beta \right] \] (3)

Where \( GT \) = generalized travel time, \( FFTT \) = free-flow travel time, \( \tau \) = time clock index, \( C \) = capacity, \( \alpha, \beta \) = parameters (\( \alpha = 0.15, \beta = 4 \)), Dollar Value of HOT Charge (\( \tau \)) = the dollar value charged for a SOV driver using the HOT lane at time \( \tau \), and VOT = Value of Time.

Without loss of generality, the presented framework selects the widely used BPR function for predicting travel time as a function of volume/capacity ratio in travel demand models. It describes the relation between travel time (or cost) and travel conditions and reflects restrictions due to road capacity and traffic congestion. The function uses two parameters to fit the equation to various types of roadways and circumstances; the values used here are taken from Highway Capacity Manual. It should be remarked that our proposed methodology can also incorporate more sophisticated but complex travel performance models, such as a spatial queue model, to estimate link travel time as a function of incoming flow and prevailing traffic conditions.

Based on the calculated generalized travel times for the lane types, the drivers’ dynamic lane-switching mechanism decides where to switch the SOV volumes. A properly chosen constant rate of five percent is applied to calculate the switching SOV volume. This rate allows five percent of SOV drivers (based on HOT volume) to switch between lane types. It is based on an allowable number of vehicles to cross over the designated access points during the three-minute interval. That is, five percent of SOV drivers are assumed to be eligible to evaluate and switch to the lane.
type (HOT or GP) with lesser travel time, and the resulting lane conditions (for the current and next time intervals) are updated accordingly. The updated lane flows are fed into the CPA in step 3. Step 3 runs the CPA, as shown in Figure 3, and calculates toll based on the updated lane flows. Next, the calculated toll is fed into the drivers’ dynamic lane-switching method for the next iteration and this process continues every three minutes for a day.

In general, the allowable lane-switching percentage needs to be systematically calibrated based on underlying facility geometry, such as how a HOT lane is separated from the GP lane, the number of access points, and the number of travel lanes. In addition, a behavior study can be useful to accurately estimate and understand how commuters receive the tolling information; how, when, and where this information triggers lane-switching decisions; and the actual willingness of drivers to switch their lanes.

Results And Discussion

Results obtained for the CPA with integrated drivers’ dynamic lane-switching method were analyzed for projecting tolls and overall freeway performance. The effectiveness of the developed tool is manifested through a comparison between the traffic conditions under initial (HOV) and post (HOT) lane condition as shown in Figure 5. The impact of adding tolls is illustrated for an average annual weekday in zone 5 for the NB direction. Figure 5(a) and 5(b) show the speed profile in the HOV and GP lanes. During HOT conditions, the speed of vehicles in the HOT lane are lowered compared to HOV conditions. This is due to an increase in SOV drivers traveling in HOT lane. Conversely, the GP lane speeds during HOT conditions are increased compared to HOV conditions as shown in Figure 5(b). This improvement in GP speeds is more for peak periods than off-peak periods, which indicates that some SOV drivers have switched lanes based on the current toll and traffic conditions.
Figure 5(c) and 5(d) illustrates the comparison between traffic volumes under HOV and HOT lane conditions. Results confirm that SOV drivers who are willing to pay tolls to use the HOT lane contribute to an increase in SOV volume during peak periods. During off-peak periods, SOV drivers appear unwilling to pay tolls and prefer GP lanes, which results in a decrease in SOV volume and corresponding increase in GP volume during off-peak hours. Overall, results indicate that by using CPA with integrated drivers’ dynamic lane-switching tool, the excess capacities of the HOT lane are effectively used with considerable improvement in GP lane speeds.

Figure 6 illustrates the corresponding toll profile. A maximum toll of $1 is applied during peak periods when the HOT speed drops, due to an increase in SOV volume. The HOT lane condition subsequently improves and the toll reduces to $0.75. When HOT lane volume exceeds its capacity (1,675 vehicles/hour) with speeds below 55 mph, the HOT lane displays “CLOSED to SOVs.” This is shown as a gap or space in the toll profile. Such matching patterns between the toll rates and HOT lane performance indicate the appropriate sensitivity and robustness of the tool.
Table 1 provides a comprehensive summary of results obtained from the CPA with integrated drivers’ lane-switching method for zones 2 to 5 in NB direction for the peak periods. To facilitate comparison of traffic conditions achieved under initial (HOV) and post (HOT) lane conditions, an improvement percentage is added for each parameter. For example, in zone 3 under HOV lane conditions, the average speed in the GP lane is 51.4 mph and that in HOV lanes is 64.9 mph. The average speed for both GP and HOV lanes is 58.1 mph. Under HOT lane conditions, the number of SOV drivers choosing the HOT lane increases from 519 to 1,220 in 2.5 hours and consequently the average GP lane speed increases to 62.5 mph (from 51.4 mph). However, the HOT lane speed does not deteriorate, maintaining an average speed for both GP and HOT lanes as 62.3 mph, indicating an overall increase in traffic mobility. Similarly, other zones also show an overall increase in traffic mobility under HOT lane conditions. Overall, an average increase of 25 percent and 90 percent are achieved under post (HOT) conditions for GP speeds and HOT volumes, respectively.
The results from the developed tool were compared to the results obtained from Zhang et al.\textsuperscript{8} for validation purpose. For a similar zone length of three miles, the developed tool correlated well (97 percent), showing similar improvements trends observed under HOT lane conditions, as illustrated in Figure 7. This validates the anticipated improvements (predictions) that could be achieved under CPA (i.e., post HOT lane condition) and thereby ensures effectiveness of the presented tool.

### Sensitivity Analysis

Sensitivity analysis is the study of how the variation in the output of a mathematical model can be apportioned, qualitatively or quantitatively, to different sources of variation in the input of the model.\textsuperscript{29} It is a technique for systematically changing parameters in a model to determine the effects

<table>
<thead>
<tr>
<th>Time</th>
<th>Lane</th>
<th>Zone</th>
<th>Length (mile)</th>
<th>HOV Lane Condition</th>
<th>HOT Lane Condition</th>
<th>Improvement %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Speed (mph)</td>
<td>Travel Time (min)</td>
<td>Volume (veh/hr)</td>
</tr>
<tr>
<td>A.M.</td>
<td>GP-HOV</td>
<td>2</td>
<td>4.0</td>
<td>56.5</td>
<td>3.3</td>
<td>1258</td>
</tr>
<tr>
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<td></td>
<td>48.2</td>
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<tr>
<td></td>
<td>HOV-HOT</td>
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<td>64.9</td>
<td>2.8</td>
<td>546</td>
</tr>
<tr>
<td></td>
<td>GP-HOV</td>
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<td>58.1</td>
<td>3.2</td>
<td>1177</td>
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<td>3.6</td>
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<td></td>
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<td>2.8</td>
<td>519</td>
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<td>6:30</td>
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<td>4</td>
<td>5.4</td>
<td>50.7</td>
<td>7.0</td>
<td>1001</td>
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<tr>
<td></td>
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<td>9.0</td>
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<td></td>
<td>64.4</td>
<td>5.0</td>
<td>801</td>
</tr>
<tr>
<td>A.M.</td>
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<td>10.2</td>
<td>52.4</td>
<td>12.4</td>
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</tr>
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<td>9.3</td>
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<tr>
<td>P.M.</td>
<td>GP-HOV</td>
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<td>4.0</td>
<td>56.2</td>
<td>3.7</td>
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<tr>
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<td>64.9</td>
<td>3.7</td>
<td>519</td>
</tr>
<tr>
<td></td>
<td>GP-HOV</td>
<td>3</td>
<td>3.0</td>
<td>54.5</td>
<td>3.5</td>
<td>1386</td>
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<tr>
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<td></td>
<td>44.1</td>
<td>4.2</td>
<td>2129</td>
</tr>
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<td></td>
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<td>5.4</td>
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<td>P.M.</td>
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<td>10.2</td>
<td>51.6</td>
<td>12.5</td>
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</tr>
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<td></td>
<td>GP lane</td>
<td></td>
<td></td>
<td>40.7</td>
<td>13.3</td>
<td>2258</td>
</tr>
<tr>
<td></td>
<td>HOV-HOT</td>
<td></td>
<td></td>
<td>62.5</td>
<td>9.8</td>
<td>1171</td>
</tr>
</tbody>
</table>

1 mile = 1.61 km

\textit{NOTE:} 2 directions were non-working

---

The results from the developed tool were compared to the results obtained from Zhang et al.\textsuperscript{8} for validation purpose. For a similar zone length of three miles, the developed tool correlated well (97 percent), showing similar improvements trends observed under HOT lane conditions, as illustrated in Figure 7. This validates the anticipated improvements (predictions) that could be achieved under CPA (i.e., post HOT lane condition) and thereby ensures effectiveness of the presented tool.

**Sensitivity Analysis**

Sensitivity analysis is the study of how the variation in the output of a mathematical model can be apportioned, qualitatively or quantitatively, to different sources of variation in the input of the model.\textsuperscript{29} It is a technique for systematically changing parameters in a model to determine the effects
of such changes. Sensitivity analysis investigate the robustness of a study when the study includes some form of mathematical modeling. Sensitivity analysis can be useful for a range of purposes, including the following:

- Playing what-if analysis exploring the impact of varying input assumptions and scenarios;
- Supporting decision making;
- Increasing understanding or quantification of the system (between input and output variables); and
- As an element of quality assurance in model development.

Thus, sensitivity analysis for traffic network equilibrium problems is important for investigating the robustness of model predictions and identifying those parameters to which the equilibrium flows are most sensitive. Performing a sensitivity analysis of a traffic forecasting model means evaluating the directions of change that occur in the flows and travel costs as parameters in the cost and demand functions change. A sensitivity analysis is particularly useful in control and pricing applications, because if we can anticipate the effects of a change in the traffic infrastructure on the behavior of the travelers, then we can utilize this knowledge to optimize these changes according to some goal fulfillment, like a reduction in flows, a higher revenue from congestion tolls, and so forth.

Deterministic sensitivity is studied to investigate the effect of changing the presented model (tool) input parameters on the resulting outputs.

**Toll sensitivity:** The study on the sensitivity of toll is an important part in the implementation of a tolling facility. State agencies need to know how high the toll price level might be and how the optimum level would be established. Toll revenue relates to the amount of HOT lane usage by the SOV drivers. If toll revenue is high, it means that the lane has been frequently used by the SOV drivers and vice versa. Therefore, toll sensitivity acts as a proxy to potential demand. There is a need to consider this parameter for sensitivity analysis to deliver an acceptable toll range. In order to take maximum advantage of this experimental setting, analysis was done with various toll levels from $0.25 to $5. All sensitivity analyses were done for rush hours, which is a.m. peak time period for NB travel lanes and p.m. peak period for SB travel lanes.

Figure 8 illustrates the sensitivity of toll rates with respect to toll revenue, volume of SOV drivers, and average travel speeds for HOT and GP lanes under HOT lane conditions. Results on toll revenue versus toll rate show that toll revenue rise for toll rates between $0.25 \leq \text{toll rates} < $3 and falls for toll rates between $3 \leq \text{toll rates} \leq $5. This trend indicates that toll revenue is sensitive to toll rates. Most SOV drivers appear unwilling to pay tolls for using the HOT lane when toll rates exceed $3. Instead, these SOV drivers prefer switching to GP lanes to avoid the higher tolls, resulting in a decline in toll revenue. Thus, there is a breaking point at $3 where toll revenue and toll rate changes its trend. This behavior of SOV drivers is likely dependent on the socioeconomic factor of the existing population.

The plot on the volume of SOV drivers traveling along HOT lane versus toll rates further establish this assertion showing a breakpoint at $3, after which the volume of SOV drivers decreases. In addition, this trend is also confirmed from the plot on average travel speeds versus toll rates. Results show that when the toll rate is less than $3, HOT lane speed decreases, indicating increased HOT lane usage. When toll rates exceed $3, HOT lane speed starts to increase, indicating decreased lane usage. Further, the GP lane speed shows an agreeable behavior when toll rates exceed $3 by a gradual drop in the travel speeds. This trend confirms that when the toll rate exceeds $3, most SOV drivers have switched from HOT to GP lanes, thereby decreasing GP lane speeds.
Figure 8: Toll sensitivity.
Effect of traffic growth on revenue forecasts: An important factor in sensitivity analyses of tolled facilities are revenue projections under projected traffic growths (increase in traffic volume) due to anticipated population and employment growth along the corridor. These results would assist in building financing plans to incorporate contingency factors to account for this anticipated increase in traffic demand by traffic agencies. Figure 9 depicts the relationship between peak period toll revenue versus average HOT lane speeds under various traffic projections. The analysis considers percentage increase in traffic volume (vehicles per hour) varying from 10 percent to 50 percent at 10 percent increments with respect to current traffic volume versus toll revenue and average HOT lane speeds.

The plot shows that an increase in traffic demand increases toll revenue and decreases average HOT lane speeds. However, this trend is consistent up to a 30 percent increase in traffic demand, after which the revenue starts decreasing. This pattern confirms that up to a 30 percent increase in traffic demand, SOV drivers tend to travel in HOT lanes, which accounts for the subsequent rise in revenue. However, further increase of traffic demand causes frequent closure of HOT lanes to SOV drivers due to HOT lane capacity limitation. Additionally, the further increase of traffic demand also increases the toll rates. Thus, the increase in toll rates and frequent closure of HOT lanes to SOV drivers causes SOV drivers to consider traveling along GP lanes, thereby allowing the HOV drivers to travel in HOT lanes for free.

Elasticity of Demand for Travel Time Savings
It is difficult to estimate the price elasticity of demand for anything, because demand depends on many things other than price, and these are likely to be unknown.29 Demand elasticity depends on the existence and cost of substitutes for the goods or services, on the income of the buyers, and on...
the prices and qualities of all other goods and services available to them. Knowing the price elasticity of demand enables estimation of the demand if prices are changed. Since correctly setting the toll for a HOT lane is key to achieving HOT lane demand that will provide high utilization and free flow, we are interested in estimating the elasticity of demand for travel time savings. Elasticity of demand measures the sensitivity of quantity of demand (travel time savings) to price (tolls). The theory behind this analysis is that the number of people using the toll lane depends primarily on the travel time savings on HOT lanes or delay on GP lanes, the total travel demand along the corridor, and the toll. This relates to the willingness of SOV drivers to pay tolls based on their travel time savings by using the HOT lane.

Figure 10(a) illustrates the percentage increase in HOT lane volume by SOV drivers at post (HOT) conditions compared to initial (HOV) conditions versus corresponding travel time savings. Analyses show that there is an increase in SOV drivers willing to travel in HOT lanes as their travel time savings increases. Figure 10(b) shows the relationship between toll rates versus the travel time savings. As expected, the toll rates increase for higher travel time savings; however, this relationship is not linear.
Overall, the results from Figure 10(a) and 10(b) show a wide distribution of SOV drivers willingness to pay tolls. About 90 percent of SOV drivers are willing to pay $1.50 to save more than 10 minutes, and up to 80 percent of SOV drivers would pay up to $5 to save more than 25 minutes. These results are a useful guide in managing demand levels relatively smoothly by varying the toll.

Conclusions

This paper presented a tool that can assess the potential of a CPA to manage and optimize a HOT lane operation on an urban freeway. To model real-life traveler reaction to changing tolls, a feedback control mechanism using the drivers’ dynamic lane-switching method was developed and integrated into the CPA. This enabled predicting and optimizing traffic operations along HOT and GP lanes to achieve the target conditions. Results provide a predeployment evaluation of HOT lane operations and predicts expected performance and tolls under the CPA based on historic data. The conclusions are as follows:

1. The developed tool is practically operational in assessing the potential of the CPA. On the basis of the traffic conditions and changing tolls, the optimal flow on the HOT lane is maintained by using the feedback mechanism. The feedback mechanism recognizes drivers’ behavioral responses to lane switching based on changing tolls and traffic conditions and dynamically optimizes HOT lane operation under the CPA. Therefore, this tool can satisfy the practicality and effectiveness required by the HOT lane system in reality.

2. The developed tool performs reasonably well under various traffic demands. Results show that an increase in HOV lane usage by 90 percent could be achieved under HOT lane conditions when the CPA becomes effective. This shows a positive association in the attitude of SOV travelers toward the dynamic pricing scheme. Through optimal toll adjustment, the SOV drivers are regulated to fully utilize the excess capacity of HOV lane without degrading operation conditions for HOV drivers.

3. The potential of the CPA is manifested by an increase in the average GP lane speeds by 25 percent under post (HOT) lane conditions during peak periods. Further, the average HOT lane speeds are maintained at 55 mph (approximately) during most of the peak periods. This indicates an overall increase in traffic mobility and efficiency along the freeway. Moreover, there were no obvious negative effects on the HOV lane, because the desired travel speed and reliability were preserved. This indicates that the developed tool has successfully evaluated the potential of CPA to optimize traffic flow along the freeway.

4. Findings from sensitivity analyses show the sensitivity of the model to changes in the toll rates and traffic volume. Results show that SOV demand and toll revenue are sensitive to toll rates. However, the willingness to pay tolls among SOV drivers are likely dependent on socioeconomic factors of the traveling population, such as income, age, trip purpose, time of day, trip distance, and amount of time saved. These results ensure the robustness of the tool to optimize changes according to some goal fulfillment, such as a reduction in flows, a higher revenue from congestion tolls, and so forth. It would be interesting to repeat this analysis after actual project implementation.

5. Although the presented tool has demonstrated favorable results by predicting expected HOT lane performance prior to deployment, there is a need for a postdeployment evaluation study. The model enhancements projected through the drivers’ dynamic lane-switching method need to be calibrated with field data when the dynamic tolling along HOT lanes becomes operational. Additional analysis on the toll structure and algorithm may also fine tune the congestion pricing default values. The findings of this paper, however, lend empirical credence to the claims of the efficacy of the implementation of CPA as a congestion or demand management strategy.
Acknowledgments

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Using Inductive Loops to Count Bicycles in Mixed Traffic

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Inductive loops are commonly used for bicycle detection both on- and off-street, but until recently, few such detectors were able to differentiate between bicycles and motor vehicles. For this reason, automated bicycle counting is usually confined to off-street locations. With bicycle use increasing around the world, particularly on shared roadway facilities such as bicycle boulevards, there is a growing need to detect bicycles in on-street traffic conditions. This study tests the accuracy of an off-the-shelf inductive-loop technology designed to count bicycles in mixed traffic conditions and compares this accuracy to similar inductive loop technology used for detection on separated bicycle facilities. The results show that the inductive loop technology is capable of differentiating bicycles from motor vehicles and counting bicycles in traffic with reasonable accuracy, but an individual bicycle may be undetected or counted more than once. Overall, there was a 3 percent undercount for the counter on the separated path and a 4 percent overcount for the counter on the shared roadway. The results show that refinements in inductive loop detector/counter software and setup have made it possible to distinguish bicycles from motor vehicles; however, care must be taken in installation, calibration, and maintenance to ensure that the counters are accurate.
Introduction

Policymakers are increasingly looking to bicycling as a sustainable mode of transportation that can reduce vehicle emissions and fuel use. Accurately quantifying bicycling levels is necessary to better understand the degree to which public policies and changes in the built environment are affecting bicycle use.

Automated detection of motor vehicles is the standard for estimating average annual daily traffic (AADT) on roadways as well as quantifying vehicle miles traveled (VMT) locally and nationally. Automated detection, usually using inductive loop detectors, has proven to be a relatively accurate and necessary part of monitoring vehicle use, as allocation of federal transportation funds is linked to VMT estimates. If bicycle use is to be similarly quantified, automated detectors using inductive loops may provide the basis for such estimates, which can also be used to evaluate current and future bicycle infrastructure investments. For these reasons, this study focuses on testing the accuracy of automated bicycle detection.

Bicycles travel on three main types of bicycle facilities: separated paths, bicycle lanes, and shared roadways. For the purposes of this study, the term “separated path” includes any bicycle facility physically separated from motor vehicle traffic; the term “bicycle lanes” includes on-street facilities separated from motor vehicle lanes by a solid line and on which bicycles are either designated or allowed to ride; the term “shared roadway” includes on-street facilities where bicycles share the motor vehicle lane whether specific signs and markings are present or not. Though it is desirable to count bicycles on all three facility types, this paper focuses primarily on methods for counting bicycles on shared roadways.

For decades, inductive loops have been used to detect bicycles at signals and to count bicycles on separated bicycle facilities such as paths. Inductive loop detectors are relatively low cost, well understood by transportation technicians, and easy to maintain. Although accurately counting bicycles on separated paths using inductive loops has proven feasible with proper setup and maintenance, bicycles on shared roadways cannot be accurately counted with conventional inductive loop technology because these detectors fail to differentiate between bicycles and motor vehicles. Even when loops are placed in bicycle lanes, motor vehicles traveling in adjacent lanes can be erroneously counted as well. In order to count bicycles on increasingly popular, mixed-traffic facilities such as bicycle boulevards, new automated methods and technologies are now emerging.

A few systems for classifying bicycles in mixed-traffic conditions have been developed. Among them only two were found to be off-the-shelf products for permanent installation in mixed traffic: the MS Sedco Intersector, which uses microwave radar to identify bicycles by speed, shape, and microwave reflectivity and the Eco-Counter Zelt, which uses inductive loop technology. Since these technologies are relatively new, little field testing has been done. Several studies of the accuracy of the Zelt are available; however, no third-party studies of the MS Sedco Intersector were found, though the manufacturer cites internal tests. The bicycle detectors (hardware only) discussed above generally range in price from roughly $2,000 to $5,000 depending on the type of location, with the loop detectors on the lower end of the range. (Installation costs can vary substantially by location. Prescribed maintenance of the Zelt is limited to annual battery replacement.)

Other permanent bicycle counting technologies for shared roadways are under development. A FHWA study found that eight of eight bicycles were correctly classified and counted using a Migma, Inc. detector, which combines stereo camera, infrared thermal camera, and acoustic sensor technologies. Piezoelectric and video-detection technologies might also be incorporated into future permanent shared-roadway bicycle detection products by other manufacturers. For temporary applications, pneumatic tube counters might also be used.
The purpose of the study was to evaluate the effectiveness of the Eco Counter Zelt inductive loop counter by comparing the accuracy of its automated bike counts on separated paths and shared roadways and to third-party studies. This study will address two key questions: Can an inductive loop detector fill the need for automated bicycle counts on shared roadways, and if so, what are its limitations? (The inductive-loop counters were installed and tested on bicycle lanes as well, but due to electrical interference at these locations, these loops are not performing properly and will be moved. For this reason, the bicycle lane locations will only be discussed tangentially herein.)

Inductive Loop Detectors

Inductive loop detectors are commonly used to detect motor vehicles at traffic signals and are the most common vehicle-sensor type in traffic management. An inductive loop circuit is composed of loops of wire embedded in the pavement and the associated lead-in cables. The detector constantly senses the inductance in the circuit by measuring the resonant frequency. When a metal object passes above the loops, it induces eddy currents in the circuit, which changes the circuit’s inductance. Bicycle detection by inductive loops was studied in detail, by modeling the extent of bicycle detection zones for typical traffic signal loop detector configurations.

A field study of 100 steel-frame bicycles and 51 aluminum-frame bicycles performed by SRF Consulting compared various automatic bicycle and pedestrian counting technologies and found no discrepancies between manual and inductive loop detector counts, while other counting technologies showed discrepancies of up to 4 percent. However, a previous study showed that after years of use in field conditions with little maintenance, conventional inductive loop detector accuracy varied substantially from 67 percent undercounts to 114 percent overcounts with average absolute percent accuracy of 81 percent and only 68 percent of the detectors considered accurate. However, the previously tested technologies are not able to differentiate between bicycles and motor vehicles and thus are limited to separated paths or perhaps bicycle lanes.

The Eco-Counter Zelt is a relatively new inductive loop technology, which claims to be able to differentiate bicycles from motor vehicles by analyzing the signals from the inductive loop or loops. Using a proprietary algorithm that takes into account variables including signal strength, vehicle speed, and wheel spacing, the manufacturer claims that the technology can determine whether a detected object should be classified as a bicycle or not.

Zelt has been evaluated in a few international studies with accuracies ranging from 74 percent to 99 percent. A detailed comparison of these studies is provided in the discussion section of this paper. While these studies are useful individually, this paper offers a comparison of these studies to better inform potential users.

While inductive loops are a proven technology for vehicle detection, some issues may confound their use for bicycle detection: carbon fiber bicycles, long-wheel base bicycles (such as tandems), bicycles with trailers, bicycles riding side by side, bicycles riding closely one behind the other, and bicyclists riding slowly. Each of these special cases is tested in this study.

Data Collection Method

The testing protocol was consistent across test locations in order to determine whether bicycles were counted accurately. There were two test parts: common bicycles and special cases. The common bicycle test was conducted twice for each location, each of which consisted of volunteer cyclists riding for at least 30 minutes on standard bicycles again and again over the loop detectors. Standard bicycles included aluminum, steel, and titanium bicycles. Volunteers rode over the loops as frequently as feasible during this time period (typically at least twice per minute per rider).
Volunteers were also stationed to count vehicles and bicycles crossing each loop and record any special circumstances that may affect the loop detector counts. Other bicyclists and vehicles (where allowed) also crossed the loops during testing, since test locations were open to the public. Because of these frequent crossings, it was not practical for the volunteer manual counter to verify whether each vehicle or bicycle was properly detected during the common bicycle test. Thus, counting was divided into one-minute bins synchronized with the loop detector’s clock.

Each detector has its own battery-powered data logger with a digital display indicating the total number of counts recorded since the counter was installed or reset. The digital display allows the volunteer manual counters to observe, in real time, whether a bicycle or other vehicle is counted or not. However, when bicycle traffic is high, it can become difficult to maintain an accurate manual count. For this reason, volunteer manual counters were asked to record the total bicyclists observed each minute and the count displayed on the data logger at the end of each minute. After the data were downloaded, these manually recorded readings were compared to the 15-minute bin outputs from the data file.

Special case testing was conducted using the same one-minute binning method described, except that volunteer riders rode specific bicycle types, or in specific ways, for three or more minutes of each case. Unless otherwise specified, the frame types of the special case bicycles below were either aluminum or steel.

Special cases that were tested include the following:

- A carbon fiber bicycle with aluminum wheels;
- A steel bicycle with a trailer;
- A tandem bicycle;
- Two bicyclists riding side by side;
- Two bicyclists riding closely, one behind the other; and
- Bicyclists walking or riding at walking speed.

**Description Of Equipment**

The inductive-loop detector was tested in two different configurations: a single loop configuration and a three-loop configuration. Two bicycle facility types were tested: a separated bicycle facility and a shared roadway. Installation locations are listed in Table 1.

<table>
<thead>
<tr>
<th>Bicycle Facility Type</th>
<th>Location</th>
<th>Model</th>
<th>Number of Loops</th>
<th>Number of Detector Channels Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shared Roadway</td>
<td>13th Street northbound</td>
<td>Eco-Twin</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Separated Path</td>
<td>13th Street southbound</td>
<td>Eco-Pilot</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bicycle Lane</td>
<td>Folsom Street*</td>
<td>Eco-Pilot</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bicycle Lane</td>
<td>Folsom Street*</td>
<td>Eco-Pilot</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

* Not tested due to electrical interference causing variable accuracy (loops to be moved).
The detectors tested in this study use diamond-shaped induction loops as described by Eco-Counter. These were installed in conjunction with Eco-Counter and the city of Boulder, Colorado, USA in late June 2010 at four locations: in north and southbound bicycle lanes of Folsom Street, on a 12.5-foot-wide shared roadway segment with one-way motor-vehicle traffic on 13th Street, and on an 8-foot-wide bicycle contraflow lane with one-way bicycle traffic on 13th Street. For the purposes of this paper, the contraflow lane is categorized as a “separated path,” since motor vehicles are separated from this section of the roadway by concrete planters and is thus too narrow for most cars and trucks. The inductive loops for the bicycle lane and separated path locations consisted of single diamond-shaped inductive loops. For the shared roadway location, three diamond-shaped inductive loops were installed. Figure 1 shows the configuration of the loops and detectors at each location.

A separate, waterproof, battery-powered detector and data logger was provided for each location. This paper focuses on results of the separated path and shared roadway locations, but results from the bicycle lane testing will also be discussed briefly.

Testing
Tests were performed on the mornings of Thursday, July 1 and Monday, July 19, 2010 between the hours of 8:00 a.m. and 11:00 a.m. with favorable weather conditions. Since the two detectors on 13th Street are

Figure 1: 13th Street loop locations (inductive loops are highlighted in the graphic).
located within 100 feet of each other, the same group of volunteer bicyclists was able to test both detectors during one testing period, though each automated detector required its own volunteer manual counter. A completely different set of riders and counters participated in the testing on each day.

After all tests were completed, the data from the data loggers were downloaded. Manual counts were compared to automated detector counts under the assumption that the manual counts were accurate. The team compared the counts for the special cases and examined the notes from the manual counters.

Analysis

As described above, the counts were aggregated into one-minute bins. Bins contained one to 10 counts each and averaged four counts per bin. The number of bins and number of counts for each location are shown in Table 2.

For each bin the percent difference, $d_i$, between the automated detector counts and the manual counts was computed.

$$d_i = c_i - m_i$$  \hspace{1cm} (1)

where:

- $d_i$ = difference per bin
- $i$ = one-minute bin
- $c_i$ = automated detector count per bin
- $m_i$ = manual count per bin

The automated detector counts were compared to the manual counter counts, using the manual counter as the baseline and assuming the manual count is completely accurate. To understand the overall errors, the average of the percent differences, $a$, was computed. To better understand the accuracy of the counters, the average of the absolute values of the percent differences, $a_{AAPD}$, also called the average absolute percent difference (AAPD), was computed as shown in the following equations.

Table 2: Common bicycle test summary.

| Bicycle Facility Type | Number of Bins $n$ | Total Manual Bicycle Counts $m$ | Total Automated Detector Counts $c$ | Total Manual Motor Vehicle Counts | $\sum d_i$ | $\sum |d_i|$ | Average Total Percent Difference $\alpha$ | Average Absolute Percent Difference (AAPD) $\alpha_{AAPD}$ | Average Absolute Percent Accuracy $1 - \alpha_{AAPD}$ | 95 percent Confidence Interval (+ or -) |
|-----------------------|-------------------|---------------------------------|-----------------------------------|----------------------------------|------------|----------|---------------------|---------------------------------|---------------------------------|-------------------------------|
| Separated Path        | 106               | 316                             | 306                               | 0                                | -10        | 24       | -3.2 percent        | 7.6 percent                    | 92 percent                      | 3 percent                      |
| Shared Roadway        | 122               | 500                             | 520                               | 182                              | 20         | 114      | 4 percent           | 23 percent                     | 77 percent                      | 4 percent                      |
where:

\( n \) = number of one-minute bins

\( m_i \) = total manual counts

\( a \) = average percent difference

\( a_a \) = average of the absolute value of the percent differences = AAPD

For these detectors, there are three types of errors: (1) counting something when a bicycle is not present (overcounting), (2) counting a bicycle more than once (overcounting), and (3) not counting a bicycle when one is present (undercounting). If traffic on the roadway could have been controlled, then the experiment would have been designed to know whether each bicycle or vehicle was counted properly. However, due to the volume of both bicycle and motor vehicle traffic on the public roadway, and the limits of human ability to both count bicycles and motor vehicles, the test was instead designed to count bicycles and motor vehicles in one-minute bins. This method allows for comparison of manual counts with detector counts, but it hides, to some extent, the different types of errors present in the bin. For example, if a bicycle is counted twice and another is not counted at all in the same bin, it will appear that there is no discrepancy when in reality the detector has a low accuracy. For this reason, the average absolute percent difference (AAPD), which reveals more of the detector inaccuracies, is used to compare the detectors. The average percent difference is also included in Table 2, since users of automated detectors may want an indication of how much to adjust the counts to better reflect actual bicycle counts.

Given that counts are discrete data, they were modeled using a binomial distribution where each manual count was considered a trial for whether the result is either zero or one. If the result of the trial is zero, this indicates that there was no difference between the automated detector count and the manual count—that is, no errors occurred. If the result of the trial is one, this indicates that one error occurred and the bicycle was either not counted or was double counted. The probability of a trial being in error is computed by dividing the total number of errors by the total manual bicycle counts. Since the total number of errors is estimated by summing the absolute values of the differences between detector and manual counts for each bin, the probability of a trial being in error is approximated by the AAPD.

Modeling the test using the binomial distribution as described above involves the following assumptions:

- One trial occurs for each manual bicycle count. This is not completely accurate, since an overcount sometimes occurs when a motor vehicle or some other non-bicycle passes over the detector. Fortunately, this type of event is rare. Only once during testing did a volunteer notice the multi-loop system on the shared roadway record a count when a motor vehicle passed. Testing by others reported that only 0.4 percent to 0.8 percent of motor vehicles passing a loop on a shared roadway were counted as bicycles;
Double counts cancelled out by undercounts within a bin are ignored. This assumption means that the AAPD will tend to underestimate the probability of a bicycle being under- or overcounted; and

If an automated detector counts a given bicycle as three or more bicycles, the AAPD will tend to overestimate the probability of a bicycle being under or overcounted. However, there were no instances when an automated detector counted a given bicycle more than twice.

Confidence intervals were calculated assuming the binomial distribution with 95 percent confidence interval estimated using the standard normal z-statistic.

Since the results from the two days of testing were similar, the data were combined for each location, with the results presented in Table 2. Generally, the automated detector on the separated path was more likely to undercount than overcount, while the automated detector on the shared roadway was more likely to overcount than undercount. The results for each case are discussed separately below.

**Separated Path**

The system in the separated bicycle path generally undercounted bicyclists with average percent difference of 3 percent undercounting but was relatively accurate with an AAPD of 8 percent.

**Shared Roadway**

The average percent difference for the system on the shared roadway was low, with 4 percent overcount overall, but the AAPD of 23 percent reveals the inaccuracies of detecting individual bicycles in an environment where motor vehicles are present.

During testing, one volunteer manual counter noticed that some bicycles were not counted while others were counted more than once. Speed and lane location are likely factors that will be discussed later. However, motor vehicles were generally not detected by the loops, confirming that the detectors can differentiate between motor vehicles and bicycles.

**Bicycle Lanes**

The loops installed on the Folsom Street bicycle lanes frequently undercounted bicycles; the manufacturer attributes this to electrical interference, and the counters will be moved to another location. The average percent difference, 27 percent undercount, and the AAPD of 29 percent measured for the southbound loop show that the loop studied is consistently undercounting. Increasing the sensitivity of the loop resulted in substantial overcounting. The loop installed on the other side of the bicycle lane, in the opposite side of the road, was so inaccurate due to interference that it was not tested. The manufacturer has offered to help the city of Boulder move the loops to a more suitable location, but this was not completed as of writing and the results from this test are not included in Table 2.

**Path Versus Roadway Comparison**

As shown in Table 2, the AAPD is lower for the path than for the shared roadway, indicating that the technology may be more accurate when bicycles are separated from motor vehicle traffic, as illustrated in Figure 2. This makes sense, since it is an easier task to detect bicycles when motor vehicles are not present.

Statistically, the AAPD for the two automated detectors were compared using a pooled estimate of a common proportion (also known as a test of proportions) to test the hypothesis that the AAPDs are the same. The p-value is less than 0.001, indicating that the AAPD for the two automated detectors are significantly different.
Potential Error Sources

Unfortunately, neither the inductive loop detectors nor the manual counts are perfect, and any test has sources of error. Human error has been identified in a previous study as one possible source of miscounting. In a previous study, volunteer manual counters slightly undercounted by 1 percent (+/- 4 percent) average percent difference and had a 6 percent average absolute percent difference (94 percent accuracy). It was also possible for manual counters to become overwhelmed by high levels of bicycle traffic, and in such cases, percent differences between manual counters were as high as 45 percent.

Another source of error is bicycles crossing loops at or near the time of the end of the one-minute bin, which may be recorded in either bin. There is a short, approximately 2-second, delay for detectors to recognize and count the bicycle, which may result in the detector putting the bicycle in a later bin than the manual counter. Analysis focusing on the average absolute percent differences is revealing but is also somewhat arbitrary in that the size of the aggregated bin influences the results.

Special Case Testing

The comparison of automated detector counts with manual counts provides overall information on accuracy, but a discussion of special cases and other observations encountered in the field may provide further insight into accuracy issues associated with the automated detectors. In order to get a sense of what special cases may confound the detectors, a few situations were specifically studied. Table 3 reports the results. The detector is designed to count bicycle wheels, not frames, so it is no surprise that the automated detectors were able to count the carbon fiber bicycle with aluminum wheels consistently. While tandem bicycles and bicycle trailers are relatively rare (generally less than 1 percent of bicycles), carbon fiber bicycles make up roughly 5 percent of bicycles observed on paths in Boulder, which is likely to be a higher percentage than in most cities.

Additionally, a steel bicycle with an aluminum two-wheel child trailer was ridden over the detectors. The automated detector consistently missed the bicycle with trailer, except in one case when it was double counted. The manufacturer does not claim to detect bicycles with trailers under standard settings, so this result is not surprising. Similar to the bicycle with trailer, the tandem bicycle with a long-wheel base (Bike-Friday brand with a steel frame) was only counted three of the 21 times it crossed the loops on the shared roadway. The manufacturer does not claim to be able to detect tandems, so the low detection of such long wheel-base bicycles is also not surprising.

Figure 2: Absolute percent accuracy of automated counters with error bars indicating the 95 percent confidence intervals.
Table 3: Special cases studied.

<table>
<thead>
<tr>
<th>Bicycle Facility Type</th>
<th>Separated Path</th>
<th></th>
<th>Shared Roadway</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observed number</td>
<td>Percent</td>
<td>Observed number</td>
<td>Percent</td>
</tr>
<tr>
<td></td>
<td>of bicycles counted</td>
<td>accurate</td>
<td>counted</td>
<td>accurate</td>
</tr>
<tr>
<td>Carbon fiber bicycle with aluminum wheels</td>
<td>8 of 8 bicycles counted</td>
<td>100 percent</td>
<td>100 percent</td>
<td></td>
</tr>
<tr>
<td>Bicycle with trailer</td>
<td>2 of 11 bicycles counted</td>
<td>18 percent</td>
<td>0 of 18 bicycles counted</td>
<td>0 percent</td>
</tr>
<tr>
<td>Tandem</td>
<td>7 of 14 bicycles counted</td>
<td>50 percent</td>
<td>8 of 8 bicycles counted</td>
<td>100 percent</td>
</tr>
<tr>
<td>Side-by-side bicyclists</td>
<td>16 of 18 bicycles counted</td>
<td>89 percent</td>
<td>5 of 10 bicycles counted</td>
<td>50 percent</td>
</tr>
<tr>
<td>Bicyclists, one behind the other</td>
<td>16 of 16 bicycles counted</td>
<td>100 percent</td>
<td>11 of 11 bicycles counted</td>
<td>100 percent</td>
</tr>
</tbody>
</table>

One of the tradeoffs of identifying bicycles when motor vehicles are present, by filtering out some signals from the inductive loops, is that some bicycle types, such as those with long wheel bases or more than two wheels, are rejected because they are not similar enough to the standard bicycle. While the manufacturer states that settings could be changed to include longer wheel base vehicles, this may result in some motor vehicles being detected that would have otherwise been rejected. Perhaps as signal interpretation algorithms become more sophisticated, this may be remedied; currently, the uncounted long wheel-base bicycles and bicycles with trailers is minimal because such bicycles are relatively rare. The more traditional loop detectors (Canoga C800) studied previously were able to correctly count these bicycle types but cannot differentiate bicycles from motor vehicles.1

Bicycles riding side by side were consistently counted as two bicycles by the multiloop system but as only one bicycle by the single-loop detector. This is probably because they crossed more than one loop when crossing the multiloop configuration but only one loop when crossing the single-loop configuration. The more traditional loop detectors studied previously counted side-by-side riders as one bicycle.3

Bicycles riding in opposite directions crossing the loops simultaneously were not tested, since such movements are illegal on this stretch of roadway. Each lane is one way only, and though wrong-way bicyclists have been observed occasionally in the southbound contraflow lane, none was observed during testing.

When two bicyclists rode closely one behind the other (less than one bicycle length), only one bicycle was counted by the multiloop system on the shared roadway, while both bicycles were counted by the single-loop system on the separated path. One possibility is that the multiloop detector was set to be more selective, since it is designed to reject any vehicle similar to a motor vehicle. A previous test of the more traditional inductive loop detectors indicated that these detectors also count two bicycles following each other closely as one bicycle.3 Thus, it is surprising that the single-loop detector on the separated path was able to count the bicycles following each other closely as separate bicycles most of the time.
When the bicyclists walked their bicycles or rode at walking speed over the detectors, both automated detectors had no trouble counting the bicycles. This is different from the behavior observed for more traditional loop detectors studied previously, whose time settings prevented them from detecting bicycles moving at walking speed, but these could have been adjusted to improve performance.3

Other Observations

During the course of testing, other situations were observed that, although not necessarily repeated, may offer additional insights about what may cause counting inaccuracies.

Children

Child-sized bicycles with 20-inch wheels and smaller were not counted by the single-loop detector, but child-sized bicycles with 24-inch wheels and larger were counted. Bicycles with child bicycle attachments, also known as tagalongs, were only encountered once for each configuration, since this case was not specifically tested. Similar to the tandem bicycle, the tagalong bicycle was not counted for the multiloop system but was counted twice by the single-loop detector.

Double Counting

Occasionally, cyclists on the shared roadway were double counted. A volunteer riding through specific locations on the loops revealed that double counting can be triggered by a bicycle crossing the detector exactly between the two northern loops as shown by the arrow in Figure 1(c). A volunteer rider on an aluminum bicycle rode over this specific point six times and was double counted four of those six times.

Nondetection

It was observed three times that a cyclist was undetected when he or she rode through the exact center of the leftmost loop of the multiloop system. Although this is not a likely location for most cyclists who tend to ride in the center or right side of the lane, it may account for some observed cases of a bicycle not being counted during the testing.

Motor Vehicles

At the shared roadway location, motor vehicles were almost always excluded from the automated detector counts, except in one case when a spurious count was observed as a semi-truck with trailer crossed the loops. Motorcycles and scooters were also not counted, probably because these vehicles have more metal than a bicycle and thus give a stronger signal to the detector, which is then able to exclude such signals as not bicycles. While no standard-sized vehicles are able to use the separated path, a small, motorized utility vehicle used for city maintenance does occasionally cross the detector; when it was observed prior to testing, it was not counted by the single-loop detector technology.

To identify whether the multiloop detectors accurately differentiated motor vehicles from bicycles, Figure 3 was plotted to show that the number of motor vehicles passing over the detector does not affect the number of over or undercounts. The regression line is so close to horizontal that it is difficult to observe in this graph. If success in differentiating motor vehicles from bicycles were to be included in the estimate of accuracy, the multiloop detector on the shared roadway has 83 percent accuracy.
While the multiloop detector on a shared-roadway does not seem to be as accurate as the single-loop detector on the separated bicycle path, it was able to consistently distinguish between bicycles and motor vehicles, a task that few other technologies can accomplish. The multiloop detector, however, may be prone to over or undercounting due to the configuration of multiple diamond loops, which seems to miscount depending upon where a bicycle crosses the loop.

The discrepancies of 23 percent absolute average difference for the loops on a shared roadway and 8 percent for the loop detector on a separated path are comparable to the 19 percent average absolute difference computed for the more traditional loop detectors studied previously (which had been in operation with little maintenance for approximately 10 years) on separated bicycle paths in Boulder. The multiloop configuration tends to undercount bicyclists traveling closely one behind the other, but other inductive loop technologies, such as those previously tested, also tend to undercount in such situations. The multiloop system can accurately count bicycles traveling side by side, which the more traditional inductive loop detector tested previously was also not able to do.

The single-loop counter in the separated path was significantly more accurate and able to distinguish metal vehicles (hand cart and four-wheel motorized utility vehicle) from bicycles and not count them. This accuracy makes sense, considering the single-loop detector’s task was much simpler: Only one loop was required, and motor vehicles were few. The accuracy of this counter exceeds that of the more traditional loop detectors studied previously (though these were installed many years prior to testing while the loop detectors studied here were installed days prior to testing), and the single-loop detector studied has the added capability of being able to differentiate between motor vehicles and bicycles.

As shown in Figure 4, accuracy as calculated by AAPD for both loop configurations is a function of the number of counts per bin, represented as bin size in minutes in the graph. The more cyclists counted per bin, the more the over and undercounts of individual cyclists cancel each other out and converge to the overall inaccuracy of 3 percent to 4 percent. The point at which the inaccuracy
converges to 5 percent or less AAPD roughly equates to counts per bin of 60 cyclists or more, which is a common bicycle hourly count for frequently used bicycle routes during peak hours. Thus, the accuracy of the inductive loop counters for hourly counts on high-frequency bicycle routes is likely to be more than 95 percent.

Comparison to International Studies

Zelt inductive-loop technology has been studied internationally. As summarized in Table 4, four studies were found that tested the accuracy of these inductive loop counters for counting bicycles on separated paths, bicycle lanes, and shared roadways. When sufficient data were provided in the published reports, the AAPD was calculated using the method presented above and reported in Table 4, which allows some comparison of the studies. The studies performed in New Zealand and Norway did not always aggregate counts into bins but may have instead been able to check count detection per trial for trials of bicycles passing over the detector, and in the New Zealand report, also for motor vehicles passing over the detector. For this reason, bin sizes for those studies are listed as “unknown” in Table 4.

Figure 4: Average absolute percent difference (AAPD) varies with number of counts per bin.
The study from New Zealand reported an error adjusted index (EAI), which was computed by subtracting the automated detector’s under and overcounts from the manual counts for a particular test, summing these for all tests and dividing by the total manual counts for all tests of that equipment type (EAI ≈ 1-AAPD).

The Swedish study reported results as the mean absolute percent error (MAPE), which is computed in the same way that AAPD is computed. However, because the bicycles per bin was so large (30 to 220 bicycles per 15-minute bin) the under and overcounts in each bin would have cancelled each other out, and the resulting reported statistic may substantially overestimate the accuracy of the detectors.¹⁰

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Table 4: Summary of international studies of Zelt loops.

<table>
<thead>
<tr>
<th>Bicycle Facility Type</th>
<th>Report</th>
<th>Number of Bins</th>
<th>Number of Reference Counts</th>
<th>Results Reported</th>
<th>AAPD*</th>
<th>95 percent Confidence Interval (+ or -)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Separate Path</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>26</td>
<td>269</td>
<td>88 percent EAI</td>
<td>12 percent</td>
<td>4 percent</td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>26</td>
<td>178</td>
<td>74 percent EAI</td>
<td>26 percent</td>
<td>6 percent</td>
<td></td>
</tr>
<tr>
<td>Sweden (10)</td>
<td>12</td>
<td>1503</td>
<td>1.1 percent MAPE</td>
<td></td>
<td>4 percent</td>
<td></td>
</tr>
<tr>
<td>Sweden (10)</td>
<td>12</td>
<td>1443</td>
<td>1.6 percent MAPE</td>
<td></td>
<td>4 percent</td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>106</td>
<td>316</td>
<td>7.6 percent AAPD</td>
<td>8 percent</td>
<td>3 percent</td>
<td></td>
</tr>
<tr>
<td><strong>Bike Lane</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>France (7)</td>
<td>102</td>
<td>201</td>
<td>1.5 percent undercount</td>
<td>6 percent</td>
<td>3 percent</td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>Unknown</td>
<td>80</td>
<td>88.8 percent EAI</td>
<td>10 percent</td>
<td>7 percent</td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>Unknown</td>
<td>96</td>
<td>72 percent EAI</td>
<td>28 percent</td>
<td>9 percent</td>
<td></td>
</tr>
<tr>
<td>Norway (15)</td>
<td>Unknown</td>
<td>557</td>
<td>97.5 percent Accuracy</td>
<td>3 percent</td>
<td>1 percent</td>
<td></td>
</tr>
<tr>
<td><strong>Shared Roadway</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>Unknown</td>
<td>227</td>
<td>79 percent EAI</td>
<td>21 percent</td>
<td>5 percent</td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>Unknown</td>
<td>142</td>
<td>88.0 percent EAI</td>
<td>12 percent</td>
<td>5 percent</td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>Unknown</td>
<td>41</td>
<td>90.2 percent EAI</td>
<td></td>
<td>4 percent</td>
<td></td>
</tr>
<tr>
<td>New Zealand (8)</td>
<td>Unknown</td>
<td>37</td>
<td>75.7 percent EAI</td>
<td></td>
<td>4 percent</td>
<td></td>
</tr>
<tr>
<td>Norway (15)</td>
<td>Unknown</td>
<td>109</td>
<td>83.5 percent Accuracy</td>
<td></td>
<td>4 percent</td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>122</td>
<td>500</td>
<td>23 percent AAPD</td>
<td>23 percent</td>
<td>4 percent</td>
<td></td>
</tr>
</tbody>
</table>

* Calculated from published data where available.

Note: “USA” indicates current study.
The accuracy reported in this study is comparable to other reports of Zelt detector accuracy. The single-loop counter on a separated bicycle path (13th Street southbound) seems to be more accurate than other similar facilities tested. Perhaps the manufacturer is improving, or the location and installation on 13th Street was particularly well suited for accurate detection. The multiloop system on a shared roadway tested herein seems to be performing slightly worse than other detectors studied but within the confidence interval of at least one of the detectors studied in New Zealand.

These international tests, in addition to the tests performed in this study, provide a full picture of the accuracy of this technology at the present time. The manufacturer continues to refine the technology, so future studies may show improved results.

Conclusions
Inductive loop technology is capable of detecting bicyclists on shared roadways with relatively high accuracy, but under and overcounts of individual bicycles do occur. Overall, the Eco-Pilot loop detector on the separated path counted bicycles with a 3 percent undercount, but looking at the average absolute percent difference (AAPD), 7.6 percent of the bicycles passing were either not counted or double counted by the detector (92 percent accuracy). For the single-loop detector on the shared roadway, there was an overall 4 percent overcount, and 23 percent of the bicycles passing the detector were incorrectly counted (77 percent accuracy). However, it was very rare for a motor vehicle to be detected as a bicycle.

While AAPD is a good metric for the academic study of bicycle detector accuracy, overall accuracy may be a more important metric for those interested in installing automated detectors. The accuracy of total daily counts reflects the overall accuracy rather than whether or not a particular bicycle is detected. Thus, the overall percent differences computed (3 percent undercount and 4 percent overcount for the single and multiloop locations, respectively) indicate that inductive loop technology can provide relatively accurate counts for the purposes of quantifying bicycle use.

The point at which the inaccuracy converges to 5 percent or less AAPD roughly equates to counts per bin of 60 cyclists or more, which is a common bicycle hourly count for frequently used bicycle routes during peak hours. Thus, the accuracy of the inductive loop counters for hourly counts on high-frequency bicycle routes is likely to be more than 95 percent.

The special cases tested led to the following conclusions:

- Long wheel base bicycles and bicycles with trailers are not usually counted by either loop configuration;
- Bicycles riding side by side are counted correctly by the multiloop configuration but were counted as a single cyclist by the single-loop configuration;
- Bicyclists riding one behind the other were counted as a single cyclist by the multiloop detector but were counted correctly by the single-loop detector; and.
- When bicycles are ridden slowly over the detectors, they were correctly counted.

Refinements in detector and data-logger software and setup have made it possible to distinguish bicycles from motor vehicles. However, care must be taken in installation and maintenance to ensure the counters are accurate. Loop detectors should not be installed at locations with electrical interference problems, which prevented the Folsom bicycle-lane detectors from being included in our study. Thus, loop detectors should not be installed in close proximity to power lines, other
inductive loops, or in any location with high electrical interference, which can be measured prior to cutting loops by using equipment provided by the manufacturer.\textsuperscript{6,13}

Counting bicycles on shared roadways such as bicycle boulevards is increasingly important for planners and engineers seeking to quantify bicycle use in a similar ways to quantifying motor vehicle miles traveled. This study shows that inductive loop technology provides an automated method to quantify bicycles on such shared roadways. While the technology is not flawless, it can provide more accurate counts and useful data on shared roadways (when properly installed and maintained) than other bicycle-detection systems.

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References


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The continuous increase in truck traffic has a considerable effect in congestion and air quality in many urban settings. Transportation agencies across the nation are in search of strategies aiming toward better accommodation of truck traffic while simultaneously reducing its impacts on urban traffic operations. In recent years there is increased interest in the use of dedicated truck lanes as a lane-management technique. Separating traffic streams that have different functional characteristics can reduce turbulence and optimize network performance.

This study examines the potential role of truck lanes strategies in addressing traffic congestion issues in the Birmingham, Alabama, USA metropolitan area. The paper first reviews the state of practice and summarizes best practices from earlier deployment efforts. Then an investigation takes place of the potential operational impacts from implementation of various truck lanes schemes along a common testbed in Birmingham. This is done through traffic modeling and analysis using VISTA, a sophisticated simulation and dynamic traffic assignment modeling tool.

The study revealed that the optimal truck lane use strategy for this study is the conversion of one existing general purpose lane to a shared-use truck lane. The research methods used and findings from this study are expected to benefit both the scientific community and those agencies and authorities responsible for planning, designing, implementing, managing, and operating transportation facilities.

Introduction

Trucks are the backbone of logistics and economic success, and national projections are that freight shipments will double in the next 10 years. This increase will have a significant impact on the...
level of congestion along our nation’s transportation infrastructure, creating new challenges and new opportunities for traffic management. Another issue to consider is that trucks have different acceleration and deceleration rates and weaving capabilities when compared to passenger cars. This often compromises the transportation network’s operational efficiency and traffic safety, as well as the comfort and convenience of all users.

One approach in addressing these concerns is the introduction of dedicated truck lanes. The main purpose of this strategy is to separate trucks from general traffic in order to increase traffic safety and network throughput. Moreover, truck-only lane facilities may reduce travel time or increase time reliability for truck users, which is a very important consideration in freight transportation. Truck facilities also have some positive impacts on the environment. The literature review suggests that the implementation of truck facilities may reduce air and noise pollution, as well as fuel consumption. Also, a 1997 study by Vidunas and Hoel looked at the economic feasibility of separating trucks and other vehicles on freeway I-81 in Virginia. The analysis indicated that user savings can be achieved if one or more lanes are designated for the exclusive use of trucks or cars. According to a study done by the Texas Transportation Institute (TTI), if the average annual daily truck traffic (AADTT) reaches 5,000 trucks per day, a truck facility should be considered.

Urban areas in Alabama face traffic management and congestion mitigation challenges similar to those identified nationwide. In 2005, for example, 12.4 million person-hours were wasted in Birmingham alone due to congestion. This translates to a cost of congestion in the area of $234 million dollars, or nearly five times the figure reported 12 years earlier ($53 million in 1993). The 2005 Urban Mobility Study by the TTI listed Birmingham as one of the medium-sized urban areas with higher congestion or faster increases in urban congestion than its counterparts. As some major corridors for freight travel traverse through urban areas in Alabama such as Birmingham, it is believed that some of the congestion and environmental issues faced there can be attributed to truck movements. In an effort to address these issues, a study was conducted to assess the potential impacts from management of truck movements through the use of truck lanes in the Birmingham area.

This paper provides an overview of available truck lane options and describes the methods used, data gathered, assumptions made, and outputs obtained from the feasibility analysis performed along a stretch of I-65 in Birmingham. The case study is expected to provide some useful insights on the potential use of truck lanes as a lane-management tool in urban settings.

**Study Objectives**

The objective of the study described in this paper was twofold:

1. Better understand available options related to designated truck lane implementation; and

2. Quantify potential operational impacts from implementation of select options in the Birmingham region.

These objectives were accomplished through an extensive literature and state-of-the-practice review of truck lane facilities, traffic simulation modeling, and comparison of selected truck lane design options considered along a common testbed.

The overall study objective was to develop a better understanding of truck lanes and their potential to address congestion issues in urban areas.
Truck Lane Facilities Options And Implementation Requirements

Types of Truck Lane Facilities
According to a study by TTI in 1985, there are seven typical types of truck lane facilities. The first type is a minimum median truck lane. It consists of a 12-foot (ft.) inside truck lane with 5-ft. inside shoulders. The non-truck traffic uses the outside lanes, and the lanes are not barrier separated. The second type has a similar configuration to the first type except for the presence of 10- to 12-ft.-long shoulders. The third type refers to a truck lane that is on a 12-ft. outside lane with 12-ft. outside shoulders. These lanes are also non-barrier separated. The next type is a four-lane facility. The two 12-ft. inside lanes are designated for trucks with 5-ft.-long inside shoulders. This type also is not barrier separated from the outside car lanes. The fifth type of truck lane design is similar to the second type. The only difference is a depressed median. Trucks travel on 12-ft. lane with 10-ft. shoulders. Another option is a protected lane with a passing lane. In this configuration, 12-ft. lanes are used with a 4-ft. inside shoulder and a 10-ft. outside shoulder. This type of truck facility is a barrier-separated facility. The last type is an elevated truck lane, which has the same configuration as the protected truck lane.

The best option for potential implementation should be chosen according to the availability of right of way (ROW), local travel patterns, geometric characteristics of the roadway of interest, and capital and operational cost considerations.

Traffic Control Devices for Truck Lane Facilities
On a truck facility, trucks tend to follow each other closely, causing signs to be blocked by the lead vehicle. For that reason, the placement of traffic signs should be considered carefully to enhance visibility. Oversize and overhead signs should be preferred. Detailed traffic control guidelines are available for truck facilities in the Manual on Uniform Traffic Control Devices (MUTCD). Traffic signs are used to inform truck drivers about lane restrictions, safe passing, merging, and diverging movements, as well as weight limits.

Operation Strategies and Enforcement of Truck Lane Facilities
Differences in acceleration rates, stopping distances, weaving capabilities, and roll stability are special characteristics of trucks that cause them to behave differently than other modes. Separating trucks from other traffic can be done spatially and/or by time of day. Spatial separation can be performed by placing trucks on exclusive truck lanes. Truck lane restrictions can also be applied to certain hours of the day. For example, trucks are not allowed on I-10 highway in Texas on weekdays during daylight hours when traffic flows are heaviest.

Various operation strategies are commonly used for truck traffic management. The first strategy allows trucks to remain in the mixed traffic stream but restricts them to certain lanes. Alternatively, trucks may be restricted from certain lanes. In other words, when trucks are restricted from the far-left lane or right lane, they are allowed to use the other lanes in mixed traffic. There should be at least three lanes on each side to apply truck lane restrictions.

According to a study performed by TTI, truck lane restrictions improve traffic operations and reduce the potential truck-car conflicts by separating low-speed vehicles from faster-moving ones. An example of a successful implementation of such truck traffic management is in Broward County, Florida, USA, where vehicles with three or more axles were restricted from the far left lane on I-95 on a 25-mile segment during the morning and afternoon peak hours.

Another truck traffic management strategy involves truck roadways or truck-only facilities that are completely separated from other traffic. Cars are not allowed on truck roadways. Such treatment is
particularly beneficial when the number of trucks and the crash rates involving trucks are high. With the introduction of truck facilities, the roadway section turns to a dual facility where there is an inner and outer roadway in each direction. One example of a truck-only facility is the New Jersey Turnpike. While the inner roadway in the New Jersey Turnpike is reserved for non-trucks, the outer roadway is a truck-preferred facility, which serves truck traffic along with passenger vehicles. Generally speaking, truck-only facilities are not widely used due to high cost and mixed public perception.

Implementation of Truck Lane Facilities

No universally accepted implementation criteria exist for truck lane implementation. For example, the Texas Department of Transportation (TxDOT) has developed specific criteria for lane restrictions for trucks; the facility should have at least three lanes in each direction, and an engineering study should be conducted before implementation. A cost-effectiveness analysis should be performed before implementation as well.

Evaluation of Truck Lane Facilities

The literature review indicates that truck traffic management in the United States primarily involves truck lane restrictions or dedicated truck lanes on shared-traffic facilities. Several states are currently considering the implementation of truck-only lanes. The state of Missouri’s 2007 long-range transportation plan, for instance, includes dedicated truck lanes on I-70 as a potential strategy to meet future needs. The expected cost of the investment is approximately $7.2 billion. In Georgia, the Georgia DOT conducted a preliminary study in 2007 that includes the construction of truck-only lanes on I-75 North, I-85 North, I-75 South, I-20 West, and I-285 in metro Atlanta. The first phase includes the construction of truck-only lanes on I-75 North, I-285 West, and I-75 South. Examples of truck management facilities currently in operation are briefly introduced next.

Los Angeles, California

The state of California has operated a 2.42-mile truck roadway near Los Angeles since the 1970s. To provide a truck roadway, the California Department of Transportation (CALTRANS) used an old roadway parallel to I-5 north of Los Angeles and just north of the I-5/I-405 interchange. Cars are allowed to use all of the truck facilities. Another truck traffic management strategy implemented in the Los Angeles area is truck bypass lanes at high-volume interchanges. Truck bypass lanes are considered at locations where safety is a concern due to speed differentials or where weaving capacity is exceeded. Lane restrictions on bypass truck facilities in California require trucks to remain in the right lanes to avoid weaving maneuvers. There are three truck bypass lanes at interchanges in the Los Angeles area, namely I-5 at I-405 north of Los Angeles, I-5 at I-405 in Orange County, and I-405 at I-110/SR-91. The trucks exit the main lanes upstream of the first exit ramp and reenter the main lanes downstream of the interchange. After the implementation of truck facilities on I-5, the number of crashes involving trucks decreased by 85 percent.

Newark, New Jersey

The New Jersey Turnpike has a dual-dual roadway configuration between Interchange 8A and Interchange 14 that extends for a distance of 32 miles. While only cars are allowed to use the inside roadway of the facility; cars, trucks, and buses use the outer roadway, as shown in Figure 2. Approximately 40 percent of total traffic uses the outer roadways. The total annual truck traffic volume on the New Jersey Turnpike was 27,649,048 vehicles in 2001 with an estimated rate of growth of truck traffic on the facility of 7 percent annually. According to turnpike authority personnel, safety concerns and congestion on New Jersey roads led to the implementation of the dual-dual facility. The New Jersey Turnpike Authority works closely with the state police and contracts towing and
emergency response services for incident management on the turnpike. Wreckers, ambulances, and firefighting equipment and personnel are available for emergencies 24 hours a day, and a specialist is also on call for any emergency involving trucks that carry hazardous materials.4

Atlanta, Georgia

The first attempt to restrict trucks to right lanes (except to pass or to make a left-hand exit) was made in Georgia in 1986.5 Twenty years later, Georgia’s State Road and Tollway Authority (SRTA) considered constructing separate truck-only lanes as a measure to ease traffic congestion in the metro Atlanta region, and a statewide truck lane needs-identification study was completed. It was found that, with the introduction of truck-only lanes and the shift of truck traffic to those lanes from general-purpose lanes, the congestion experienced would be reduced as a result of the reduction of the percentage and number of trucks in the general purpose (GP) lanes. Moreover, a reduction in the number of crashes was projected.6

New Orleans, Louisiana

The Port of New Orleans, Louisiana (Port NOLA) receives 70 percent of the cargo arriving in Louisiana, and 80 percent of this freight is carried by trucks. In 1983, the city restricted trucks from this historic area. To address the needs of freight transportation, the Tchoupitoulas Truckway was built as an exclusive truck facility. The facility had one 12-ft. lane in each direction and 8-ft. shoulders on both sides and was able to handle 2,000 trucks per day.

The Netherlands

In The Netherlands, unmanned trucks carry sea containers on a Combi-Road Driverless Truck Guideway. Trucks are driven on dedicated tracks with active longitudinal guidance from seaports to inland terminals.9

Study Design

Study Area

As mentioned earlier, the objective of this case study is to determine the impact of truck lane implementation on traffic operations in the Birmingham, Alabama region. The section of I-65 extending from I-459 to I-20/59 was chosen for further analysis. The section is within the area that shows greatest promise for truck lane implementation as per the recommendations of an earlier regional fatal flows study.10 The following paragraphs provide information about the geometric design, demand, and operational characteristics of the study site.

Geometric Characteristics

The I-65 freeway is an interstate facility of major importance to the mobility of Alabamians and also a north-south route of national significance for the movement of people and goods. Extending as far north as Lake Michigan, I-65 connects the city of Birmingham with Nashville, Tennessee, and Indianapolis, Indiana, to the north, and Montgomery and Mobile, Alabama, to the south (Figure 1). It also provides direct access to the Birmingham freeway system, including interstates I-20, I-59, and I-459, which serve local mobility needs as well as connect Birmingham to Atlanta, Georgia, to the east and Tuscaloosa, Alabama, and New Orleans, Louisiana, to the west and south.
The study site as illustrated in Figure 2 is an approximately 10-mile long median-divided freeway section and extends from Valleydale Road (Exit 247) to I-20/59 (Exit 261). The mainline has typically three 12-ft. lanes of traffic per direction with auxiliary lanes added near ramp locations. The posted speed limit along the I-65 study corridor is 60 miles per hour (mph) and 45 mph on the ramps.

Birmingham Area Travel Patterns

Among U.S. metropolitan areas with populations greater than 500,000, Birmingham ranks third in the number of vehicle miles driven per day per capita with an average of 34.8 miles per day (Schrank, et al. 2005). Between 1995 and 2000, the total travel vehicle miles in Jefferson County increased by 8.5 percent, while the increase in Shelby County was 18.8 percent.

Birmingham serves as a hub for goods movement within Alabama. Historically the city has had strong rail freight service, due mostly to the steel and coal industries. The convergence of Interstates 20/59, and 65 have also contributed to the area’s growing truck freight industry.10
Operational Characteristics of I-65 Corridor

Based on traffic counts reported by the Alabama Department of Transportation (ALDOT), the 2005 daily traffic volumes along the study segment of I-65 ranged from 75,000 to 125,000. By 2030, daily traffic volumes are expected to exceed 125,000 along the entire I-65 study section. The percentage of truck traffic on I-65 is nearly 8 percent of all vehicle traffic during peak hours based on 2005 traffic count data collected by the ALDOT.\textsuperscript{10}

Alternatives Analysis

Prior to a potential implementation of truck-only lanes along the I-65 corridor, a detailed alternatives analysis should be performed that uses traffic analysis tools to predict the impact of these strategies on traffic operations in the Birmingham area. Such analysis is the main objective of this study and requires the following steps:

1. **Model selection:** Model selection refers to the selection of appropriate traffic analysis tools with the ability to model truck lanes;

2. **Data collection and processing:** Collection of required data (such as traffic volumes, geometric data, and so forth) and development of a model of I-65 and selected transportation facilities in the Birmingham area, using the simulation tool identified in step 1; and

3. **Data analysis:** Use of the simulation model developed in step 2 to examine traffic operations with and without the presence of truck lane strategies as well as assess different configurations of designs. The impact from implementation could be measured using selected measures of effectiveness (MOEs), such as travel speeds, travel times, delays, and fuel consumption.

The following sections provide details on simulation model selection, data collection and processing, and data analysis for the Birmingham case study.

Simulation Model Selection

A detailed review of the model approaches, capabilities, and limitations, along with considerations related to the availability of models and other resources, led to the selection of the Visual Interactive System for Transport Algorithms (VISTA) as the simulation tool for this study. VISTA utilizes a mesoscopic simulator called RouteSim and a dynamic traffic assignment (DTA) routine to emulate the behavior of individual drivers and how they distribute themselves into the transportation network. RouteSim is based on an extension of Daganzo’s cell transmission model introduced by Ziliaskopoulos and Lee.\textsuperscript{11} In this model, the roadway is divided into small cells where the cells are adjustable in length; larger cells are used for a midsection of a long highway segment, and smaller cells are used for intersections and interchanges. Vehicles are considered to be moving from one cell to another in platoons. The simulator keeps track of the flow in each cell and, every time-step, calculates the number of vehicles that are transmitted between adjacent cells.

Initially, the RouteSim simulator in VISTA is run with vehicles assigned to the free-flow shortest paths. The link travel times resulting from that assignment pattern are then used to calculate a new set of shortest paths, and the simulation is repeated with vehicles assigned to a combination of the paths in the previously calculated path set. At first, the link flows generated by the free-flow shortest paths vehicle assignment can be different from the link flows generated by the simulation using the new set of calculated paths. Thus, iterations continue between the mesoscopic simulation and vehicle assignment until the link flows converge. This procedure accounts for vehicle path choice with changes in traffic conditions.
The VISTA simulation model can be used for a wide range of applications in transportation engineering and planning. Some of the capabilities of VISTA are as follows:\textsuperscript{12}

- VISTA runs over a cluster of Unix/Linux machines and is easily accessible to any authorized users via Internet/intranet. This allows access to and use of the model by a variety of users and eliminates the need to install new software and software upgrades;

- VISTA uses a universal database model that can be accessed through a web interface or geographic information system (GIS) interface. The GIS interface enables users to edit on the network;

- VISTA has excellent capacity for handling large networks. The model provides dynamic traffic assignment (DTA) capabilities. Dynamic user equilibrium (DUE) is the main traffic assignment technique employed in VISTA. As a result, no user can switch paths to decrease his or her travel time;

- VISTA is capable of distinguishing between informed and noninformed road users, as well as user classes, such as normal passenger cars, buses, and trucks in terms of operational characteristics;

- Congestion management strategies such as incident management, ITS technologies, and work zone management activities can be modeled easily; and

- VISTA offers a number of preconfined reports to provide information on various types of measures of effectiveness (MOEs), such as travel time, delays, and vehicle miles traveled (VMT). VISTA also offers other customized outputs by running queries to database directly in the Web interface.

As a mesoscopic simulation-based DTA model, VISTA can meet the requirements of the study tasks by modeling the route choice of individual drivers and other important driver behaviors but limiting the level of detail when modeling driver interactions with the infrastructure and other drivers. This is accomplished by using various modules, a brief description of which follows. Additional details are available at www.vistatransport.com.

**Truck Lane Scenarios**

Three scenarios were designed to analyze their operational effectiveness vis-à-vis truck lanes. A consistent naming scheme was devised for easy reference. The name of each test scenario starts with three letters referring to the type of truck lane strategy considered (BNT=base case—no truck lane, ETL=exclusive truck lane—no passenger cars allowed, or STL=shared truck lane—Passenger cars allowed), followed by a numeral referring to the number of lanes per direction (3=3 lanes, or 4=4 lanes). More specifically:

- **Scenario BNT3** describes network operations under current conditions to provide the baseline for comparisons;

- **Scenario BNT4** assumes that a lane is added to the current network, and all lanes are available to be used by mixed traffic;

- **Scenario STL3** assumes that a lane is converted to a truck lane. Trucks are required to use the truck lane, while passenger cars may elect to use it as well;

- **Scenario ETL3** assumes that a lane is converted to a dedicated truck lane to be used exclusively by truck traffic; and

- **Scenario ETL4** assumes that a dedicated truck lane is added to the network to be used exclusively by truck traffic.

A sensitivity analysis was performed in all scenarios to consider the impact of various percentages of truck traffic in the traffic stream. Truck traffic considered ranged from 4 percent to 12 percent in increments of 4 percent. Table 1 summarizes details of the scenarios tested in this project.
Table 1: Case study scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Number of Lanes per Direction</th>
<th>Number of Truck Lanes</th>
<th>Truck Lane Type</th>
<th>Sensitivity Analysis Performed (%trucks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNT3</td>
<td>3</td>
<td>0</td>
<td>–</td>
<td>Yes (4%, 8%, 12%)</td>
</tr>
<tr>
<td>BNT4</td>
<td>4</td>
<td>0</td>
<td>–</td>
<td>Yes (4%, 8%, 12%)</td>
</tr>
<tr>
<td>STL3</td>
<td>3</td>
<td>1</td>
<td>shared</td>
<td>Yes (4%, 8%, 12%)</td>
</tr>
<tr>
<td>ETL3</td>
<td>3</td>
<td>1</td>
<td>exclusive</td>
<td>Yes (4%, 8%, 12%)</td>
</tr>
<tr>
<td>ETL4</td>
<td>4</td>
<td>1</td>
<td>exclusive</td>
<td>Yes (4%, 8%, 12%)</td>
</tr>
</tbody>
</table>

Data Analysis

Network models were developed in VISTA to represent the conditions in the scenarios discussed above. In truck lane networks, a series of links were added in parallel to the general purpose links to represent the truck lane. When a scenario called for lane addition, such links represented the added lanes. When a scenario simulated general purpose lane conversion to truck lane, the general purpose lanes along the I-65 mainline were reduced by one to accurately model the proper number of lanes. This approach was followed to overcome a difficulty created by the fact that the RouteSim simulator’s working principle is based on links and not lanes, and thus a lane-by-lane analysis is not feasible.

Ten variable message signs (VMS) were also added to selected locations throughout the study corridor to inform both truck and passenger car drivers about the truck lane option and divert the truck traffic while letting passenger car drivers to choose the shortest path during their journey as in real life as long as it is permitted throughout the scenario. For the purpose of choosing the shortest path some routes were defined as truck lane routes and others as general purpose routes, and comparisons between their operational characteristics were allowed. Four of the VMS were located on the southbound direction, and six VMSs were on the northbound direction of the study corridor.

Simulation Results

Base Case Results (BNT3 and BNT4 Scenarios)

Table 2 presents results from the sensitivity analysis performed under the current configuration (BNT3). Consideration of the network total delay time shows that the network performs optimally for 8 percent truck traffic. When a general purpose lane is added (BNT4) significant savings in delay time (43 percent) and total travel time (4 percent) are realized, as expected, along with a slight increase in average travel speed.

Table 2: Base case scenarios results (BNT3 and BNT4 scenarios).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Travel Time (veh-hrs)</th>
<th>Total Delay Time (veh-hrs)</th>
<th>Avg. Travel Speed (mph)</th>
<th>Delay Time (min/veh-mile)</th>
<th>Total Time (min/veh-mile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNT3 (4%)</td>
<td>131,715.14</td>
<td>10,328.23</td>
<td>45.426</td>
<td>0.129</td>
<td>1.434</td>
</tr>
<tr>
<td>BNT3 (8%)</td>
<td>131,947.14</td>
<td>9,832.21</td>
<td>45.321</td>
<td>0.126</td>
<td>1.432</td>
</tr>
<tr>
<td>BNT3 (12%)</td>
<td>136,938.75</td>
<td>14,627.06</td>
<td>45.159</td>
<td>0.166</td>
<td>1.473</td>
</tr>
<tr>
<td>BNT4 (4%)</td>
<td>126,051.90</td>
<td>5,941.87</td>
<td>45.761</td>
<td>0.094</td>
<td>1.395</td>
</tr>
<tr>
<td>BNT4 (8%)</td>
<td>126,123.11</td>
<td>5,883.47</td>
<td>45.714</td>
<td>0.094</td>
<td>1.396</td>
</tr>
<tr>
<td>BNT4 (12%)</td>
<td>126,663.44</td>
<td>6,363.93</td>
<td>45.631</td>
<td>0.098</td>
<td>1.401</td>
</tr>
</tbody>
</table>
**Converting Lane Case Results (STL3 and ETL3)**

**Simulation Results**

Table 3 summarizes the results obtained when converting an existing general purpose lane into a truck lane for shared (STL3) or exclusive (ETL3) use. The results are from simulation studies performed in VISTA assuming that the users continue to use their regular paths when the truck lanes are first implemented and demonstrate the network performance soon after the implementation of the truck lane scenarios.

Several observations can be made from the analysis of the results. First, it becomes apparent that for the same percentage of truck traffic the dedicated truck lane works better under the shared traffic option (i.e., when cars are allowed to use the truck lane) rather than the exclusive truck-use option. For instance, for 12 percent trucks in the traffic stream, the shared truck lane option yielded total network delay time of 10,494 vehicle hours, or 13 percent less than the exclusive truck lane option (11,858 vehicle hours). A likely reason for this is that in the ETL3 scenario, the dedicated truck lane is underutilized for the percentage of trucks considered in the analysis. It should be noted that the performance of the exclusive truck lane option improves as the percentage of truck users increases (from 14,782 vehicle hours of total delay in ETL3 (4 percent) to 11,858 in ETL3 (12 percent), or a 20-percent improvement). The comparison of the converting lane case results to the base case (BNT3) in Table 2, which further indicates that the conversion of a general purpose lane to a truck lane can only be justified for the 12 percent truck option.

**Table 3: Converting lane case simulation results (STL3 and ETL3 scenarios)—unfamiliar users.**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Travel Time (veh-hrs)</th>
<th>Total Delay Time (veh-hrs)</th>
<th>Average Travel Speed (mph)</th>
<th>Delay Time (min/veh-mile)</th>
<th>Total Time (min/veh-mile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>STL3 (4%)</td>
<td>135,030.45</td>
<td>14,091.21</td>
<td>44.426</td>
<td>0.155</td>
<td>1.468</td>
</tr>
<tr>
<td>STL3 (8%)</td>
<td>131,261.44</td>
<td>11,156.70</td>
<td>44.447</td>
<td>0.134</td>
<td>1.452</td>
</tr>
<tr>
<td>STL3 (12%)</td>
<td>128,917.38</td>
<td>10,494.17</td>
<td>44.440</td>
<td>0.139</td>
<td>1.461</td>
</tr>
<tr>
<td>ETL3 (4%)</td>
<td>128,883.84</td>
<td>14,782.31</td>
<td>44.064</td>
<td>0.162</td>
<td>1.479</td>
</tr>
<tr>
<td>ETL3 (8%)</td>
<td>126,101.80</td>
<td>11,915.19</td>
<td>44.087</td>
<td>0.141</td>
<td>1.463</td>
</tr>
<tr>
<td>ETL3 (12%)</td>
<td>124,199.39</td>
<td>11,858.29</td>
<td>44.081</td>
<td>0.149</td>
<td>1.475</td>
</tr>
</tbody>
</table>

**DTA Optimization Results**

Table 4 summarizes the results obtained when converting an existing general purpose lane into a truck lane for shared (STL3) or exclusive (ETL3) use, assuming that the users are now familiar with the treatment. The results are from optimization studies performed in VISTA using its DTA capability, assuming that the users have been considering new path options to further optimize their travel in the presence of the truck lanes. These results demonstrate the network performance in the long term, when the users become familiar with the implementation and impact of the truck lanes on local traffic operations.

The results in Table 4 show that the conversion of an existing lane to a truck lane yields best results under the shared traffic mode of operation as compared to exclusive truck traffic use. The total travel time and total delay are lower in STL3 scenario and travel speeds are slightly higher than in ETL3 for similar percentages of truck traffic. Comparison of results in Tables 4 and clearly demonstrates that both lane conversion options (STL3 and ETL3) result in improved network
performance, compared to the baseline (BNT3) for any percentage of truck traffic considered. Among the two lane-conversion options tested, the STL3 option is preferable as it leads in greater gains in network operational performance (up to a 50 percent reduction in total delay for 12 percent truck traffic). Furthermore, comparison of findings in Tables 4 and 3 indicates that while no to moderate improvement in network performance should be expected soon after the implementation of the lane-conversion strategy, significant gains will be realized in the long run, as users become familiar with the treatment and seek ways to further optimize their travel routes.

**Adding Lane Case Scenario Results (DTL4)**

Scenario DTL4 assumed that a lane is added to the network to serve truck traffic. A sensitivity analysis was performed where the percentage of truck usage was varied incrementally to evaluate short- and long-term performance measures (i.e., unfamiliar and familiar users). The results from the analysis are summarized in Table 5.

**Table 5: Add lane case—simulation and optimization results (DLT4).**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Modeling Option</th>
<th>Total Travel Time (veh-hrs)</th>
<th>Total Delay Time (veh-hrs)</th>
<th>Avg. Travel Speed (mph)</th>
<th>Delay Time (min/veh-mile)</th>
<th>Total Time (min/veh-mile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTL4 (4%)</td>
<td>Simulation</td>
<td>120,984.90</td>
<td>6,392.01</td>
<td>44.957</td>
<td>0.103</td>
<td>1.420</td>
</tr>
<tr>
<td>DTL4 (8%)</td>
<td>Simulation</td>
<td>119,349.74</td>
<td>6,483.14</td>
<td>45.329</td>
<td>0.105</td>
<td>1.412</td>
</tr>
<tr>
<td>DTL4 (12%)</td>
<td>Simulation</td>
<td>131,310.41</td>
<td>9,313.17</td>
<td>44.899</td>
<td>0.119</td>
<td>1.429</td>
</tr>
<tr>
<td>DTL4 (4%)</td>
<td>Optimization</td>
<td>126,724.59</td>
<td>6,052.51</td>
<td>45.689</td>
<td>0.095</td>
<td>1.398</td>
</tr>
<tr>
<td>DTL4 (8%)</td>
<td>Optimization</td>
<td>126,515.50</td>
<td>5,847.69</td>
<td>45.676</td>
<td>0.094</td>
<td>1.398</td>
</tr>
<tr>
<td>DTL4 (12%)</td>
<td>Optimization</td>
<td>128,551.25</td>
<td>6,872.44</td>
<td>45.388</td>
<td>0.102</td>
<td>1.408</td>
</tr>
</tbody>
</table>

The comparison of total delays and speeds in Table 5 (DLT4) and Table 2 (BNT4) reveal that in the case of a lane addition, no improvement in system performance is achieved by designating the lane as a truck lane for any percentage of truck traffic within the study range. In other words, the added capacity serves well the needs of all users and no further improvement is expected from separating truck traffic from the rest of the traffic stream. Thus, a designated truck lane is not justified under the study assumptions when a lane is added on the study facility.
Conclusions

This paper first investigated the impacts from conversion of a freeway lane to truck lane for shared or exclusive use by trucks along a testbed in Birmingham, Alabama. Then, addition of a lane was considered with the added lane being a general purpose lane or a lane designated for truck use. The VISTA environment was employed to construct the models. VISTA allowed for consideration of near- and long-term impacts from potential implementation as it allows for both simulation and DTA/DUE optimization. Analysis of the study findings revealed the following:

- In the short term, a general purpose lane conversion to a truck lane is justified only for 12 percent truck traffic and above. However, in the longer term, significant gains in delays and travel time are to be realized as drivers become familiar with the new treatment and seek alternative routes to optimize their travel. Thus the lane conversion to a truck lane is justified on the basis of operational impacts;

- Should a general purpose lane be converted to a truck lane, shared use of the truck lane would lead to greater benefits in network performances compared to those expected from exclusive use of the truck lane by trucks; and

- Addition of a lane on the study network further improves the overall network performance; however, designation of the added lane as a truck lane has little to no impact on traffic operations and thus is not justified;

It is recommended that further calibration and validation studies are performed to improve modeling accuracy and the confidence in the model findings. Moreover, additional analysis can be performed to explore alternative congestion management strategies that may be more appropriate to address current and future travel needs in the Birmingham area. Examples include high occupancy vehicle lanes (HOV), speed harmonization, temporary shoulder use, and dynamic signing and rerouting.

Moreover, the success of implementation greatly depends on public support for the project and positive public perception. Thus, the role of public education in the early planning stage is critical and should not be overlooked. Focus groups, open public discussion forums, public information sessions, and media coverage are useful tools that can assist local agencies to obtain input from the public and other local stakeholders and educate truck drivers and other road users about the new treatment.

Finally, it is recommended that a cost-benefit analysis be performed to estimate potential benefits and costs, including capital, operation, and maintenance costs for the public and private sectors from the implementation of truck lane strategies in the Birmingham region.

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References


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Tailgating is a dangerous driving behavior and is a leading cause of rear-end crashes. Understanding tailgating situations on highways and exploring means to mitigate tailgating behavior is a priority to many urban traffic management authorities. A three-part study was conducted to investigate the tailgating issue and possible counter-tailgating measures.

To assess the causes and effects of tailgating and its impact on urban highway traffic, the study started with a questionnaire survey and a vehicle headway analysis. The questionnaire survey was launched to find the leading causes of tailgating and to identify drivers’ perceptions on tailgating behavior. Most of the participating drivers identified heavy traffic as the top tailgating cause, and most felt that they had been affected by tailgaters and had reacted in some way. The survey also found that 94.8 percent of participating drivers had an incorrect sense regarding proper vehicle headway and thus tailgated when driving on highways. A vehicle headway analysis was next conducted by examining vehicle headways on specific segments of urban highways in Rhode Island, USA. It was found that more than 60 percent of vehicles were tailgating during rush hours and about 40 percent during non-rush hours. The findings confirmed that serious tailgating was present on urban Rhode Island highways. To advise drivers and mitigate their tailgating behaviors, counter-tailgating measures such as advisory signs and educational videos were then developed. The effectiveness of these measures was assessed through a driving simulation experiment. It was found that tailgating behavior could be limited when advisory signs were posted along highways. The effect was even more pronounced if the subject viewed the educational video prior to the simulation. Participants’ driving behaviors were further investigated through a field study. Most participants found it difficult to maintain a safe following distance in a real driving environment, since there is currently no measure employed to treat tailgating behaviors. Based on the results, it is recommended that the proposed counter-tailgating measures be adopted into a more sophisticated tailgating treatment system.
Introduction

This paper presents a three-part study that investigated the tailgating issue on urban highways and possible means to mitigate tailgating behaviors. Tailgating, or following with insufficient vehicle headway, is a leading cause of rear-end crashes. It is believed that driver’s reaction time varies depending on the complexity of the driving situation from about 0.5 seconds for simple situations to 4 seconds for complex situations and that the reaction time in braking is about 2.5 seconds. Similarly, Green and Summala reported in their studies that simple reaction time was often less than 1 second while decision reaction time, such as the time it takes to tap the brake, could take much longer. According to this, a quantified safe following distance has been written into the rules of the road. It varies from state to state, but is mostly in the form of a “2-second rule.” Drivers are advised to keep a vehicle headway of at least 2 seconds between their own car and the vehicle ahead of them. Vehicle headway is the time between successive vehicles as they pass a common reference point. Following with a vehicle headway of less than 2 seconds is considered unsafe. Rear-end crash risk increases as vehicle headway decreases. When vehicle headway reduces to zero, a rear-end crash occurs.

“Tailgating” is generally considered as a severe form of aggressive driving, which is defined by the National Highway Traffic Safety Administration (NHTSA) as “an individual committing a combination of moving traffic offenses so as to endanger other persons or property.” Among many driving patterns considered aggressive, tailgating is among the most dangerous and is a major cause of rear-end crashes. According to the National Center for Statistics and Analysis (NCSA), out of an annual average of 5.9 million police-reported automobile accidents in the United States during 2006–2008, rear-end crashes ranked the highest, with more than 1.8 million cases (30.4 percent) and resulted in more than 2,200 fatalities and approximately half a million injuries each year. Data from the Federal Highway Administration (FHWA) indicate that, each year, approximately 2.2 percent of total licensed drivers in the United States are involved in rear-end crashes. Two factors are primarily responsible for rear-end crashes: inattention and tailgating—while the latter is the major contributing cause with a deadly consequence. To help reduce crashes caused by tailgating, effective means are needed to help drivers maintain proper vehicle headway.

A wide range of factors such as drivers’ behavior, traffic and road conditions, vehicle and roadway design, state law and regulation, social norms, and even personality could affect vehicle headway. Ohta suggested that drivers tend to drive in a comfortable zone in which headways vary between 1.1 and 1.7 seconds, while maintaining closer headways when traffic volume is high. Ohta also concluded that both stable personality factors and transient motivational differences can influence drivers’ headways. Evans conducted a series of observational studies with his colleagues to identify factors that could lead to risk-taking behaviors such as tailgating. One study found that drivers’ headways increased with age and that females adopted longer headways. In another study, drivers not wearing seat belts were found maintaining shorter headways.

Hutchinson conducted an in-depth investigation in Australia on rear-end crashes and tailgating and the correlation between them. Counter-tailgating measures such as advisory signs, pavement markings, and enforcement by the police were recommended in his study to help reduce rear-end crashes.

Rama and Kulmala conducted a field study in Finland and investigated the effects of two dynamic message signs (DMS) on drivers’ car-following behavior. The signs warned of slippery road conditions and advised drivers to keep a minimum following distance. The study was performed as a before-and-after experiment at three test sites. Results showed that the slippery road conditions sign reduced the mean speed by 1–2 kilometers per hour (km/hr). Part of this may be attributable to the decrease in speed caused by the adverse road conditions. The minimum following distance sign reduced the proportion of cars with a headway of less than 1.5 seconds by more than 30 percent, in addition to a speed reduction of 1 km/hr.
Michael, Leeming, and Dwyer22 implemented a method to collect tailgating data in an urban setting and assessed the effectiveness of two handheld roadside signs admonishing drivers not to tailgate. (One read “Please Don’t Tailgate” and the other read “Help Prevent Crashes, Please Don’t Tailgate.”). Data collected from more than 25,000 drivers were studied. The research found that the sign with a reference to crashes had a greater impact on drivers’ vehicle headway, increasing the average headway by 0.18 seconds when compared to the other one.

To help drivers gauge their following distances, research was conducted to assess the effects of regularly spaced markings on highway pavement. Lertworawanich23 conducted a study to estimate safe car-following distance according to speed limit and developed the “dot” treatment pavement markings. Headways in terms of distance were examined before and after the implementation of “dot” markings. Lertworawanich found that headways at a given flow rate were increased after the marking implementation, and the likelihood of rear-end collisions was reduced at the study site. Chevron spaced 131 feet apart were painted on a United Kingdom motorway in a study by Helliars-Symons, Webster, and Skinner.24 The markings were implemented with signs advising drivers to “Keep Your Distance” and “Keep Apart 2 Chevrons” in an effort to achieve vehicle headways of more than 2 seconds at 70 mile per hour (mph) speeds. The results were encouraging, with a large reduction (56 percent) in crashes at the study site.

Tailgating treatment programs employing the “dot” markings were pilot tested in Pennsylvania and Minnesota, USA. The Pennsylvania Department of Transportation’s (PENNDOT) program was considered the most successful and was honored in 2001 with the National Highway Safety Award. On a portion of US Route 11 that previously experienced high rates of tailgating, aggressive driving and tailgating dropped 60 percent after the implementation of reflective dots and advisory signs that helped motorists gauge their distance behind leading vehicles.25 Before the implementation, there were 135 crashes per year, costing approximately $1.9 million. After the implementation, yearly crashes decreased to 60, at a reduced cost of $1.3 million. Statistics showed that crash reductions remained fairly constant many months after the implementation, pointing to the success of the program.

Minnesota DOT and Public Safety piloted a similar project in 2006. The project’s goals were to educate motorists on how to identify and maintain a minimum safe following distance and to ultimately reduce rear-end crashes. Minnesota used similar engineering elements as the Pennsylvania program: elliptical pavement dots, static roadside advisory signs with a “Keep Minimum 2 Dots Apart” message, and a strong public information campaign. A section of State Highway 55 in Wright County was painted with 47 elliptical dots in each direction, spaced 225 feet apart. If a motorist was traveling at 55 mph with a 3-second following distance, then two dots were visible between their car and the car in front of him or her. Vehicle headway data collected prior to and after the treatments showed that the average headway increased from 2.36 to 2.62 seconds, or 22.89 feet at the midpoint of the test site.26

Findings from the above studies demonstrated the effectiveness of advisory signs and pavement markings in reducing tailgating behavior. Although measurable benefits of the PENNDOT and Minnesota DOT programs were identified, there were reported complaints about the pavement markings as they might distract drivers. Compared to pavement markings, advisory signs are less intrusive and distinctive to drivers. They are also easier to implement and maintain. Given these advantages, a few different advisory signs in this study were proposed and assessed through a driving simulation.

Following review of the relevant literature on previous studies related to tailgating and counter-tailgating measures, the current study was designed with a goal of mitigating tailgating behaviors on urban highways.
Description of the Study

Three instruments were employed in this study. First, a questionnaire survey was conducted on drivers’ opinions regarding the causes and effects of tailgating and their experiences and perceptions of tailgating behavior. A vehicle headway analysis was next conducted to assess the tailgating situation on urban highways in Rhode Island, USA. Since there are measures that could help drivers maintain safe following distance and reduce rear-end collisions, advisory signs and an educational video were next developed to advise and educate drivers about safe following distance. Findings from the survey and the vehicle headway analysis led to a driving simulation that allowed a real-time test on drivers’ responses to proposed counter-tailgating measures. Participants’ driving behaviors were further examined in real driving through a field study.

Questionnaire Survey

Survey Design

A questionnaire survey was designed and deployed using Microsoft PowerPoint and Visual Basic macros to present questions and collect subjects’ answers. Nineteen questions were presented to help identify the causal factors of tailgating and to gain insights about drivers’ experiences and perceptions regarding tailgating on urban highways. The survey also assessed drivers’ attitudes when they were following other vehicles or being followed.

Survey Administration

The survey was conducted at multiple locations in Rhode Island in order to obtain a representative sample of the Rhode Island driving population. The University of Rhode Island and the Warwick Mall were among several sites where the survey took place. Subjects with a valid driver’s license were randomly recruited at the survey sites with voluntary participation. Prior to taking the survey, each participant read and gave his or her consent on an electronic consent form, approved by the university’s Institutional Review Board. The subject would then take the survey, presented as PowerPoint slides on a laptop computer. Survey questions were presented one at a time with no time limit. Answers were given either directly on the computer or via verbal responses given to the survey assistant.

A total of 210 subjects participated in the survey. Among them, 91 (43.3 percent) were between 18 and 40 years old, 72 (34.3 percent) were between 41 and 60, and 47 (22.4 percent) were older than 60. There were 107 females (51.0 percent) and 103 males (49.0 percent). Age and gender percentages of the survey resembled the Rhode Island population.

Vehicle Headway Analysis

To assess the tailgating issue on urban Rhode Island highways, traffic videos collected at three test sites within the Providence metropolitan area were analyzed. The three test sites were I-95 at Detroit Ave., I-195 at Rte. 114, and I-295 North at Exit 6 (Figure 1). The study examined highway traffic surveillance videos that captured eight lanes of traffic taken by three highway surveillance cameras at the test sites (only four lanes of I-295 were studied due to the poor video quality of southbound traffic).

Data Collection

Videos that captured the weekday traffic during a two-week period in December 2008 were provided by Rhode Island Department of Transportation (RIDOT). On each day, videos taken between 7:30 a.m. and 8:00 a.m. and between 10:00 a.m. and 10:30 a.m. were analyzed. Since rush hour is typically defined as periods from 6:00 a.m. to 9:00 a.m. and from 4:00 p.m. to 7:00 p.m. during weekdays,
videos taken between 7:30 a.m. and 8:00 a.m. were considered to be rush hour videos, and non-rush hour videos were those between 10:00 a.m. and 10:30 a.m.

From each of the 30-minute video clips, three 5-minute intervals were randomly selected for analysis. Vehicle headway data and traffic volume data were collected from these intervals. To determine the vehicle headway for a vehicle, a fixed reference line was drawn in the recorded scene, and based on the time stamp (in increments of 0.01 seconds) embedded in the video, the time when the front bumper of a vehicle reached the reference line was recorded. By calculating the time difference between two consecutive vehicles crossing the reference line, vehicle headway in hundredths of seconds was determined for the following vehicle. Traffic volumes were collected by counting vehicles that appeared in the surveillance videos in each lane during the randomly chosen 5-minute time intervals.

**Data Analysis**

In the analysis, vehicles in different lanes were recorded by their vehicle headways in units of seconds. According to the 2-second rule, they were classified as either tailgaters or non-tailgaters. Vehicles that broke the 2-second rule, which means their headways were between 0 and 2 seconds, were marked as tailgaters, and the rest were labeled non-tailgaters. Percentages of tailgaters among vehicles at each test site and in each individual lane were calculated and used as indicators of the degree of tailgating.

To find out whether traffic volume was a significant factor affecting tailgating, a paired t-test was employed to compare the degree of tailgating between rush hours and non-rush hours at the three test sites. These analyses were further stratified by lane and bound, since all three test sites were eight-lane highways with traffic in both directions. The hypotheses of the test are as follows:

\[ H_0: \mu_d = 0 \]
\[ H_1: \mu_d > 0 \]

where \( \mu_d = \mu_{\text{rush hour}} - \mu_{\text{non-rush hour}} \)

Since traffic volume varied significantly between rush hours and non-rush hours, the study further investigated the functional relationship between tailgating and traffic volume through a correlation analysis. The percentages of tailgaters at the randomly chosen time intervals during rush hours and non-rush hours were regressed against respective traffic volumes in these time intervals. Analyses were made on different lanes as well as at different test sites.
Driving Simulation

Simulator

Participants operated a fixed-base driving simulator (L-3 Communications, Inc.) consisting of a regular vehicle driving module and three plasma monitors. Five networked computers generate the simulation by processing the driver’s inputs to the vehicle’s controls while perpetually updating the audio stream and the driving scene on four visual channels. Three of the channels display the drivers’ forward view. One supports the LCD front panel. Participants interacted with the simulator using the sedan’s steering wheel and pedals that provided force feedback.

Counter-Tailgating Measures

Among several alternatives, two advisory messages were selected to be tested in the simulation, which were “Keep Minimum 2 Seconds Apart” and “Keep a Safe Following Distance.” The advisory message was posted on either a static roadside sign or an overhead dynamic message sign (DMS) (see Figure 2). The first message, similar to the advisory message used in the Minnesota tailgating project, used the words “2 Seconds” to alert drivers about the 2-second vehicle headway recommendation. Rather than the quantitative advice given in the first message, the second message used qualitative advice. The design of the driving simulation experiment will allow a comparison to be made on the effects of these two messages and two presentation formats.

Through the questionnaire survey, it was found that most drivers lacked the correct sense regarding safe vehicle headway. To help drivers gauge their vehicle headway, an educational video was developed with both auditory and visual instructions on how to maintain a safe following distance. In the video, drivers were instructed to use a roadside reference point, such as a sign or a marking pole, to keep a 2-second vehicle headway and were advised to slow down if the vehicle headway was less than 2 seconds.

Figure 2: Two advisory messages posted on a static sign and a DMS.

Driving Simulation Experiment Design

In the experiment, the effectiveness of the advisory signs and educational video was assessed. An approximately 8-minute baseline highway driving simulation scenario was first developed. Different advisory messages posted on different types of signs were used in the scenario to create different experiment settings. About 1 minute into the scenario, the driver entered the sign zone, where
advisory messages were either posted on an overhead DMS or on a static sign on the left side of the high-speed lane. A participant’s driving behavior was recorded from this point until the completion of the simulation. To assess the effect of traffic conditions on vehicle headway, traffic conditions were placed in the experiment. A participant could start driving with heavy traffic that changed halfway through the simulation to light traffic or vice versa by random assignment.

In the experiment, participants were randomly divided into four groups in which they would see different advisory signs shown in the scenario. A description of the groups and the use of advisory signs and the educational video in each group is shown in Table 1.

Table 1: The four groups and the use of advisory signs and educational video in the three runs.

<table>
<thead>
<tr>
<th>Group</th>
<th>1st Run</th>
<th>2nd Run</th>
<th>3rd Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No sign</td>
<td>“Keep a Safe Following Distance” on a static roadside sign</td>
<td>Educational video</td>
</tr>
<tr>
<td></td>
<td>No video</td>
<td>No video</td>
<td>No video</td>
</tr>
<tr>
<td>2</td>
<td>No sign</td>
<td>“Keep Minimum 2 Seconds Apart” on a static roadside sign</td>
<td>Educational video</td>
</tr>
<tr>
<td></td>
<td>No video</td>
<td>No video</td>
<td>No video</td>
</tr>
<tr>
<td>3</td>
<td>No sign</td>
<td>“Keep a Safe Following Distance” on a DMS</td>
<td>Educational video</td>
</tr>
<tr>
<td></td>
<td>No video</td>
<td>No video</td>
<td>No video</td>
</tr>
<tr>
<td>4</td>
<td>No sign</td>
<td>“Keep Minimum 2 Seconds Apart” on a DMS</td>
<td>Educational video</td>
</tr>
<tr>
<td></td>
<td>No video</td>
<td>No video</td>
<td>No video</td>
</tr>
</tbody>
</table>

During the simulation, each participant was asked to drive through the scenario three times (three runs, as shown in Table 1). In the first run, a driver drove through the baseline scenario with no advisory signs present and traffic conditions changed halfway through. The driver was asked to drive the same way that he or she does in real life. Baseline data were collected in this run. The particular advisory sign associated with the participant’s group appeared in his or her second and third runs along with the change of traffic condition. The educational video was displayed before the third run, instructing drivers on how to maintain a safe following distance while driving on highways.

Simulation Data Analysis

In each of the three runs, eight vehicle headways were collected at random points (four per traffic condition), and a total of 24 headway data points were collected from each participant. Analysis of variance (ANOVA) was conducted to investigate the effect of the following factors on vehicle headways: the presence of advisory signs, the advisory message, the type of sign, the use of the educational video, and the traffic condition.

The effect of the presence of advisory signs could be assessed by comparing vehicle headways collected from the first and the second runs. Headways collected in the second run provided a means to assess the effect of advisory messages and the type of sign and the interaction between them. The effectiveness of using the educational video could be demonstrated by comparing vehicle headways collected from the second and the third runs. Traffic condition was assessed as a blocking factor in each ANOVA.
Field Study

Participants’ driving behaviors were further examined in real driving. Participants who completed the driving simulation experiment were invited to participate in a field study. Each participant was driving his or her own vehicle, accompanied by a researcher. All participants took the same route by entering I-95 South from Exit 15 in Rhode Island and leaving at Exit 12 and returning through the reverse route on I-95 North. They were advised to stay in the inner lanes while driving on the highway to avoid traffic entering and exiting the highway. They were also advised to maintain a 2-second vehicle headway following the instructions given in the educational video. The whole driving process was recorded by a video camera on a tripod from the driver’s view. These recorded videos were transferred to a computer and analyzed frame by frame. Eight headway data points were randomly collected, four from each direction for each participant.

Results and Discussion

Questionnaire Survey

In the questionnaire, participants’ understandings and perceptions of tailgating issues were surveyed. They were first asked to select and rank the top three causes of crashes from among 13 options. According to the weighted scores (three points for the first ranked, two points for the second, and so forth), the top three leading causes of crashes were distraction, speeding, and tailgating, followed by road rage, DUI, changing lane without signaling, running red lights, and so forth. “Heavy traffic,” “slow car ahead of my vehicle,” and “I am in a hurry” were the top three choices for tailgating (Table 2).

<table>
<thead>
<tr>
<th>Table 2: Applicable causes of tailgating (multiple-choice).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Which of the following could cause you to tailgate while driving on highways? Mark all that apply.</td>
</tr>
<tr>
<td>Heavy traffic</td>
</tr>
<tr>
<td>36.1%</td>
</tr>
</tbody>
</table>

* An act of driving using techniques that maximize fuel economy such as closely following a truck to reduce wind resistance.

When participants were asked about their reactions when being tailgated, most indicated that they were affected by tailgaters but reacted passively as indicated by their top choice, “change lanes to let the tailgater pass” (Table 3).

<table>
<thead>
<tr>
<th>Table 3: Reactions when being tailgated (multiple-choice).</th>
</tr>
</thead>
<tbody>
<tr>
<td>How would you react if you were followed too closely? Mark all that apply.</td>
</tr>
<tr>
<td>Change lanes to let the tailgater pass</td>
</tr>
<tr>
<td>34.1%</td>
</tr>
</tbody>
</table>
Most subjects (70 percent) indicated that they did not usually follow others while driving on highways, and 67.6 percent indicated that they never intentionally followed other vehicles too closely. When asked about the reasons for not following other vehicles, 49.5 percent indicated that it’s safer not following others. Most subjects (73.8 percent) indicated that keeping a safe vehicle headway was very important. When asked about safe vehicle headways, the majority of subjects (77.1 percent) indicated that they knew what the proper vehicle headway was, and 90.5 percent believed that they always kept a safe vehicle headway or at least did so most of the time. From these results, it did not appear that a serious tailgating problem existed, but further questions indicated otherwise.

When asked about the definition that best described tailgating, 76.2 percent of the subjects chose “following too close to the vehicle ahead” and only 11.4 percent chose “insufficient following distance.” This indicated that most drivers had only a qualitative idea of what tailgating means instead of a quantitative one. When questioned “how much distance do you maintain when driving at 60 miles per hour (mph) on highways,” 94.8 percent of subjects indicated that they maintained a vehicle headway of less than 11 car lengths, and almost half maintained less than four car lengths (Figure 3). A 2-second vehicle headway requires a following distance of 11 car lengths when driving at 60 mph (assuming a car length of 15 feet). The survey showed a severe tailgating issue, as most drivers did not know what the proper vehicle headway was and drove with insufficient following distance. Although 75.2 percent of subjects indicated in another question that they maintained a vehicle headway equal to or greater than 3 seconds, it is not likely that they kept 3 seconds of headway, which would require about 16 car lengths. Subjects’ opinions on vehicle headway expressed in car lengths could be more reliable, since 78.6 percent of them preferred using car lengths to measure vehicle headway. The findings from the survey indicated that the majority of Rhode Island drivers might have an incorrect sense regarding safe vehicle headway and follow other vehicles closely on highways. The survey results confirmed serious tailgating on urban Rhode Island highways identified in vehicle headway analysis.

**Vehicle Headway Analysis**

The distributions of vehicle headways during both rush hours and non-rush hours at the three test sites are shown in Figure 4. Collected vehicle headways ranged from less than 1 second to more than

![Figure 3: Vehicle headways maintained by drivers when driving at 60 mph.](image-url)
30 seconds. It should be noted that large vehicle headways were not generally considered “following,” and thus the distributions displayed here include only up to 10 seconds of vehicle headways. There were more than 60 percent of drivers (ranging from 51.8 percent to 66.9 percent at the three test sites) who drove with vehicle headways of less than 2 seconds during rush hours, and almost 35 percent drove with headways of less than 1 second. During non-rush hours, less tailgating behaviors were observed and the majority of tailgaters occurred in the 1–2 second interval, which is the comfortable zone mentioned in Ohta’s study.18

The proportions of vehicles following with less than 2 seconds of vehicle headway at the three test sites on Rhode Island interstate highways are tabulated in Table 4. The statistics are shown by test site, by day of the week, and by time of the day. From the analysis, 61.2 percent of vehicles were tailgating during rush hours and 39.2 percent during non-rush hours. Tailgating situations during rush hours and non-rush hours were compared through paired t-tests and were found to be significantly different (p values = 0) at all three locations. The tailgating percentages during rush hours were consistent, regardless of the day of the week. Similar results were observed during non-rush hours.

To further assess the tailgating situation, the percentages of tailgaters were stratified by lane and direction. Table 5 shows that vehicles in the high-speed (innermost) lane exhibited the worst tailgating behavior (highest tailgating percentage during rush hours) while the outermost lane had the lowest tailgating percentage (except for the test site on I-295). This could be due to the fact
that tailgating is correlated with speed, and vehicles traveling in high-speed lanes tend to follow other fast-driving vehicles. Higher percentages of tailgaters were observed on I-95 northbound and I-195 westbound, especially during rush hours. This might be due to the heavy traffic entering the Providence metropolitan area during rush hours. Tailgating situations during rush hours and non-rush hours in each individual lane were further compared through paired t-tests and were found to be significantly different (p values < 0.05) in each of the four lanes.

From the statistics shown in Table 4 and Table 5, it was found that the tailgating situation was more serious during rush hours than non-rush hours. Since traffic is much heavier during rush hours, this confirmed the survey results that heavy traffic was the major cause of tailgating. A correlation between the percentage of tailgaters and the traffic volume could exist.

Linear regressions were conducted to investigate the functional relationship between tailgating and traffic volume at all test sites. Figure 5 shows that strong correlations existed at all three test sites with high R² values. It is concluded that tailgating increases as traffic volume increases. The two clusters that appear in each plot represented the traffic at rush hours and at non-rush hours.
To assess the correlations for different lanes, additional regression analyses were conducted, and the results are shown in Table 6. As seen from Table 6, strong correlations existed between tailgating and traffic volume in all lanes (R² values ranging from 73.7 percent to 84.3 percent). Although the innermost lane had the lowest slope among all four lanes, its large intercept value (about twice the value of any other lane) made it the lane with the most serious tailgating problem.

The vehicle headway analysis provided strong evidence that serious tailgating occurred on major urban highways in Rhode Island. It is believed that similar tailgating situations could be found on other urban highways and could pose severe traffic safety concerns for highway driving. Although higher traffic volume could lead to more serious tailgating issues, there were still 39.2 percent of vehicles tailgating during non-rush hours. Effective counter-tailgating measures are needed on urban highways.

### Driving Simulation

A total of 36 licensed drivers participated in the simulation study. Among them, 10 were females and 26 were males; 26 were between 18 and 40 years old, and 10 were between 41 and 60 years old. Twelve participants from the driving simulation experiment participated in the follow-up field study. Among the 12 participants, six were females (50 percent) and six were males (50 percent); 11 (91.6 percent) were between 18 and 40 years old, and one (8.4 percent) was between 41 and 60.

The driving simulation participants were equally divided into four groups with nine people in each group. None of the participants had previous experience with the driving simulator. Average vehicle headways categorized by group, run, and traffic condition are shown in Table 7.

As noted from Table 7, average vehicle headway in the first run was 1.02 seconds when no advisory sign was used. The average vehicle headway was increased by 0.22 seconds in the second run when advisory signs were posted. When static signs were posted (group 1 and 2), the average vehicle headway was increased by 0.14 seconds, while the presence of DMS increased the average vehicle headway of groups 3 and 4 by more than twice that amount, 0.30 seconds. This might be due to the fact that drivers paid less attention to static roadside signs. It should also be noted that advisory signs were not able to help drivers maintain a sufficient following distance, as the average vehicle headway in the second run was still less than 2 seconds (1.24 seconds). Significant increases in vehicle headways were observed in all four groups in the third run after the educational video was shown to the drivers. As noted from Table 7, drivers were able to maintain a 2-second vehicle headway in the third run. The effect of traffic
Table 6: Correlations between percentage of tailgaters (p) and traffic volume (v) in four different lanes.

<table>
<thead>
<tr>
<th>Lane</th>
<th>Model</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innermost Lane</td>
<td>P = 0.2827 + 0.01344V</td>
<td>83.3%</td>
</tr>
<tr>
<td>2nd Lane</td>
<td>P = 0.1401 + 0.01576V</td>
<td>82.1%</td>
</tr>
<tr>
<td>3rd Lane</td>
<td>P = 0.1336 + 0.01574V</td>
<td>84.3%</td>
</tr>
<tr>
<td>Outermost Lane</td>
<td>P = 0.1505 + 0.01457V</td>
<td>73.7%</td>
</tr>
</tbody>
</table>

Table 7: Average vehicle headway (seconds) by group, run, and traffic condition.

<table>
<thead>
<tr>
<th>Group</th>
<th>1st run*</th>
<th>2nd run**</th>
<th>3rd run***</th>
<th>Traffic condition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Light</td>
<td>Heavy</td>
<td>Light</td>
<td>Heavy</td>
</tr>
<tr>
<td>1</td>
<td>1.06</td>
<td>1.15</td>
<td>2.05</td>
<td>1.50</td>
</tr>
<tr>
<td></td>
<td>(“safe following” on a static sign)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.92</td>
<td>1.11</td>
<td>1.99</td>
<td>1.44</td>
</tr>
<tr>
<td></td>
<td>(“2 seconds” on a static sign)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1.01</td>
<td>1.29</td>
<td>2.18</td>
<td>1.62</td>
</tr>
<tr>
<td></td>
<td>(“safe following” on a DMS)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1.08</td>
<td>1.40</td>
<td>2.07</td>
<td>1.60</td>
</tr>
<tr>
<td></td>
<td>(“2 seconds” on a DMS)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>1.02</td>
<td>1.24</td>
<td>2.07</td>
<td>1.54</td>
</tr>
</tbody>
</table>

* baseline driving
** with advisory sign
*** with advisory sign and educational video

Table 8: ANOVA table regarding the effect of the advisory signs.

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sign Presence</td>
<td>1</td>
<td>7.012</td>
<td>7.012</td>
<td>54.37</td>
<td>0.000*</td>
</tr>
<tr>
<td>Traffic Condition</td>
<td>1</td>
<td>4.849</td>
<td>4.849</td>
<td>37.60</td>
<td>0.000*</td>
</tr>
<tr>
<td>Error</td>
<td>573</td>
<td>73.769</td>
<td>0.129</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>575</td>
<td>85.630</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significant at α= 0.05

Conditions also have an impact on vehicle headway. Compared with heavy traffic conditions, light traffic allowed larger vehicle headways. This confirmed the conclusion made in Ohta’s study that drivers tended to maintain closer headways when traffic volume is high.

As shown in the ANOVA table (Table 8), the presence of advisory signs was a significant factor (p value = 0). With the presence of advisory signs, average vehicle headway increased from 1.02 seconds to 1.24 seconds (Figure 6). Traffic conditions also proved to be significant, with a p value equal to 0. Average vehicle headway decreased from 1.22 seconds with light traffic to 1.04 seconds when traffic was heavy (Figure 6). This indicated that participants tended to follow closely with heavy traffic.
The effect of the advisory message, type of sign, and the interaction between them was assessed through ANOVA on the second run results. The type of sign affected participants' vehicle headway in a significant way, with a p-value equal to 0, while the advisory message was not a significant factor (p value = 0.440) and neither was their interaction (p value = 0.090). Main effects plots regarding the effect of advisory message and type of sign are shown in Figure 7. Compared to static signs, advisory messages posted on overhead DMSs were found to be more effective in increasing vehicle headway (0.21 seconds more). Using “Keep a
Safe Following Distance” or “Keep Minimum 2 Seconds Apart” as the advisory message did not make a significant difference.

ANOVA results regarding the use of the educational video are shown in Table 9. Compared to vehicle headways collected in the second run, the use of the educational video before the third run did significantly increase the vehicle headway (p value = 0) by 0.84 seconds (Figure 8). Participants were able to maintain a safe following distance after reviewing the educational video. Traffic conditions still affected vehicle headway in a significant way (p value = 0). The average vehicle headway was 1.75 seconds with light traffic, and it decreased to 1.56 seconds when traffic was heavy (Figure 8).

Driving behaviors of 12 simulation participants were further assessed in field studies. Most of the field studies were conducted during non-rush hours, mainly between 10:00 a.m. and 4:00 p.m. Through a frame-by-frame analysis on the recorded videos from all drivers, it was found that the average vehicle headway was 1.83 seconds. Despite the participants’ efforts to maintain a 2-second vehicle headway, it was observed that other drivers often cut in and thus reduced following distances. The field study results indicated that maintaining a safe following distance in real driving was difficult without an effective tailgating treatment system in place. The advisory sign proposed in this study would be an ideal component to be included in the system.

Figure 8: Effects of the use of educational video and the traffic condition on vehicle headway (2nd and 3rd runs).

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Video Use</td>
<td>1</td>
<td>5.532</td>
<td>5.532</td>
<td>33.95</td>
<td>0.000*</td>
</tr>
<tr>
<td>Traffic Condition</td>
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<td>100.292</td>
<td>100.292</td>
<td>615.39</td>
<td>0.000*</td>
</tr>
<tr>
<td>Error</td>
<td>573</td>
<td>93.270</td>
<td>0.163</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>575</td>
<td>199.094</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significant at $\alpha = 0.05$
Conclusion and Future Works

This study surveyed drivers regarding the causes and effects of tailgating and examined the tailgating situation on urban highways in Rhode Island. The survey found that the majority (94.8 percent) of respondents did not know what the proper vehicle headway was and maintained insufficient vehicle headways while following other vehicles on highways. Among many causes of tailgating, heavy traffic was considered the top factor by most drivers.

Through the vehicle headway analysis, serious tailgating (61.2 percent) was identified during rush hours. This confirmed the results found from the survey. Through the hypotheses tests and correlation analyses, it was found that tailgating was strongly correlated with traffic volume. Although less tailgating was observed during non-rush hours, there were still 39.2 percent of vehicles following with insufficient headways. Tailgating percentages by lane and bound showed that tailgating was worse in the innermost lanes and on bounds with high traffic volumes. The serious tailgating situation in the innermost lanes was also confirmed in the correlation analysis. The findings indicated a need for counter-tailgating measures on urban highways.

The use of advisory signs and an educational video as counter-tailgating measures to advise drivers to maintain a safe following distance was studied. The study employed a driving simulation to assess the effects of these proposed counter-tailgating measures. As a comparison, participants’ driving behaviors were also examined in real driving.

The findings of the driving simulation showed that tailgating problems could be mitigated by the proposed counter-tailgating measures such as advisory signs and educational video. Advisory messages posted on overhead DMSs were found more effective in limiting tailgating behaviors than fixed roadside sign messages. With the viewing of an educational video, drivers learned to better gauge their vehicle headways and maintained longer headways compared to those measured before they watched the video. The wording of the message, whether quantitative or qualitative in nature, did not significantly affect drivers’ vehicle headways. Most participants were able to maintain a safe following distance in the driving simulation after viewing the educational video. It was, however, difficult for them to maintain a 2-second vehicle headway in real driving. This confirmed that serious tailgating existed in Rhode Island. A more sophisticated tailgating treatment system including the proposed advisory signs would be needed to mitigate the tailgating problem on urban highways.

The effect of the treatment could be significantly augmented through education as demonstrated in the study. Multiple tailgating treatment systems could be developed based on the findings from this study, and driving simulations could be employed to help assess these systems. Before-and-after traffic and crash data could be collected and analyzed to further assess the effectiveness of a system after its implementation. It is hoped that this project could help lead the way in developing effective tailgating treatment systems for U.S. urban highways and encourage more research in this area.

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References


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