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Truck Travel Characteristics as an Indicator of System Condition and Performance

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16. Abstract
The effect of trucks on the level of service is determined by considering passenger car equivalents (PCE) of trucks. The Highway Capacity Manual (HCM) uses a single PCE value for all tucks combined. However, the composition of truck traffic varies from location to location; therefore a single PCE-value for all trucks may not correctly represent the impact of truck traffic at specific locations. Consequently, the Indiana Department of Transportation wanted to develop separate PCE values for single-unit and combination trucks to replace the single value provided in the HCM. Traditionally, equivalent delay and microscopic simulations have been used to estimate PCE values. In order to facilitate the development of site specific PCE values, an alternative PCE-estimation methodology was explored in the present study on the basis of lagging headways measured from field traffic data. The study used data from four locations on a single urban freeway and three different rural freeways in Indiana. Three-stage-least-squares (3SLS) regression techniques were used to generate models that predict lagging headways for passenger cars, single unit trucks, and combination trucks. The estimated PCE values for single-unit and combination truck for basic urban freeways (level terrain) were 1.35 and 1.60, respectively. For rural freeways, the estimated PCE values for single-unit and combination truck were 1.30 and 1.45, respectively. However, due to the lack of sufficient quality data for rural freeways, the estimated PCE values for rural freeways are not recommended for use. As expected, traffic variables such as vehicle flow rates and speed have significant impacts on vehicle headways. The use of separate PCE values can have significant influence on the LOS estimation. This study also explored regional variation of PCE values. The results of the likelihood ratio test indicated that it is appropriate to combine data from similar locations (freeway sections at different geographical locations) for the PCE analysis.

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EXECUTIVE SUMMARY

TRUCK TRAVEL CHARACTERISTICS AS AN INDICATOR OF SYSTEM CONDITION AND PERFORMANCE

Introduction

Truck traffic has significantly increased in past decades. The effect of trucks on the level of service is determined by considering passenger car equivalents (PCE) of trucks. The Highway Capacity Manual (HCM) uses a single PCE value for all tucks combined. However, the composition of truck traffic varies from location to location; therefore, a single PCE-value for all trucks may not correctly represent the impact of truck traffic at specific locations. Consequently, the Indiana Department of Transportation (INDOT) identified a need to develop separate PCE values for single-unit and combination trucks to replace the single value provided by the HCM. Traditionally, equivalent delay and microscopic simulations have been used to estimate PCE values. In order to facilitate the development of site specific PCE values, an alternative PCE-estimation methodology was explored in the present study on the basis of lagging headways measured from real traffic data. 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. The study used data from four locations on a single urban freeway and three different rural freeways in Indiana. Three-stage-least-squares (3SLS) regression techniques were used to estimate models that predict lagging headways for passenger cars, single-unit trucks, and combination trucks. The models were then expanded to predict lagging headways for each of nine vehicle-following combinations which were used to predict class average lagging headways. After determining lagging headways by vehicle class, the PCE values were calculated as the ratio of the lagging headway of each truck class to that of passenger cars.

Findings

The present study determined separate PCE values for single-unit and combination trucks. The estimated PCE values for single-unit and combination truck for basic urban freeways (level terrain) were 1.35 and 1.60, respectively. For rural freeways, the estimated PCE values for single-unit and combination trucks were 1.30 and 1.45, respectively. Due to the lack of sufficient quality data for rural freeways, the estimated rural PCE values are not recommended for use. As expected, traffic variables such as vehicle flow rate and speed have significant impacts on vehicle headways. Further, the study results indicated that not only do different vehicle classes have different headways, but they directly depend on headways of other vehicle classes. The study further examined the impact of headway models on predicted LOS values. The separate PCE values can have significant influence on the LOS estimation. Since roadway design depends on estimated LOS, estimated PCE values may result in different design specifications and different conclusions from evaluation studies as compared to standard HCM procedure.

This study also explored regional variation of PCE values by developing headway models using data from different sources and from different geographical locations. The results of the likelihood ratio test indicated that it is more appropriate to combine data from similar regions (freeway sections at different geographical locations) for the PCE estimation. It was found that 9-equation 3SLS models (expanded models estimated to predict lagging headways for each of nine vehicle-following combinations, thus used to predict class average lagging headways) predicted more accurate headways than that of 3-equation 3SLS models. Forecasting accuracy comparisons showed that these alternative modeling techniques reliably predict vehicle class lagging headways.

Implementation

A PCE value of 1.6 for combination trucks and 1.35 for single-unit trucks can be used by INDOT to assess the impact of trucks on LOS as compared to a single PCE value provided by HCM. These numbers are applicable to only level terrain urban freeways. The developed headway models allow for the prediction of site-specific PCE values. In the case of the 3-equations 3SLS model, one can accurately predict lagging headways, thus PCE values; using only 6 simple inputs (the speed and number of vehicles for each class i.e., passenger cars, single-unit and combination trucks) for any desired freeway segment. These inputs can be observed using existing traffic monitoring infrastructure/ procedures, and the output (lagging headways and PCE values) can be calculated using a simple Excel spreadsheet.

The developed models are expected to enhance INDOT's ability to assess the impact of changes in number of single-unit and combination trucks at a level terrain urban freeway segment in the state highway network. This way the agency may be in a better position to monitor site specific impacts of various compositions of truck traffic on highway LOS.

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1 INTRODUCTION

1.1 Background

A typical traffic stream is composed of passenger cars, single-unit trucks, combination trucks, 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 differences in traffic behavior among the vehicle classes. Also, heavy vehicles have a physical impact on other vehicles and psychological impact on drivers in adjacent lanes due to their larger size and maneuvering difficulties (Al-Kaisy 2002, Krammes 1986). The physical and performance gaps between trucks and passenger cars require that truck operations are accounted for in a manner different from that of passenger cars, for design and evaluation purposes.

In general, the traffic operational performance of basic freeway sections is judged on the basis of the "Level of Service" (LOS) they provide. LOS, a qualitative measure of a traveler's trip quality under prevailing roadway and traffic conditions, nominally amalgamates factors such as density, driver comfort, lateral restrictions, etc. (TRB, 2000). However, vehicle density, measured in passenger cars per mile per lane, is a dominating factor in LOS estimation. The Highway Capacity Manual provides a density-based LOS gradation: six levels from A (free flow conditions) to F (complete congestion) (TRB, 2000).

As density is expressed in passenger cars, there is a need to convert the other vehicle classes to passenger cars in order to obtain LOS for a mixed traffic stream. Passenger car equivalent (PCE) values can be used to carry out this conversion. Thus, with different PCEs for different vehicle classes and road conditions, one can compute passenger car density and LOS for most situations.

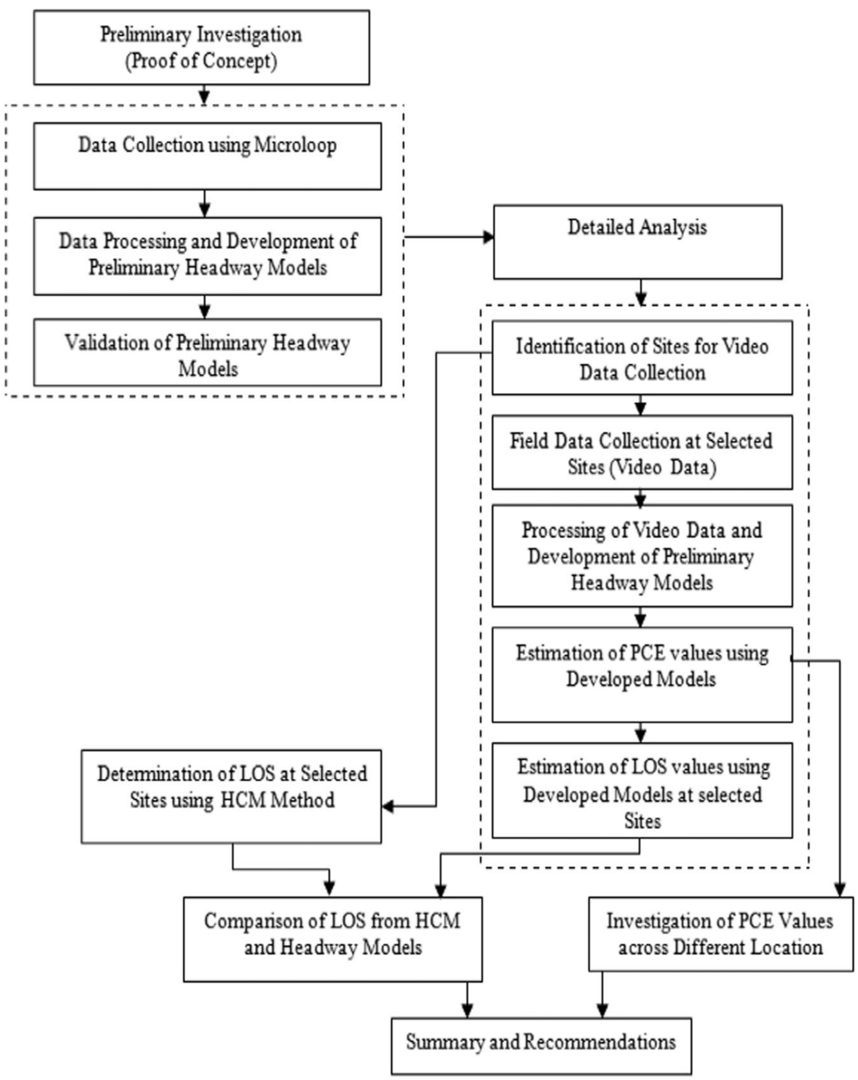


Figure 1.1 Study Framework

Both recent editions of the Highway Capacity Manual (HCM) (TRB, 2000; TRB, 2010) provide a single PCE value for all truck types. However, the traffic impact of various truck types may be different. The INDOT wanted to develop separate PCE values for single-unit and combination trucks in order to improve the assessment of the impact of trucks on various Indiana highway sections.

As density is the dominating factor in the LOS estimation, it seems sensible to specify PCEs primarily from the perspective of traffic density. Spatial lagging headway (the distance from the rear bumper of a leading vehicle to the rear of one following is the lagging headway of the following vehicle) can provide a suitable alternative approach to density, and thus for determining PCEs. Different vehicles maintain different spacing in a traffic stream depending on number of factors, and measuring these spacings can help to determine the average amount of space consumed by a particular vehicle class in a traffic stream (Elefteriadou et al., 1997). These spacings are measurable at the individual vehicle level which could be aggregated to establish the contribution of a particular vehicle class to density and thus to the LOS. Since inter-vehicle spacing is the inverse of density, measuring spacing directly provides density which, as previously stated, is the key input for LOS calculation. Inter-vehicle spacings, can be measured using headways.

Furthermore, the HCM makes no allowances for the subtle character of regional variation. Two roads may have similar geometry and traffic volume yet have different traffic operating characteristics (such as vehicle headway) due to differences in surrounding land use, design standards, or driving culture. Therefore, it may be worthwhile to investigate the regional stability of PCE's.

1.2 Study Objectives

The primary objective of the study was to develop PCE values separately for single-unit and combination trucks. In order to accomplish this objective the study used a novel PCE calculation approach suitable to incorporate site specific field data. The study also sought to compare results from the developed methodology to PCE values presented in the Highway Capacity Manual.

1.3 Organization of the Report

This report has eight chapters. Chapter 1 introduces the general research problem and reviews the motivation and goals of the study. The literature review in Chapter 2 describes past work in the area of PCEs, noting milestones in research or interesting alternatives. Chapter 2 also describes the basic methodology used in the present study. Chapter 3 covers the issues related to data, and explains how data from different sources were used. Chapter 4 describes the statistical methodology and presents the preliminary headway models estimated using limited data from a Microloop. Chapter 5 explains the Video data collection and processing for developing the headway models. Chapter 6 presents and discusses headway models for rural and urban interstates, establishes PCEs for single-unit trucks and combination trucks, and determines the LOS using the proposed method and the traditional HCM method. Chapter 7 discusses investigation of PCE variations across different locations and Chapter 8 presents the study summary and conclusions. A general outline of the study approach is shown in Figure 1.1.

2 LITERATURE REVIEW

2.1 PCE Computation (Highway Capacity Manual)

In the years following the first edition of the HCM, PCE calculations have expanded in rigor, accuracy, and complexity. In the 1950 edition of the 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 the 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). For the 1985 version of the HCM, analytical procedures were adopted and the volume to capacity (v/c) ratio approach, developed by Linzer et al. (1979) was used for calculating PCEs.

In the current version of HCM (TRB, 2010), LOS determination requires estimating the density of a traffic stream comprised entirely of passenger cars and vehicles other than passenger cars were converted into passenger car equivalents. In the HCM, PCEs vary according to the percentage of trucks, grade intensity, and length of grade. Equation 2.1 is the formula used in the HCM PCE calculation procedure. P_i is the proportion of vehicle type i in the traffic stream, E_i is the PCE value for the vehicle class i, and f_{HV} is the heavy vehicle factor. Passenger car flow divided by f_{HV} yields the equivalent flow of pure passenger cars. Through such calculations, one may account for trucks in LOS estimation and subsequent for the evaluation or design of freeway sections.

$$f_{HV} = \frac{1}{1+\sum Pi(E_i-1)} \tag{2.1}$$

The methodology used by the HCM for developing PCEs utilizes traffic simulations instead of real field observations (Elefteriadou et al., 1997). Huber (1982) used simulations to derive PCE equations using three different criteria: speed and density of a base stream (passenger cars only) and a mixed steam, and passenger car speed in the 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. The Huber equation is;

$$PCE = \frac{1}{\Delta p}\left[\frac{q_B}{q_M} - 1\right] + 1 \quad (2.2)$$

where Δp is the proportion of trucks in mixed traffic stream

The Huber procedure is only for 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 passenger cars, as follows:

$$PCEs = \frac{1}{\Delta p}\left[\frac{q_B}{q_S} - \frac{q_B}{q_M}\right] + 1 \quad (2.3)$$

where q_B is a base flow rate of pure passenger cars, q_M is a mixed flow rate of a stream of $(1-p)\%$ passenger cars and $p\%$ some other vehicle type, q_s is the flow of the subject vehicle type i ($\Delta p\%$ subject vehicle, $p\%$ other vehicle, and $1-p-\Delta p\%$ cars). This calculation is made with flows such that the simulated performance measure (speed, delay, etc.) is equal in all three cases.

Demarchi and Setti (2003) pointed out a number of issues with this method. For example an individual simulation run may not be consistent in the case of multiple truck types. Although the inclusion of a mixed flow helps capture some of the interactions among truck types, this effect is apparently not fully accounted for. More generally, though these simulations may be calibrated and verified, their scope, nevertheless, is limited compared to real field data.

Any methodology for determining PCEs must consider an appropriate performance measure. In previous studies, various methodologies have been used for calculating the PCEs for different types of facilities including the arterials and two-lane highways. The dominant criteria for PCE determination include: headways (Warener et al., 1976), speed (Hu and Johnson, 1981), delay (Cunagin and Messer, 1983), volume/capacity ratio (Linzer et al., 1979), density (Webster et al., 1999), platoon formation (Van Aerde and Yagar, 1984), travel time (Keller and Saklas, 1984), and queue discharge flow (Al-Kaisy et al., 2002). This study focuses on the basic freeway segment, and it is important to realize that a basic freeway segment has different critical characteristics than a signalized arterial and a rural two-lane highway. Several factors govern freeway LOS, but the most primary factor is vehicle density (TRB, 2000). Other factors, such as percentage trucks, lane width, and driver behavior, are considered as density-modification factors.

Equation 2.3 was developed by Sumner et al. (1984), who used the premise that PCEs should be estimated from traffic streams with equal delay in vehicle-hours. Recognizing the infeasibility of acquiring data with sufficient variety in flow rate and other attributes, they chose to deploy a trio of microscopic simulations. Under the geometric and highway conditions of interest, the first model simulates a stream of pure cars across a variety of flow rates. At each flow, the delay in vehicle-hours is plotted. This is the curve labeled, "Base," in Figure 2.1. This procedure is repeated for a mixed flow of cars and some proportion, p, of another vehicle type, say trucks. The new curve is labeled, "Mix." A final simulation at a single flow rate involving the previous flow mix and a proportion Δp of the subject vehicle of interest (for instance, trucks) results in a plot similar to that shown as Figure 2.1. The flow variables indicated in Figure 2.1 (q_S, q_M, q_B) are determined by calculating the flow associated with same impedance level. Graphically, one draws a horizontal line through the subject point and draws vertical lines where this horizontal intersects the flow curves. These verticals intersect the flow axis at the relevant variable values. Substituting these into Equation 2.3 yields the PCE values.

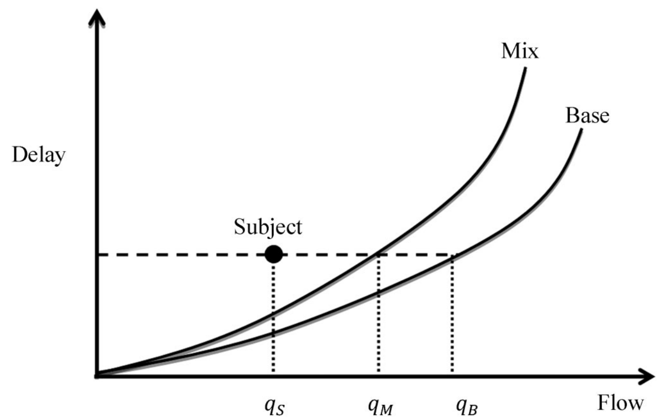


Figure 2.1 PCE Calculation using the Equivalent Delay Method

The reason for the "subject" flow is to capture some of the interactions between different truck types. Limiting the analysis to only two flows would be a similar, but less accurate calculation. By varying the initial conditions as done in Sumner et al. (1984), one can effectively establish the PCE values for a variety of highway and traffic conditions.

The original PCE calculation method of Sumner et al. (1984) was developed for urban arterials. Other studies, however, have extended it to other road classes. Webster and Elefteriadou (1999) examined a wide range of conditions affecting basic freeway sections. More recently, Rakha et al. (2007) considered an even broader set of simulated variables on freeways that yielded tabulated PCE values. The HCM uses PCE tables from the work of Elefteriadou et al. (1997) for two-lane highways, arterials, and freeways. For that study, however, the performance measure of interest was speed, not delay. In all of these studies, calibrated simulations were used to establish PCE values.

The method of using equivalent delays for determining PCEs has the beneficial effect of incorporating societal cost in PCE calculation. However, it implicitly assumes that every vehicle has equal value of travel time – an assumption that is unduly restrictive. Another drawback of this method is that obtaining the flow curves of Figure 2.1 is intractable. In other words, as done in the simulations, keeping the same proportion of vehicles on the same road yet varying the total flow over such a wide range without accounting for the effect of other vehicle classes is nearly impossible on field conditions. To address this, Sumner et al. (1984) attempted to carry out the micro simulations (i.e. individual vehicles), duly calibrated to reflect conditions at the road segment of interest. While this effort introduced increased integrity in the simulation methods, the lack of real data remained to be a striking limitation.

2.2 Alternative Methods for PCE Computation

Elefteriadou et al. (1997) briefly discussed alternative approaches to developing PCEs. Keller and Saklas (1984) employed macroscopic simulations and travel times to calculate PCEs for arterials that vary with volume, classification, and signal timing. Van Aerde and Yagar (1984) developed a model for PCEs based on length of a platoon and postulated that PCEs should be the ratio of the marginal impact of trucks on platoon length divided by the marginal impact of passenger cars (in a linear regression equation, this is just the ratio of coefficients). This is reasonable for two-lane highways where passing is restricted but not as applicable to a freeway where passing is normally unrestricted.

Werner and Morrall (1976) were first to apply the concept of headway ratio for finding PCEs. Werner and Morrall (1976) who derived the relationship for determining PCE for level terrain as follows:

$$PCE=\left[\frac{H_M}{H_{PC}}-P_{PC}\right]\Big/P_T \tag{2.4}$$

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 passenger cars and trucks, respectively, in the traffic stream. The study results produced by Werner and Morrall (1976) provided generalized PCEs for trucks, buses and recreational vehicles on two-lane highways. Another model by Cunagin and Messer (1983) determined PCEs to be a ratio of passenger car delay caused by other vehicle types to passenger car delay caused by other passenger cars. Cunagin and Messer (1983) also discussed the ratio of spatial headways as a possible PCE value. Several studies (McShane and Roess, 1990; Seguin et al., 1998) provide various forms of the following PCE calculation formula by expressing the amount of space "consumed":

$$PCE_{ij}=\frac{H_{ij}}{H_{pcj}} \tag{2.5}$$

where H_{ij} is the total lagging headway of following vehicle class i under condition j, H_{pcj} is the passenger car lagging headway, and PCE_{ij} indicates the PCE value for vehicle class i under roadway condition j.

The lagging headway concept is more suited to freeways where density is the primary determinant of LOS. Although this framework is well suited for density, Elefteriadou et al. (1997) mentioned that actually predicting the inter-vehicle spacing is intractable in terms of data. Cunagin and Messer (1983) did not actually predict headways but directly used measured headways to calculate specific PCEs. In general, researchers seem to agree that developing consistent and feasible headway estimates can help establish a PCE model that is reliable and broadly applicable.

3 DATA COLLECTION FOR THE PRELIMINARY HEADWAY MODEL

3.1 Data Requirements

To be usable for predicting lagging headways, a dataset must furnish a certain minimum set of information. Calculating the lagging spatial headway requires two data items: a time stamp of when the vehicle passed a reference point and the vehicle's speed at that time. The relevant equation is:

$$H_i^* = 1.4667S_i(t_i - t_{i-1}) \tag{3.1}$$

where H_i* is the headway in ft, t_i is the time stamp in seconds, S_i is the speed in mph, and t_{i-1} is the timestamp of the leading vehicle. As most detection systems stamp time when they first sense a vehicle, Equation 3.1 returns the leading spatial headway. To convert this into lagging headway (H_i), one simply subtracts another necessary data point, the leading vehicle length (L_{i-1}) and adds the current vehicle length (L_i) as Equation 3.2 depicts.

$$Hi = H* - L_{i-1} + Li \tag{3.2}$$

Figure 3.1 schematically depicts what is being measured. As discussed, most detection systems return H_i*, the leading headway. This study, however, seeks to measure H_i, the lagging headway, which is the rear bumper to bumper distance between a given vehicle, *i,* and its leading vehicle, *i-1*.

To use this framework, one must have an established vehicle classification scheme. Ideally, the system detecting vehicles would classify them in place according to some standard such as the Federal Highway Administration (FHWA) 13-class system. Without such vehicle classification, one might consider classification into a few categories based on vehicle length. Classifying vehicles into fewer classes may not be as realistic as FHWA 13-class system, but it offers a simple and consistent basis.

Although individual data points are simple, the size of the raw dataset may be immense. For headway calculations to be meaningful, the detection system must report every single vehicle that drives by a specific point in a given lane. Certain weigh-in-motion systems

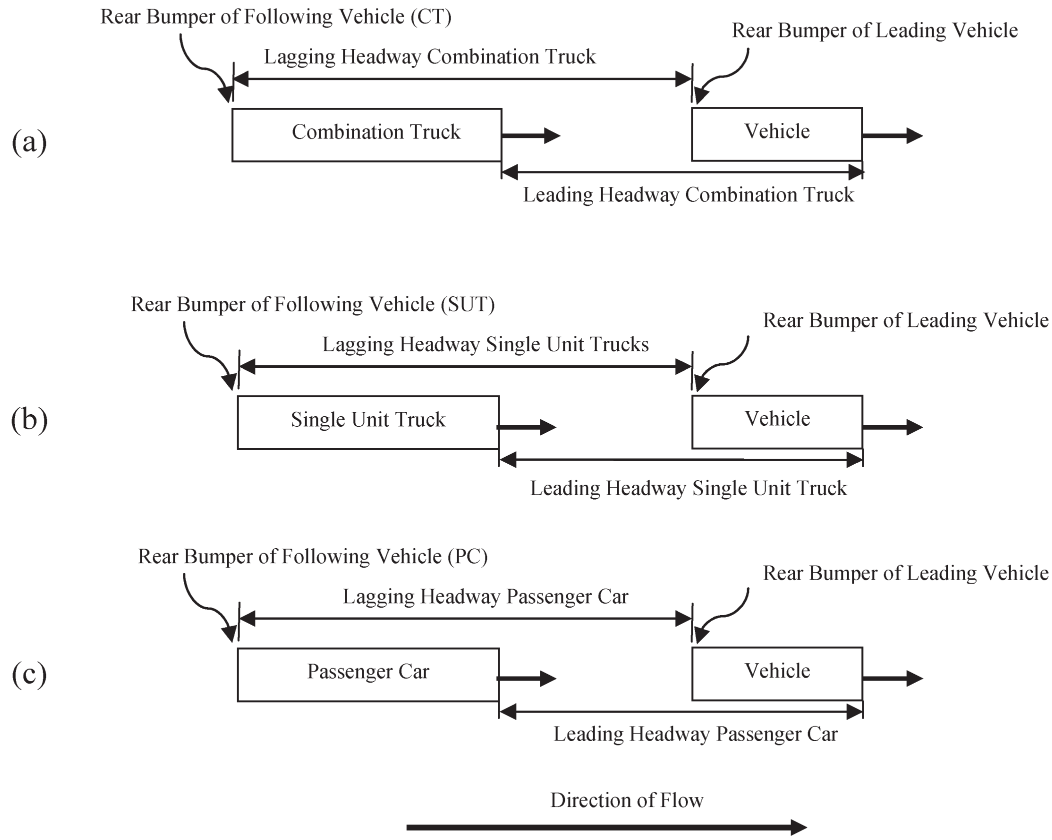


Figure 3.1 Schematic Headway Diagrams

fail this criterion, because they filter out vehicles of non-interest (e.g., non-trucks) from the data stream, thus precluding the calculation of headways.

The scope of the study also influences the size of the required dataset. To assess only traffic variables, only a single road section might be adequate, but the time span of data collection should be a minimum several days. One should strive, however, to choose a data collection location with sufficient variability of traffic conditions ranging from free-flow to congestion. A variety of data collection locations at different freeways sections would be even better, but not critical. However, when assessing geometric impacts, a large variety of sites becomes essential. With perhaps 100 sites, one might not need more than the peak period from each. Of course, understanding geometric impacts would further require knowledge of highway geometry (grade, length, number of lanes, lane width, etc.) for each segment. Similarly, testing geographic factors would require data from different locations. The data collected for testing geographic factors should be similar in all respects except location. Irrespective of the scope however, the simple data requirements can become complex due to the large scale of data requirement.

3.2 Microloops

Microloops used for vehicle detection are somewhat similar to the familiar inductive loops seen at many intersections. As Ernst et al. (2008) note, "whereas inductive loops measure the relative change in inductance caused by mutual inductive coupling, Microloops measure the inductive response to changes in the local magnetic field caused by a ferromagnetic object (such as a vehicle)". The Indiana Department of Transportation (INDOT) has a Microloop installation for vehicle detection at mile marker 128 (near Indianapolis) on Interstate 65 northbound in both lanes.

Figure 3.2, which depicts typical output from a Microloop, contains all the information needed to determine headways. The peak in relative inductance,

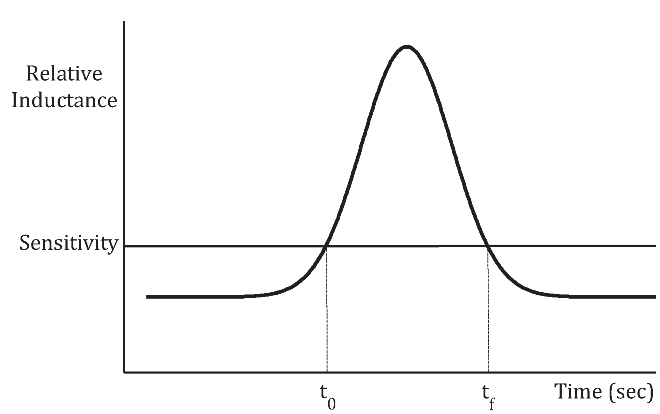


Figure 3.2 Microloop Vehicle Detection Process

TABLE 3.1
Classification by Vehicle Length

Present Study Class	Vehicle Type	FHWA Classes
1	Passenger Car	1–3
2	Single-unit Truck	4–7
3	Combination Truck	8–13

$\frac{\Delta L}{L}$, where L is the inductance in henrys, caused by a changing magnetic field due to passage of a vehicle over the loop. The horizontal solid line is the sensitivity threshold; relative inductance above this value indicates vehicle presence. The difference in time ($t_f - t_o$) is the duration of vehicle presence. With two detectors at a fixed distance apart, one can also determine speed of the vehicle. Combining the speed and duration returns the vehicle length, which could then be used to classify the vehicle. Table 3.1 lists the vehicle classification scheme used for the present study. Figure 3.3 displays a few lines of output from a Canoga C800 card which reads data from a Microloop detector. Among the many variables, one finds the required time stamp (to the nearest second), speed (nearest mph), and length (nearest ft).

While the data shown above is rather raw, it could be processed into a standard form. This study employs the "awk" programming language for data processing. This language reads text files line by line, performing directed actions when it finds a matching regular expression. For example, the field indicating "length" determines the vehicle class as dictated by Table 3.1. Most of the processing is simply picking out the desired information from the stack present. There are, however, some nuances and details to the processing structure. The time stamp, accurate only to the nearest second, allows potential cancellation errors as well as general imprecision. To avoid cancellation, one can add the "L-L Duration," which is measured to the nearest millisecond, to the initial time. Note that this is not the same duration as depicted in Figure 3.2. This duration is the time the front bumper takes to traverse the distance between the two Microloop sensors, and it preserves the nature of time shown in Equation 3.1. Another issue arises from erroneous extreme values. The sensor is not perfect; it sometimes returns absurd speeds, lengths, or headways. Rather than simply removing these data points, this study truncates them at reasonable values. Lengths exceeding 120 ft are considered excessive (this is only few feet greater than the maximum vehicle length (114 ft) that is specified by the American Association of State Highway and Transportation Officials (AASHTO) "Green Book" (AASHTO, 2001). Speed is limited to 135 mph, a speed outside the range of most trucks and not actually exceeded by any cars in this dataset. Further, it is sensible to truncate the lagging headway by limiting the inter-vehicle spacing ($H_i - L_i$) to the stopping sight distance (SSD). Headway values, greater than the SSD represent are unaffected by traffic. One can define SSD with Equations 3.3 and 3.4 as (AASHTO, 2001):

$$\text{Coefficient of Friction, } f = \frac{1.4667a}{32.2} \tag{3.3}$$

$$\text{Stopping Sight Distance, } SSD = 1.4667vt + \frac{v^2}{30(f+g)} \tag{3.4}$$

where a, the deceleration constant, is 7 mph/sec for passenger cars and 4.5 mph/sec for trucks (AASHTO, 2001), v is the vehicle speed in mph, t is the perception-reaction time, usually 2.5 sec, and g is the grade in ft/ft (TRB, 2000).

```
C800ECS Real-Time Vehicle Log V1.3
C824T-F,0090399CG4FT,C800  V1.3 ,255,,
Entry #,*,Ch.,Loop Desc.,Date,Time,Speed (MPH),Length (ft.),Dur.,L-L
1, ,,<Clear Log>,2/5/2009,5:42:19 PM, , , , ,
2, ,3,I65N Lane 2 Lead,2/5/2009,5:42:21 PM,-,-,0.174,-,
3, ,4,I65N MM127.8 Lane 2 Lag,2/5/2009,5:42:21 PM,73,19,0.209,0.188,
4, ,3,I65N Lane 2 Lead,2/5/2009,5:42:23 PM,-,-,0.232,-,
5, ,4,I65N MM127.8 Lane 2 Lag,2/5/2009,5:42:23 PM,65,20,0.244,0.211,
6, ,3,I65N Lane 2 Lead,2/5/2009,5:42:25 PM,-,-,0.186,-,
7, ,4,I65N MM127.8 Lane 2 Lag,2/5/2009,5:42:25 PM,68,15,0.185,0.201,
8, ,1,I65N Lane 1 Lead,2/5/2009,5:42:25 PM,-,-,0.163,-,
9, ,2,I65N MM127.8 Lane 1 Lag,2/5/2009,5:42:26 PM,67,13,0.163,0.200,
```

Figure 3.3 Sample Data Output from Microloop

3.3 Weigh-in-Motion

Another potential data source is the weigh-in-motion (WiM) station. The Indiana Department of Transportation (INDOT) uses WiM on its highways for traffic counts and weight limit enforcement. A typical WiM installation is a combination of inductive loops, weight sensors, and strip axle sensors. The inductive loops work as a secondary tool to the system, but function in a manner similar to Microloops.

WiM stations use principles that are different from that of loops, with certain consequences. While loops respond to changes in electrical or magnetic properties, weight and strip axle sensors activate under pressure. This means that WiM detects discrete axles. As the summary of data output from a typical Weigh-in-Motion station in Figure 3.4 shows, WiM data can contain precise information on speed (nearest 1 mph), time (nearest 0.0001 second), FHWA Class (a 13-class system based on axle count and spacing) (FHWA, 2001), and wheelbase (WB, nearest 0.1 ft). Wheelbase is an approximate measure of vehicle length, as it measures the distance between the front and back axles. To determine length, this part of the study uses two possibilities: If the WB is less than AASHTO (AASHTO, 2001) length for that class, then the AASHTO length is used; If, however, the WB is larger, then the length is the WB plus the front and rear overhang specified for that class (AASHTO, 2001). For unlisted or unclassified vehicles, the length is fixed at 106% of the WB and the front overhang is 3 ft. This length specification is somewhat arbitrary, but vehicles must necessarily have a length greater than or equal to their wheelbase. The front overhang constant, however, is a conservative value based on AASHTO (2001). This prepares the data for headway processing.

The actual processing of data from WiM stations is similar to that of Microloops. There is no need to augment the time as the WiM output provides adequate precision. The truncations present in the Microloop processing return unchanged in this program. The headway, however, requires additional adjustment. To correct for time stamping the first axle instead of the front of the vehicle, one should add the leading front overhang and subtract the current front overhang. With this, the WiM data is ready for aggregation.

3.4 Data Aggregation Process

The data from WiM or Microloop processing is standard, but this form is still too raw for statistical modeling. To refine it further, another AWK script aggregates the data into 15-minute bins. A bin width of 15 minutes is used because this matches the peak hour period used by the HCM (TRB, 2000). This AWK script determines, for each vehicle class the following operational characteristics:

- Average leading headway, ft
- Average lagging headway, ft
- Average inter-vehicle spacing, ft
- Average time-headway, sec
- Average speed, mph
- Average length, ft
- Vehicle count

Thus, any single statistical observation consists of roadway identification, lane number, 15-minute bin number, the above variables for each of the 14 classes (13 + 1 for unclassified vehicles), and a total vehicle count for that period. From here, one may combine the classes to form more general groupings. This study groups them into the three categories defined in Table 3.1: passenger cars, single-unit trucks, and combination trucks. With data aggregated in this fashion, one can statistically model significant traffic variables.

3.5 Auxiliary Issues

The nature of the data presents challenges beyond the modeling framework. Many 15-minute periods in the data lack vehicles from a certain class. While the structure of the data processing plants a value of zero that class' average lagging headway, it is actually undefined. Naturally, headways cannot be measured for vehicles that do not exist. As such these entries must be expunged from the dataset. All observations must include at least one vehicle from each class of interest (passenger cars, single-unit trucks, combination trucks) in order to yield data for modeling headways of each class. The discarded data points may, however, be useful in alternative models that are restricted to certain classes such as cars and combination trucks (no single-unit

```
SeqNo.,Date,Time,DayofWeek,StationID,Travel,Lane,Class,Speed(mph),
ESAL,Violation,GrossWt(lbs),No. Axles,WB(ft)
1,04/14/08,00:00:09:0484,2,779,3,1,2,67,0,1.00E+018,3500,2,8.7
2,04/14/08,00:00:29:0281,2,779,7,1,2,59,0,0,4000,2,8.4,,,
3,04/14/08,00:00:31:0250,2,779,7,1,2,63,0,0,4600,2,9.1,,,
4,04/14/08,00:00:50:0062,2,779,3,1,3,66,0.01,1.00E+018,8400,2,13.9,,,
```

Figure 3.4 Sample Data Ouput from Weigh-in-motion Station trucks). Such models may be useful for estimating LOS at segments that are restricted to only certain vehicle classes or for enhanced understanding of specific interactions between vehicle classes.

Another challenge in this study arises from the use of temporal data. Although the data is aggregated into 15-minute periods, it is possible that the current average headway is affected by the previous average headway. This is known as serial correlation. According to Washington et al. (2003), the price of ignoring this effect is generally not grave: OLS estimates lose efficiency (variables lose significance) but are otherwise unbiased. Of course, the removal of otherwise significant variables could lead to bias in the remaining parameters. To measure the extent of serial correlation, one calculates the Durbin-Watson (DW) statistic (Durbin and Watson, 1951): a DB value close to 2 indicates the absence of serial correlation. This study considers a DW between 1.7 and 2.3 to be acceptable. To stay within these bounds, one has multiple options. One option is to incorporate the serial correlation into the error term and transforming the dependent variables to include lagged (previous time segment) variables (Washington et al., 2003). This is attractive because it directly addresses the problem; however, applying this in a simultaneous equation framework can be computationally intensive. Further, there is a more tractable, even if mundane, method: including exogenous variables that account for serial correlation. In time-series data, time-of-day may be such a proxy. Of course, any variable which accounts for apparent serial correlation should suffice. With these challenges overcome, a 3SLS model should be properly specified and reliable. This model is described in detail in next chapters.

3.6 Chapter Summary

Building statistical models to predict LOS requires skilled data management. Calculating lagging headways requires information on every vehicle passing a particular point. Such data may be obtained from Microloop equipment, WiM stations or other similar sources. For modeling purposes, however, the data must be averaged at some reasonable level; here the data is aggregated into 15-minute periods. Once this is done, it is possible to perform a statistical estimation of lagging headways for each vehicle class. The ratio of the predicted headway of a class to the predicted headway of a passenger car yields the PCE value.

4 DEVELOPMENT OF THE PRELIMINARY HEADWAY MODEL

4.1 Introduction

For incorporating the effect of trucks into the Level of Service (LOS) calculations, the current edition of the HCM (TRB, 2000) uses a robust, if somewhat indirect, method to determine passenger car equivalence (PCE) values. Present PCE calculations derive from Elefteriadou et al. (1997) whose work in turn draws from Sumner et al. (1984). These studies used microscopic simulations of equivalent delay, as shown in Figure 2.1 and Equation 2.2, to calculate PCEs under various roadway and traffic conditions.

Headway ratios, as established by Cunagin and Messer (1983), may be an attractive alternative to the HCM method. Headways are particularly useful because they are reciprocal of density, a dominant factor of freeway LOS. In this framework, one invokes Equation 2.3, dividing the vehicle type *i* average lagging headway by the passenger car average lagging headway. Cunagin and Messer (1983) determined PCEs with measured rather than predicted headways. On specific roads and traffic conditions, this approach yields an appropriate response, but it precludes interpolation among data points. Predicting headways offer a more general application as headways for specific roads and traffic conditions are obtained by employing a suitable statistical technique instead of just using the measured headways.

The use of headway ratios implies certain restrictions on PCEs. Figure 4.1 depicts how a PCE value for vehicle type i might be restricted with respect to traffic density on a flat grade. Point A reflects the no-flow condition; there is so little traffic that trucks and passenger cars have the same effective headway, so the overall PCE is unity. Point B occurs when spacing starts to become cramped, but trucks still require more headway compared to passenger cars. At point C, all vehicle headways have decreased due to traffic, and passenger car headways may shrink considerably more as cars platoon behind slow-moving vehicles and are unable to pass. Finally, point D represents bumper-to-bumper traffic; the only headway a vehicle has is its length. While one is unlikely to encounter the extreme scenarios, they are important boundary conditions on the model.

Such a model, however, is still relatively untested. The present study seeks to examine the feasibility of predicting headways and then using the headway ratio approach for PCE calculation.

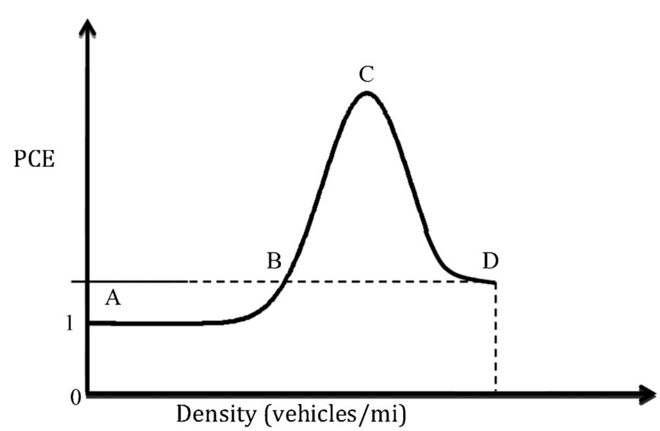


Figure 4.1 Microloop Vehicle Detection Process

4.2 Statistical Methodology

Using the dataset collected and processed that contains information regarding average lagging headway and traffic characteristics, the present study seeks to determine truck PCEs through the estimation of average lagging headways. Now, for an individual vehicle i, the lagging headway, Hi is bounded as follows:

$$\mathrm{Length_i} \leq \mathrm{H_i} \leq (\mathrm{SSD_i} + \mathrm{Length_i}) \qquad (4.1)$$

where $\mathrm{Length_i}$ is the length of vehicle (usually in ft.) and $\mathrm{SSD_i}$ is the stopping sight distance of vehicle i. Each bound is an extremum of traffic congestion. The lower bound is total congestion; a vehicle with a lagging headway equal to its length (bumper-to-bumper with other vehicles). SSD as an upper bound is somewhat arbitrary. While it is physically possible for lagging headway to exceed the SSD, such conditions suggest that the minimal traffic does not impact the vehicle's headway.

The estimation of headway is intended for a 15-minute class average as data has been aggregated to 15-minute bins and this is used for model building. As the average headway is a continuous variable, regression seems like the appropriate statistical tool. One should note, however, that although average headway does not have the same bounds as individual headway, bounds still exist. The same extremes apply: the minimum is the vehicle length and the maximum is the SSD. This suggests some form of truncation or censoring. In this set, however, the data scarcely reaches the bounds. Furthermore, while a Tobit model (Tobin, 1958) might be appropriate for the shifting and potentially unknown upper bound, this might preclude extrapolation of large headways. More importantly, traffic streams with such large headways are unlikely to be operating near capacity, so any errors in estimation will probably not affect that segment's LOS.

There is another, more serious, specification problem. This study seeks to estimate average headways for each class. Naturally, one might expect the headway of one class to impact the other classes. For example, if passenger cars increase their headway to make room for trucks, the trucks may respond similarly, increasing their headway. Also, it is conceivable that the behavior of one class of trucks may impact that of other classes. This effect may be difficult to quantify as trucks are typically present in small numbers. Nevertheless, as one will see, trucks still affect each other indirectly through their impact on passenger cars.

To apply this framework of regression and simultaneous estimation, the appropriate form is three-stage least squares (3SLS). The 3SLS structure for estimating headways for passenger cars (PC), single-unit trucks (SUT), and combinations trucks (CT), is as follows:

$$\mathrm{H_{pc}} = \beta_{\mathrm{pc}}\mathrm{X_{pc}} + \lambda\mathrm{H_{sut}} + \tau\mathrm{H_{ct}} + \varepsilon_{\mathrm{pc}} \qquad (4.2)$$

$$\mathrm{H_{st}} = \beta_{\mathrm{st}}\mathrm{X_{sut}} + \delta\mathrm{H_{pc}} + \varepsilon_{\mathrm{st}} \qquad (4.3)$$

$$\mathrm{H_{ct}} = \beta_{\mathrm{ct}}\mathrm{X_{ct}} + \phi\mathrm{H_{pc}} + \varepsilon_{\mathrm{ct}} \qquad (4.4)$$

Where;

$\mathrm{H_i}$ is the average rear bumper to rear bumper spacing of vehicle type i,

β_i is a vector of estimable parameters,

X is a vector of known traffic data such as segment speed, total vehicle flow, and percent trucks,

λ, τ, δ, and φ are estimable scalars, and

ε_i is the disturbance term.

The 3SLS method is an extension of traditional methods such as two-stage least squares (2SLS). In 2SLS, there are two steps. Stage 1 applies Ordinary Least Squares (OLS) to each endogenous variable (class average lagging headway, $\mathrm{H_i}$'s) using only exogenous variables (traffic characteristics, X's). Stage 2 uses the predicted headways from stage 1 as proxies for the endogenous terms in Equations 4.2 – 4.4 in OLS estimation for each equation. As per Washington et al. (2003), the results of 2SLS are consistent, but not unbiased.

The 3SLS method offers a solution that is more likely to be unbiased. Here, the first stage is actually to compute the 2SLS parameter estimates. Stage 2 uses these results to estimate cross-equation correlations. These correlations appear in stage 3 as part of generalized least squares (GLS) estimation. The results of this GLS estimation comprise the final output of 3SLS estimation.

Estimation from the 3SLS method provides knowledge of the parameters and how they impact the dependent variables. With the presence of endogenous variables in various equations, even if the exogenous variables are given, headways cannot be predicted directly. To predict the class average headway, one must solve analytically the system of Equations 4.5 – 4.7, as follows:

$$H_{pc} = \beta_{\mathrm{pc}}\mathrm{X_{pc}} + \lambda\left(\frac{\beta_{\mathrm{pc}}\mathrm{X_{pc}} + \lambda\beta_{\mathrm{st}}\mathrm{X_{st}} + \tau\beta_{\mathrm{ct}}\mathrm{X_{ct}}}{1 - \lambda\delta - \tau\phi}\right) \qquad (4.5)$$

$$H_{st} = \beta_{\mathrm{st}}\mathrm{X_{st}} + \delta\left(\frac{\beta_{\mathrm{pc}}\mathrm{X_{pc}} + \lambda\beta_{\mathrm{st}}\mathrm{X_{st}} + \tau\beta_{\mathrm{ct}}\mathrm{X_{ct}}}{1 - \lambda\delta - \tau\phi}\right) \qquad (4.6)$$

$$H_{ct} = \beta_{\mathrm{ct}}\mathrm{X_{ct}} + \phi\left(\frac{\beta_{\mathrm{pc}}\mathrm{X_{pc}} + \lambda\beta_{\mathrm{st}}\mathrm{X_{st}} + \tau\beta_{\mathrm{ct}}\mathrm{X_{ct}}}{1 - \lambda\delta - \tau\phi}\right) \qquad (4.7)$$

where symbols have their usual meanings.

4.3 Database

The preliminary modeling dataset comprises four days of real-time vehicle information taken from a

TABLE 4.1
Summary Statistics of the Microloop Data

Variable	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	542.437	115.793	97.17	854.45
Average ST lagging headway (ft)	637.088	259.575	127.26	2019.68
Average CT lagging headway (ft)	724.959	171.628	202.74	1504.86
PC Flow (PC/15 min)	72.881	46.572	3	266
ST Flow (SU/15 min)	3.773	3.209	1	17
CT Flow (CT/15 min)	19.739	14.570	1	62
Percent ST	0.046	0.035	0.003861	0.2
Percent CT	0.22989	0.167112	0.008772	0.878049
Average PC Speed (mph)	69.5701	2.94715	23.26	74.37

Microloop detector on I-65 MM128 northbound outside Indianapolis. Individual vehicle variables were truncated according to Section 4.2. From this individual vehicle information, one can determine average lagging headway, speed, and count, all aggregated into 15-minute bins, by vehicle class. The three classes of interest are passenger cars (PC), single-unit trucks (ST), and combination trucks (CT). After retaining only those 15-minutes time periods with at least one vehicle of each type, (thus providing lagging headway for each vehicle class) the final dataset includes 494 observations for each class. One might consider additional models that may consist of only passenger cars and combination trucks. This type of model would be useful only in specialized scenarios where certain vehicle classes are restricted. Further, because of the class restriction, there are a very limited number of data points with which to build a model. Retaining bins with all types yields the broadest yet robust dataset.

Table 4.1 is a summary of significant variables in the dataset. Also, note the large difference in mean headway among the three classes. This is a clue (but not conclusive evidence) that they should be modeled separately.

4.4 Modeling Framework

When predicting vehicle headways, one expects the headway of one class to influence that of another. As discussed in Section 4.2, the three-stage least squares (3SLS) approach accounts for such endogenous correlations. Recall that Equations 4.2 – 4.4 formulate the core system, and Equations 4.5 – 4.7 represent the solved prediction equations. With predicted headways, one can calculate PCEs for both single-unit and combination trucks. This, in turn may lead to a new LOS value for given traffic and roadway condition.

This framework, however, is far from ideal. Theoretically, it may predict negative headways. While some type of censored Tobit (Tobin, 1958) or truncated model may be appropriate, in practice, predictions do not breach this barrier. From above, there is also nominal censoring due to the stopping sight distance. This is actually a classic problem that could be solved by a Tobit model with unique upper limits for each observation. Aggregation averaging and the scarcity of censored data, however, mitigate this issue. Finally, headway conditions do not necessarily conform to the boundary conditions de-picted in Figure 4.1. Without data on such conditions, however, one would not expect such conformity to occur. It may be worthwhile to impose the restrictions mathematically, but the computation may be laborious. Further, as extreme bounds, one is unlikely to encounter such conditions on a real freeway. Thus, the possible errors in the model specification are not expected to invalidate the results under normal operating conditions.

4.5 Results of the Preliminary Model

Table 4.2 displays the results of the 3SLS estimation. The first column is a descriptive list of the significant variables. The next column presents the estimated X vectors, and the third column presents the significance

TABLE 4.2
Three-Stage Least Square Model Estimation Results – Prelinimary Model

Variable	Coefficient	t-stat	Mean
Passenger Cars			
PC Flow (PC/15 min)	−1.190	−15.977	72.881
ST Flow (SU/15 min)	−4.424	−4.039	3.773
CT Flow (CT/15 min)	−1.088	−4.089	19.739
Average PC Speed (mph)	6.209	18.594	69.570
Percent ST	297.202	3.365	0.046
Percent CT	76.732	3.808	0.230
Average CT lagging headway (ft)	0.321	13.063	724.959
Average ST lagging headway (ft)	−0.045	−2.659	637.088
Adjusted R2	0.7321		
Durbin-Watson	1.9346		
Single-unit Trucks			
PC Flow (PC/15 min)	0.560	2.800	72.881
CT Flow (CT/15 min)	−2.045	−2.847	19.739
Average PC lagging headway (ft)	1.172	37.690	542.437
Adjusted R2	0.1728		
Durbin-Watson	1.9817		
Combination Trucks			
PC Flow (PC/15 min)	0.512	4.703	72.881
Average PC lagging headway (ft)	1.268	74.629	542.437
Adjusted R2	0.2998		
Durbin-Watson	2.0105		
N	494		

of each variable; a |t-stat| ≥ 1.96 indicates the 95% confidence interval. Those variables which failed to meet this criterion are not part of final model. For easy reference the last column provides the mean of the variable.

4.5.1 Passenger Car Following

The adjusted R^2 value of 0.7321 indicates a rather strong correlation between the predicted and measured passenger car headways. This is not surprising as passenger cars comprise the least varied data. All of the vehicle flow rate variables decrease headway. Obviously, adding more vehicles takes up space on the road, necessarily decreasing headway. Curiously, single-unit trucks decrease the headway to a greater extent compared to other vehicle types. Each single-unit truck reduces the average passenger car lagging headway by over 4 ft while each passenger car or combination truck reduces it only by about 1 ft. This may reflect the intermediate nature of the effect of single-unit trucks; passenger car drivers may be willing to draft behind and drive aggressively around single-unit trucks. Average passenger car speed is another significant variable, though it increases headway. Each mph adds over 6 ft. This represents the larger stopping distance required at higher speeds. One can consider calculating the exact distance required, but drivers are not beholden to it and actually use a distance that is less or greater than the exact distance required.

The percentage of each truck type is significant for both single-unit and combination trucks and both increase headway. This is somewhat expected; although some passenger cars may draft, others exercise caution in the presence of a large percentage of trucks. This appears particularly true for single-unit trucks, where a 1% increase in proportion is an additional 3 ft of passenger car headway. Finally, both of the endogenous variables are significant. The positive relationship of combination trucks to passenger cars indicates that passenger car drivers may note larger headways from combination trucks and adjust their own headway accordingly. It may also reflect some unaccounted similarities between combination truck and passenger car drivers. The single-unit truck coefficient, however, is slightly negative, which indicates that the more headway single-unit trucks use, the less is available for passenger cars. This may include effects similar to combination trucks as well, but the net effect of one single-unit truck on passenger car lagging headway is −0.045 ft only.

4.5.2 Single-Unit Truck Following

The truck models are neither as involved nor as strongly correlated as the passenger car model. The adjusted R^2 for single-unit trucks is just 0.1728, which is not particularly strong but provides some indication of perceptible relationship. As with the passenger car model correlation, this is expected because single-unit trucks are few in number and so exhibit significant variation in their headways. Different flows for single-unit trucks have different effects on their headway. The model suggests that each passenger car adds approximately0.5 ft headway. At first, this seems perplexing, but could be explained: passenger cars are likely to overtake single-unit trucks; the resulting headway for single-unit trucks may be rather large as a passenger car speeds away. Further, this may be compensating for the passenger car lagging headway. Conversely, each combination truck reduces the single-unit truck headway by 2 ft. This may represent both the large space that combination trucks occupy on the road as well as opportunities for drafting. The endogenous variable (passenger car headway) indicates that single-unit truck headway is strongly affected by passenger car headway, although the former is generally larger. The other variables in this equation are minor modifications to this base value.

4.5.3 Combination Truck Following

Combination trucks, display somewhat different model characteristics than single-unit trucks. The adjusted R^2 of 0.2998 represents a fairly strong correlation. With combination truck flow numbers between that of single-unit trucks and passenger cars, this is logical. The only exogenous variable for combination trucks is passenger car flow rate. The sign and magnitude are similar (though smaller) to those present in single-unit trucks; the effect is probably the same. The endogenous variable is also similar to single-unit trucks at around 1.25. One should note however, that this is almost 0.1 higher than single-unit trucks, which is an extra 10% of passenger car headway being added. This indicates that combination trucks simply require more headway than other vehicle classes.

4.5.4 Model Accuracy

Figure 4.2 compares the predicted values of headway to the measured values. The passenger car points form a relatively tight line; the combination truck points are less tight, and the single-unit truck points only somewhat resemble a trend. Clearly, a larger database is required to further refine the models, before the results can be used for PCE calculation.

While the model in Table 4.2 may be interesting in its own right, its real impact is in how it affects LOS. Consider a typical traffic stream within the range of values in Table 4.1. Consider the scenario presented by Table 4.3 in the first four rows of values. Based on the model in Table 4.2, this implies the average headways listed just below the input in Table 4.3. Calculating the PCEs using the ratio in Equation 2.3, one finds that $PCE_{SUT} = 1.75$ and $PCE_{CT} = 2.18$. The resulting LOS=D follows from an otherwise standard Highway Capacity Manual (TRB, 2000) procedures for a flat road with wide lanes and shoulders. If the traditional HCM PCE of 1.5 was used in this scenario, the

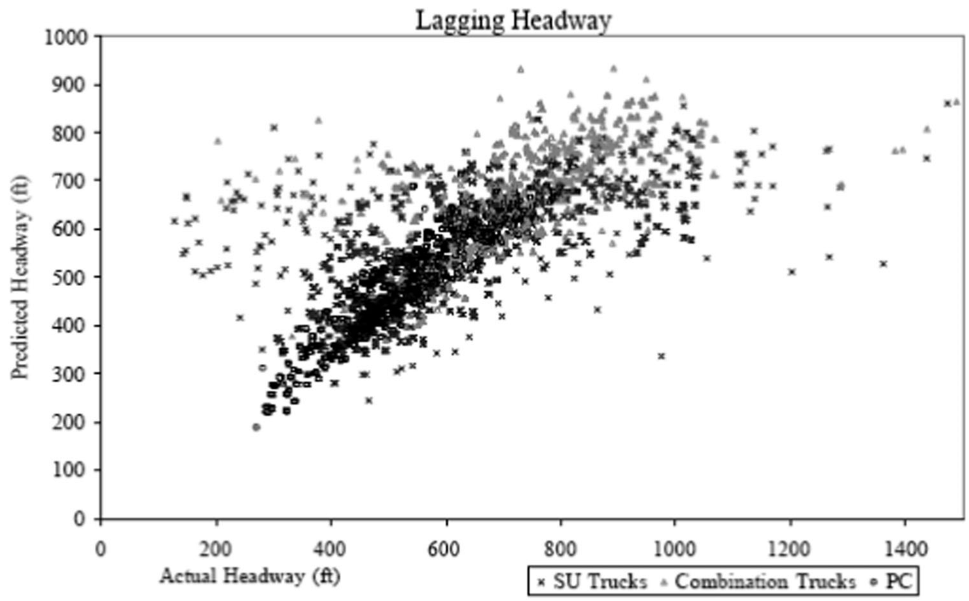


Figure 4.2 Predicted vs. Measured Lagging Headways – Preliminary Headway Models

resulting LOS is C. Table 4.3 summarizes the example results. A change of LOS by one degree may not seem significant, but the difference between LOS C and D may be the difference between acceptable and unacceptable levels of congestion. A road with LOS D may require improvement while one with LOS C may remain unchanged. This disparity in LOS does not always occur, but this example shows that it is possible under typical traffic conditions. Under more extreme, but still plausible, traffic, the disparity may grow. Table 4.4 presents such a scenario, with a large traffic flow and many combination trucks but few single-unit trucks.

Following the same procedure as before, the new LOS is E under the proposed headway model while the traditional methodology yields LOS C. A difference by one degree may or may not be marginal, but a difference of two is a severe disparity. Further, LOS E represents a very congested road section. Clearly, this alternative methodology may result in different LOS values and thus, different results of roadway design and evaluation studies.

4.6 Chapter Summary

This chapter presents an alternative methodology for determining PCEs for multiple truck types. Rather than using equivalent-delay and microscopic simulations, this study shows that it is feasible to use estimated headway ratios and Microloop data to determine PCE values for different truck types. Being directly based on field data, this method has some appeal over simulations. However, preliminary analysis indicated that the revised PCE values may lead to marginally or drastically disparate LOS values compared to the traditional method depending on traffic conditions. Therefore, while the 3SLS prediction of headways has the advantage of field data over simulation methods,

TABLE 4.3
Hypothetical LOS Comparison using Interpolated Data

Variable	Headway Method	HCM Method
PC/15 min	260	
ST/15 min	15	
CT/15 min	30	
Speed PC (mph)	74.8	
Head-P (ft)	145.868	
Head-S (ft)	255.024	
Head-C (ft)	318.025	
PCES	1.748	1.5
PCEC	2.180	1.5
fh v	0.867	0.931
vp	1406.527	1310
Density(veh/mi)	18.804	17.513
LOS	C	B

TABLE 4.4
Hypothetical LOS Comparison using Extrapolated Data

Variable	Headway Method	HCM Method
PC/15 min	300	
SU/15 min	5	
CT/15 min	45	
Speed PC (mph)	67	
Head-P (ft)	28.773	
Head-S (ft)	109.529	
Head-C (ft)	190.015	
PCE_S	3.807	1.5
PCE_C	6.604	1.5
f_h v	0.568	0.933
v_p	2464.856	1500
Density(veh/mi)	36.789	22.388
LOS	E	C

this approach would require the collection of sufficient quality data for model specification. In the preliminary phase of this study, the data set was relatively small and the model developed in this chapter was considered exploratory in order to establish that the concept of lagging headway could provide suitable alternative PCE values.

5 DATA COLLECTION FOR DETAILED HEADWAY MODEL

5.1 Introduction

As seen in Chapter 4, the initial analysis using Microloop data helped to establish the concept of estimating PCEs using lagging headway and the 3SLS statistical technique. The initial analysis was based on data collected for four days using Microloop at a single location. The estimated model provided indications that the preliminary study methodology could be further improved with additional data collection from more locations. Also, another motivating reason was the need for peak period data collection which was not included in the initial phase of this study. The data aggregation at 15-minutes intervals seemed to work well and same bin duration was retained for the second phase of the study where more detailed investigations were carried out. This chapter describes the data collection and data collation for building a detailed and comprehensive model.

Figure 5.1 Interior of the Mobile Traffic Laboratory

5.2 Collection of Detailed Data using Video

Video recording is a potential technique that can be used to extract vehicle counts and other necessary information required to generate a headway model. Purdue University's mobile traffic laboratory, which is equipped with video cameras and the necessary recording system, was used for data collection. Figure 5.1 presents the interior of the mobile traffic laboratory. Figure 5.2 shows the laboratory parked at the side of the roadway. A telescoping mast raises a pair of video cameras to a maximum height of 50 ft. above ground level. Each camera is then adjusted so that it captures the vehicles as they approach the subject road section from either direction. Working in unison, the pair of cameras provides a comprehensive record of the traffic experienced at that location.

The first step in video data collection is the determination of the number of data collection sites required to yield sufficient information regarding traffic and roadway geometric characteristics. In order to study the impact of roadway geometric characterizes (grade, grade length, number and width of lanes) on lagging headway hundreds of road segments are needed. Since this study primarily deals with the basic freeway sections, a total of seven data collection sites

Figure 5.2 Exterior Setup of the Mobile Traffic Laboratory (Vehicle parked at a road that is parallel to the Interstate section under investigation)

were selected and data was collected over a longer time horizon (October 2009 to March 2010).

Of the seven data collection sites, four were urban interstate sections located at Interstate 465 near Indianapolis. Two sites were located south of the city centre and two sites were located north (Figure 5.3). The details of individual sites are given in Appendix-I.

The three sites for rural interstate were from three different highways. The sites which were selected are located at I-65, I-74, and I-70 (Figure 5.4). The details of the individual sites are given in Appendix-II. The sites were selected due to their high variability in traffic conditions. The data from these locations were collected during the months of October 2009 to March 2010.

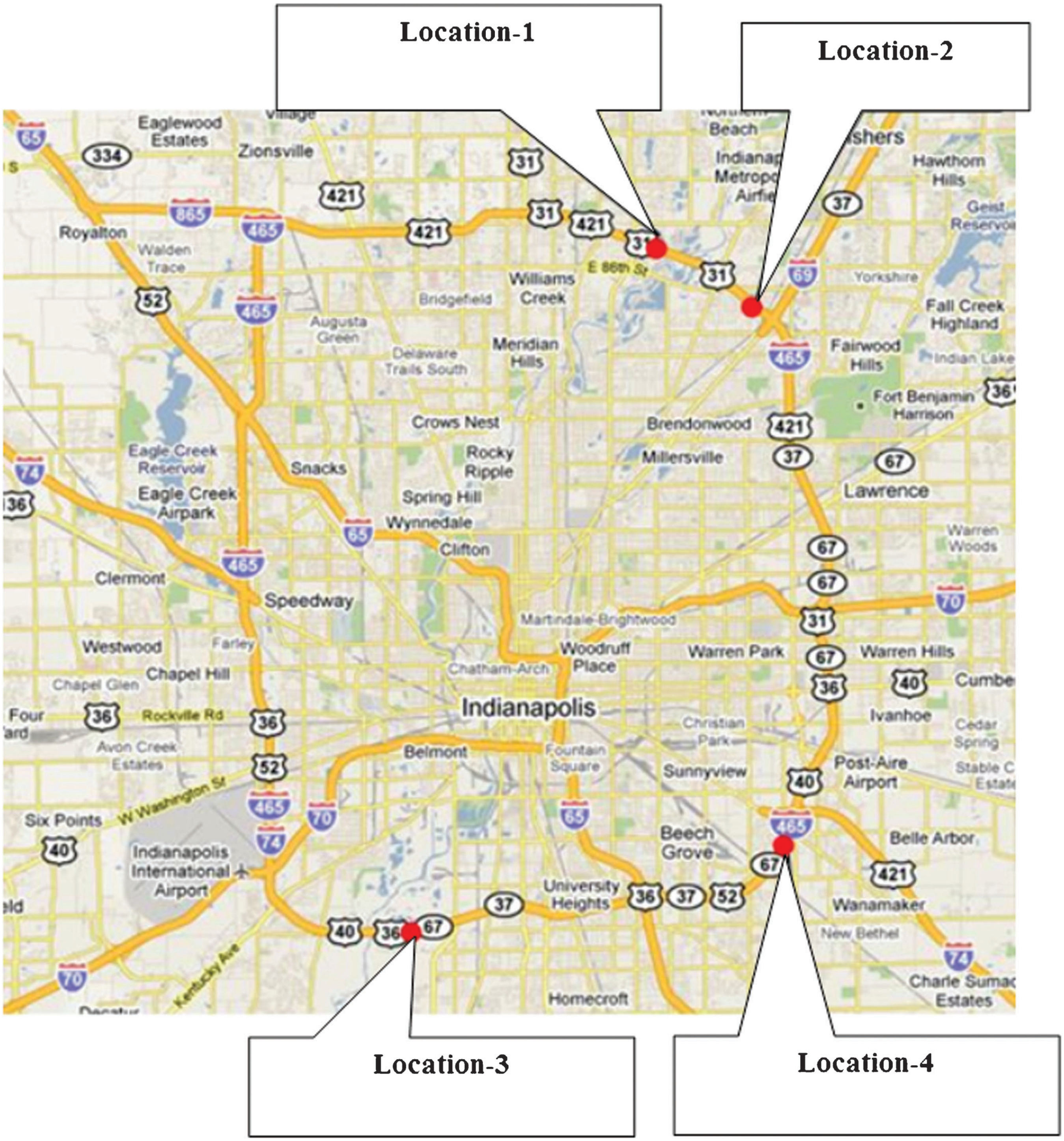


Figure 5.3 Data Collection Locations -Urban Interstates

Figure 5.4 Data Collection Locations - Rural Interstates

5.3 Processing of Video Recorded Data

The raw data collected using the mobile traffic laboratory is a simple video clip; each clip containing an immense amount of information. The video clip can be replayed to extract any information required for a specific study. Since the present study deals with estimation of lagging headways for different vehicle classes, only the required information was extracted for this purpose. Specifically, the vehicle's class (based on the simplified three class systems used for this study), time stamp, and speed was required. The recorded video does not output this information automatically, so the required information had to be extracted using an appropriate software package. For the purpose of this study, a software tool "Traffic Tracker", was used. All the recorded video clips were first split into 15-minute videos. Each fifteen minute video was processed by two research assistants working simultaneously. Each lane of traffic was analyzed separately; for instance, if a road section in a video clip consists of three lanes, then the same video was processed three times to extract the required information (vehicle count for each class and time stamp for calculating the lagging headway).

At the start of data extraction process, the Traffic Tracker software was initialized and then the data extraction process was commenced. In the second step, two reference points with a known distance apart were selected from screen shot of video clip. The time stamp of each individual vehicle passing these reference points was recorded (time when the front bumper of individual vehicle reaches the first reference point and time when the front bumper of individual vehicle reaches the second reference point). Roadway lane markings (white broken marking line separating different travel lanes in same direction) were used as reference for the start and end point reference points thus recording the time of entry and exit of individual vehicles. Since the length and spacing between these lines is known, reference points can be generated at each location depending upon the zoom angle and quality of the recorded video. Selection of reference points using roadway markings eliminates the need of actually measuring distances on the ground for each data collection site. Once a location was selected, neither the position of the mobile traffic laboratory nor the angle of the cameras was changed for the duration of the recording process for that location. Typical entry and exit reference points are shown in Figure 5.5. Three white markers and three

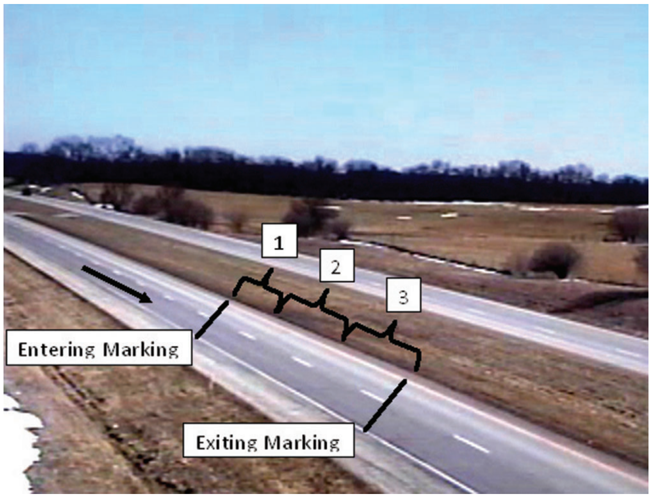


Figure 5.5 Vehicle Entry and Exit Reference Points

spacings are defined as the ends of two reference points. The minimum distance between selected reference points was fixed at 210 ft. The reference points were marked on the computer monitor using nonpermanent, neon label-stickers.

Traffic Tracker software recognize each vehicle by different keyboard clicks. For the purpose of this study, the vehicles were divided into three classes; passenger car, single-unit truck and combination truck. Therefore six different keys were assigned; one each for a vehicle (of a certain class) reaching the first and second reference point. The various keys assigned for different classes of vehicle are as shown in Figure 5.6.

To ensure accuracy during the recording process the 15-minute videos were played at a lower speed - fifty percent of their actual speed. A research assistant was assigned to click the three entry keys whenever a vehicle of a particular class crossed first reference point and other research assistant was assigned to click the exit keys at the time when individual vehicle crossed the second reference point.

This method was repeated for each lane for each 15-minute video. At the culmination of each video, the keystroke data representing the vehicle class and entry and exit times was extracted into a spreadsheet. A typical output from the software is shown in Figure 5.7; different columns show the time when individual vehicles cross the entry and exit reference points.

The next phase is the calculation of lagging headways. The time difference when the front bumper of a vehicle reaches the first reference point and when it reaches the second reference point yields the total time spent by individual vehicle between two reference points. As the video clips were played at half the actual speed, the time differences were halved to obtain the actual time taken by an individual vehicle to traverse the entry and exit reference points. Since the total distance between the entry and exit reference points is known, then the calculation of speed S_i, of individual vehicles is as follows:

$$S_i = \frac{L_{ST}}{(t_2 - t_1)} \qquad (5.1)$$

Where, L_{ST} is the total distance between the entry and exit reference points; and t_1 and t_2 are the times when a vehicle crosses entry and exit reference points, respectively.

Since the speed and time stamp for individual vehicles are knows, Equation 5.1 can be used to calculate the leading and lagging headway for individual vehicles as was done in the preliminary phase of this study (Chapter 4) where data analyzed were from a Microloop.

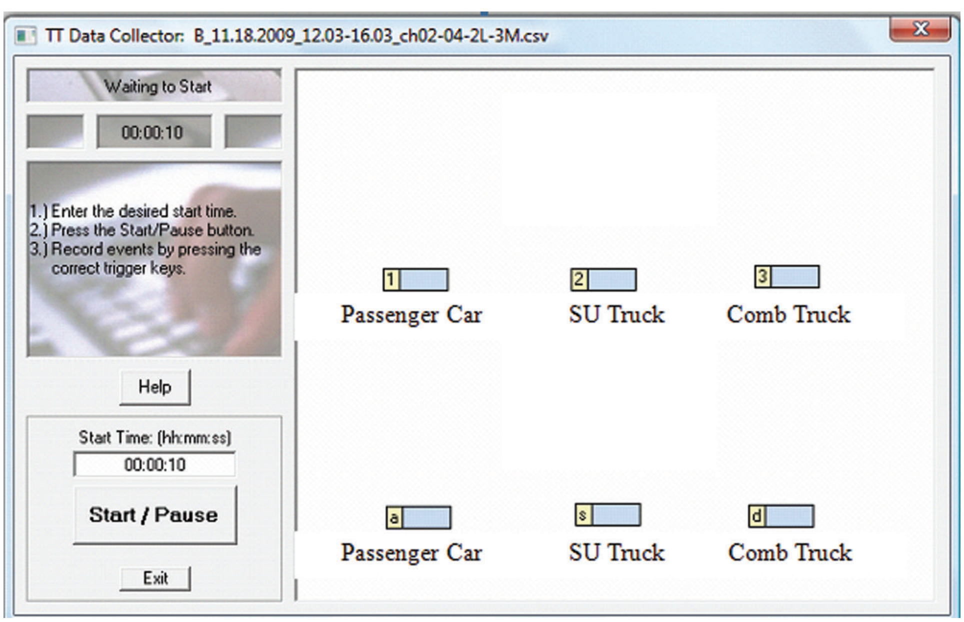
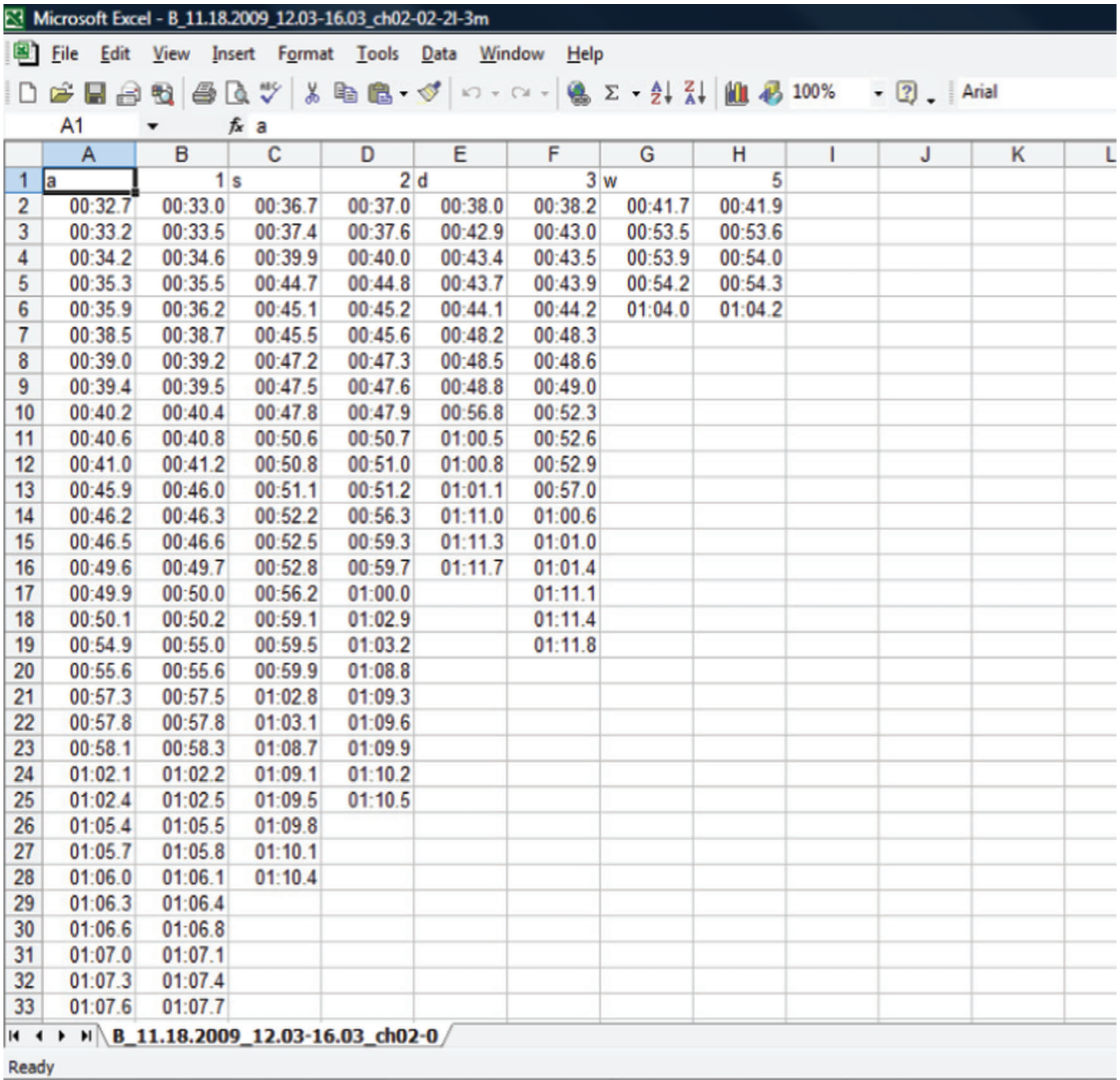


Figure 5.6 Traffic Tracker Software (Key Designations)



	A	B	C	D	E	F	G	H	I	J	K	L
1	a	1	s	2	d	3	w	5				
2	00:32.7	00:33.0	00:36.7	00:37.0	00:38.0	00:38.2	00:41.7	00:41.9				
3	00:33.2	00:33.5	00:37.4	00:37.6	00:42.9	00:43.0	00:53.5	00:53.6				
4	00:34.2	00:34.6	00:39.9	00:40.0	00:43.4	00:43.5	00:53.9	00:54.0				
5	00:35.3	00:35.5	00:44.7	00:44.8	00:43.7	00:43.9	00:54.2	00:54.3				
6	00:35.9	00:36.2	00:45.1	00:45.2	00:44.1	00:44.2	01:04.0	01:04.2				
7	00:38.5	00:38.7	00:45.5	00:45.6	00:48.2	00:48.3						
8	00:39.0	00:39.2	00:47.2	00:47.3	00:48.5	00:48.6						
9	00:39.4	00:39.5	00:47.5	00:47.6	00:48.8	00:49.0						
10	00:40.2	00:40.4	00:47.8	00:47.9	00:56.8	00:52.3						
11	00:40.6	00:40.8	00:50.6	00:50.7	01:00.5	00:52.6						
12	00:41.0	00:41.2	00:50.8	00:51.0	01:00.8	00:52.9						
13	00:45.9	00:46.0	00:51.1	00:51.2	01:01.1	00:57.0						
14	00:46.2	00:46.3	00:52.2	00:56.3	01:11.0	01:00.6						
15	00:46.5	00:46.6	00:52.5	00:59.3	01:11.3	01:01.0						
16	00:49.6	00:49.7	00:52.8	00:59.7	01:11.7	01:01.4						
17	00:49.9	00:50.0	00:56.2	01:00.0		01:11.1						
18	00:50.1	00:50.2	00:59.1	01:02.9		01:11.4						
19	00:54.9	00:55.0	00:59.5	01:03.2		01:11.8						
20	00:55.6	00:55.6	00:59.9	01:08.8								
21	00:57.3	00:57.5	01:02.8	01:09.3								
22	00:57.8	00:57.8	01:03.1	01:09.6								
23	00:58.1	00:58.3	01:08.7	01:09.9								
24	01:02.1	01:02.2	01:09.1	01:10.2								
25	01:02.4	01:02.5	01:09.5	01:10.5								
26	01:05.4	01:05.5	01:09.8									
27	01:05.7	01:05.8	01:10.1									
28	01:06.0	01:06.1	01:10.4									
29	01:06.3	01:06.4										
30	01:06.6	01:06.8										
31	01:07.0	01:07.1										
32	01:07.3	01:07.4										
33	01:07.6	01:07.7										

Figure 5.7 Typical Output from Traffic Tracker

Using Traffic Tracker, it was possible to classify all vehicles as per the Federal Highway Administration (FHWA) 13-class system; however this approach would have required a large amount of time and effort. In order to simplify the approach, the study grouped the vehicles into three broad classes, as presented in Table 5.1.

This detection system, unlike loop detectors, detects every vehicle. Where there exists a need to extract further information or confirm extracted data, the video was played back.

TABLE 5.1
Vehicle Classification Scheme for the Video Data

Present Study Class	Vehicle Type	FHWA Classes
1	Passenger Car	1–3
2	Single-unit Truck	4–7
3	Combination Truck	8–13

5.4 Chapter Summary

The field data collection for the detailed phase of this study started in October, 2009 and ended in March 2010. For urban interstates, a total of 90 hours of video was recorded (this is equivalent to 540 lane-hours of video recorded traffic data, with three traffic lanes in each direction). Of the 540 lane-hours, only the peak 15-minutes of data was considered for final model building. Thus, the processing of urban data yielded a total of 540 observations. Of these 540, 452 observations with at least one passenger car, one single-unit truck and one combination truck were used for model building. In the case of rural interstates, the detailed data collection effort yielded 31 lane-hours of video recorded traffic data at three different rural interstate locations (I-65, I-70 and I-74). The processing of rural interstate video data yielded 94 observations which had at least one passenger car, one single-unit truck and one combination truck. Thus a total of 94 observations

TABLE 5.2
Summary Statistics of the Video Recorded Data – Urban Interstates

Variable	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	213.062	42.459	101.214	350.311
Average SUT lagging headway (ft)	302.550	127.446	92	1707.273
Average CT lagging headway (ft)	347.672	101.701	145	1482.143
PC Flow (PC/15 min)	218.646	74.452	12	461
SUT Flow (SUT/15 min)	13.066	7.370	1	45
CT Flow (CT/15 min)	28.162	16.259	1	75
Total Vehicles in 15 minutes	259.874	77.791	19	485
Average PC Speed (mph)	61.241	7.314	29.535	111.393
Average SUT Speed (mph)	60.599	8.810	19.180	145.533
Average CT Speed (mph)	59.939	7.993	33.333	115.758
Percent PC	83.742	9.200	51.397	99.216
Percent SUT	5.184	3.200	0.392	19.186
Percent CT	11.074	6.895	0.322	30.928

TABLE 5.3
Summary Statistics of the Video Recorded Data – Rural Interstates

Variable	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	311.29	93.34	130.52	606.66
Average SUT lagging headway (ft)	438.00	231.86	89.46	1303.13
Average CT lagging headway (ft)	451.98	144.12	150.34	1089.94
PC Flow (PC/15 min)	85.27	31.36	30	174
ST Flow (SUT/15 min)	4.60	3.35	1	15
CT Flow (CT/15 min)	35.90	19.70	4	88
Total Vehicles in 15 minutes	125.77	36.64	39	215
Average PC Speed (mph)	68.43	11.99	42.30	104.27
Average SUT Speed (mph)	67.24	15.97	38.76	125.00
Average CT Speed (mph)	64.98	14.04	39.22	110.86
Percent PC	68.21	14.38	29.70	91.18
Percent SUT	3.58	2.38	0.61	11.88
Percent CT	28.21	13.59	6.35	66.67

were available for building the headway model for rural interstates. Tables 5.2 and 5.3 present a summary of significant variables in the dataset collected for urban and rural interstates, respectively.

6 DEVELOPMENT OF THE DETAILED HEADWAY MODEL

6.1 Modeling Framework

For modeling the collected data in the detailed phase of this study, the statistical methodology was the same as that used for the preliminary phase. The exception is that in the detailed phase, the natural log of dependent variables was used for model building. This is because the natural log of dependent variables provided a better fit. Also, because headways cannot be negative, the developed models can only predict positive values of headways. Mathematically, the system of regression models can be represented as follows by Equations 6.1 to 6.3.

$$ln(H_{pc}) = \alpha_1 + \beta_{pc}X_{pc} + \lambda ln(H_{sut}) + \tau ln(H_{ct}) + \varepsilon_{pc} \tag{6.1}$$

$$ln(H_{sut}) = \alpha_2 + \beta_{sut}X_{sut} + \delta(lnH_{pc}) + \alpha ln(H_{ct}) + \varepsilon_{sut} \tag{6.2}$$

$$ln(H_{ct}) = \alpha_3 + \beta_{ct}X_{ct} + \phi ln(H_{pc}) + \pounds ln(H_{sut}) + \varepsilon_{ct} \tag{6.3}$$

Where:

$ln(H_i)$ is the natural logarithm of the average "rear bumper to rear bumper" spacing of vehicle type i

β_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)

λ, τ, δ, α £ and φ are estimable scalars, and ε_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, $ln(H_{pc})$, $ln(H_{sut})$ and $ln(H_{ct})$ are endogenous variables, meaning $ln(H_{sut})$ belongs to the set of independent variables of $ln(H_{pc})$ and $ln(H_{ct})$. Similarly $ln(H_{pc})$ and $ln(H_{ct})$ belong to the set of influential factors of $ln(H_{sut})$, and so on. Since the dependent variables are endogenous and the error terms are correlated, the 3SLS method is appropriate to estimate simultaneously the parameters of the equations (Washington et al., 2003).

6.2 Discussion of Results – Urban Interstate

Headway models have been estimated separately for both rural and urban interstate separately using the developed methodology. Table 6.1 displays the results of the 3SLS estimation for urban interstate. This is a three-equation 3SLS model that was developed using 452 observations (each 15-minute video-clip constitutes

TABLE 6.1
Three-stage Least Square Model Estimation Results- Urban Interstate

Variable	Coefficient	t-stat	Mean
ln(Average PC Lagging Headway) (ft)			
Constant	3.259	20.231	
PC Flow (PC/15 min)	−0.007	−9.464	218.646
SUT Flow (SUT/15 min)	−0.003	−4.319	13.067
Average PC Speed (mph)	0.017	14.877	61.240
Average SUT Speed (mph)	−0.002	−2.403	60.598
ln(Average SUT lagging headway (ft))	0.142	6.748	5.650
ln(Average CT lagging headway (ft))	0.956	3.386	5.819
Adjusted R2	0.6543		
Durbin-Watson	2.0647		
ln(Average SUT Lagging Headway) (ft)			
Constant	−1.696	−3.725	
Average PC Speed (mph)	−0.015	−4.720	61.240
Average SUT Speed (mph)	0.009	4.434	60.598
ln(Average PC lagging headway (ft))	0.733	7.750	5.341
ln(Average CT lagging headway (ft))	0.644	10.340	5.819
Adjusted R2	0.2605		
Durbin-Watson	1.7968		
ln(Average CT Lagging Headway) (ft)			
Constant	2.254	8.056	
SUT Flow (SUT/15 min)	0.003	2.033	13.066
Average CT Speed (mph)	0.004	2.653	59.938
ln(Average PC lagging headway (ft))	0.248	4.153	5.341
ln(Average SUT lagging headway (ft))	0.352	10.465	5.650
Adjusted R2	0.2435		
Durbin-Watson	1.9911		
N	452		

one observation). Each of these observations included at least one vehicle from each of the three vehicle classes. The first column is a descriptive list of the significant variables. The next column hosts the estimated exploratory factors. The third is the significance of each variable; a $|\text{t-stat}| \geq 1.96$ indicates the 95% confidence interval. For easy reference the last column provides the mean of the variable.

6.2.1 Passenger Car Following

The adjusted R^2 value of 0.6543 indicates reasonably strong correlation between the predicted and measured passenger car headways. The sign of the variables PC Flow (PC/15 minutes) and ST Flow (ST/15 minutes) indicates that, all else being equal, an increase in flow rate of passenger cars or single-unit trucks decreases the predicted lagging headway of passenger cars. This is an intuitive result: as more vehicles are added to the traffic stream, the spatial constraints increase, resulting in a decrease in headway. The average passenger car speed is another significant variable which increases passenger car headway. This is somewhat intuitive as larger stopping distance is required at higher speeds, thus a driver is more likely to leave greater room between their vehicle and the vehicle ahead of them. Conversely, as single-unit truck speed increases, the passenger car headway decreases. This suggests that passenger cars are more comfortable with faster moving single-unit trucks than slower moving single-unit trucks. Both endogenous variables have a significant positive relationship, meaning an increase in lagging headway of single or combination trucks increases passenger car lagging headway. This may be due to certain unaccounted similarities between the travel behaviors of these three vehicle classes. The single-unit truck coefficient, which is slightly higher than that of combination truck coefficient, suggests that the headway of passenger cars is more influenced by single-unit trucks.

6.2.2 Single-Unit Truck Following

The single-unit truck equation is not as strongly correlated as that for passenger cars. The adjusted R^2 for the single-unit truck headway model is 0.2605, which is considerably lower than the R^2 for passenger cars. This is not unexpected as single-unit trucks are relatively few in number in a traffic stream (on average, single-unit trucks comprise 5% of the overall traffic stream). Both, the speed of passenger cars and single-unit trucks have significant correlation with the single-unit trucks lagging headway. However, increasing the speed of passenger cars decreases the lagging headway of single-unit trucks, while an increase in speed of single-unit trucks increases the single-unit truck lagging headway. This suggests that when single-unit trucks increase their speed, they exercise due caution and leave more space between themselves and the leading vehicle, while an increase in passenger car speed actually makes the single-unit trucks more comfortable thus decreasing their headway. Both of the endogenous variables are positive and significant. An increase in passenger car and combination truck lagging headway is associated with an increase in lagging headway of single-unit trucks.

6.2.3 Combination Truck Following

The combination truck equation has a comparable fit to the single-unit truck equation. The equation has an adjusted R^2 of 0.2435 indicating that some of the variance in lagging headway data is explained, but not as much as in the passenger car headway model. The results also suggest that single-unit truck flow is an important variable that affects the lagging headway of combination trucks. An increase in single-unit truck flow results in increase in lagging headway of combination trucks. This suggests that in the presence of single-unit trucks, combination trucks exercise more caution by keeping a greater distance from the leading vehicle. In addition, as combination trucks increase their speed, they increase their headways. This result suggests that at higher speeds, combination trucks tend to provide themselves with greater room because they need a greater distance for braking should the need arise. Lastly, as was the case for the passenger car and single-unit truck headway models, the results suggest that

TABLE 6.2
MAPE Values by Model Type – Urban Interstate

Variable	MAPE Value for different Vehicle Classes
PC Average Headway	0.087
SUT Average Headway	0.210
CT Average Headway	0.046

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 classes increase their headway accordingly.

6.2.4 Model Accuracy

To evaluate the predictive accuracy of the developed models, the Mean Absolute Percent Error (MAPE) is estimated as follows (Washington et al., 2003);

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|PE_i| \tag{6.4}$$

where $PE_i = 100 \bullet (X_i - F_i)/X_i$ is the percentage error for observation i of the actual and predicted headway X_i and F_i, respectively.

The resulting MAPE is presented in Table 6.2 for the 3-equation 3SLS models by vehicle class. Values closer to zero signify greater accuracy. For example, a MAPE of 0.087 (as in the PC average headway of the 3-equation 3SLS model) suggests that on average, the forecasts underestimate or overestimate the true values by 8.7%. Figure 6.1 through Figure 6.3 present the predicted over the actual values of the headways by vehicle class and graphically illustrates that the predictive accuracy of the 3-equation 3SLS models is satisfactory. In Figure 6.1 through Figure 6.3, the straight line indicates the equivalence of predicted and actual values.

The developed models do not have any issue of serial correlation as the value of Durbin-Watson statistics for all models falls between 1.7 and 2.3 which is a reasonable range (Washington et al., 2003).

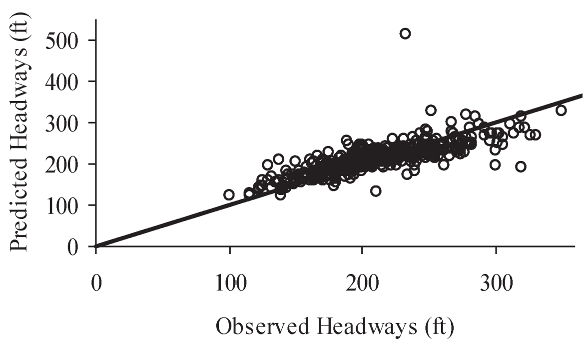


Figure 6.1 Predicted vs. Observed PC Headways (3-Equation 3SLS Model - Urban Interstate)

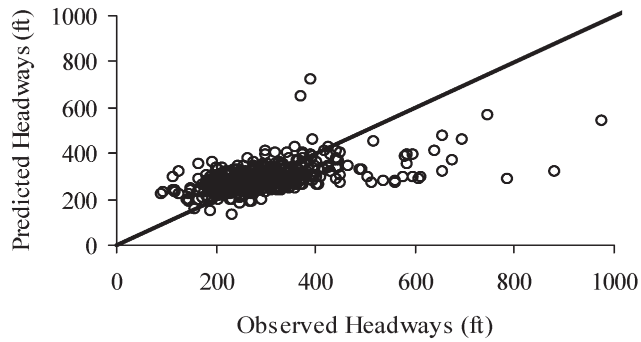


Figure 6.2 Predicted vs. Observed SUT Headways (3-Equation 3SLS Model - Urban Interstate)

6.3 Discussion of Results – Rural Interstate

Table 6.3 displays the results of the 3SLS estimation for rural interstates. This is a three-equation 3SLS model that was developed using 94 observations (each 15-minute video-clip constitutes one observation). The 94 observations were only those observations where at least one vehicle from each vehicle class was observed to be following a vehicle of other class in traffic stream (at least one passenger car, single-unit truck or combination truck following any other vehicle). The first column is a descriptive list of the significant variables. The next column hosts the estimated X vectors. The third is the significance of each variable; a |t-stat| ≥ 1.96 indicates the 95% confidence interval. The last column presents the mean of each variable.

6.3.1 Passenger Car Following

The adjusted R^2 value of 0.7284 indicates a rather strong correlation between the predicted and measured passenger car headways. The sign of the variables PC Flow (PC/15 minutes) indicates that, all else being equal, an increase in flow rate of passenger cars decreases the predicted lagging headway of passenger cars. This is an intuitive result; as more passenger cars are added to the traffic stream, the spatial constraints increase, resulting in a decrease in headway. The sign of the variable CT Flow (CT/15 minutes) indicates that, all

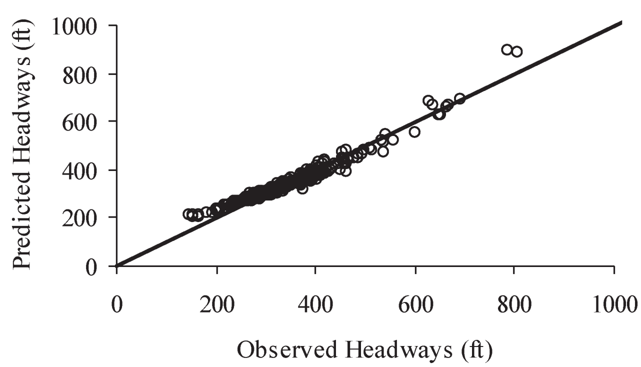


Figure 6.3 Predicted vs. Observed CT Headways (3-Equation 3SLS Model - Urban Interstate)

TABLE 6.3
Three-stage Least Square Model Estimation Results- Rural Interstate

Variable	Coefficient	t-stat	Mean
ln(Average PC lagging headway) (ft)			
Constant	3.354	8.154	
PC Flow (PC/15 min)	−0.003	−5.694	85.265
CT Flow (CT/15 min)	0.002	2.357	35.904
Average PC Speed (mph)	0.015	6.938	68.435
ln(Average SUT lagging headway) (ft)	0.073	1.961	5.9440
ln(Average CT lagging headway) (ft)	0.180	2.157	6.0680
Adjusted R2	0.7284		
Durbin-Watson	1.7459		
ln(Average Single-unit Truck lagging headway) (ft)			
Constant	2.5411	2.503	
Average SUT Speed (mph)	0.0120	2.957	67.238
Ln(Average PC lagging headway) (ft)	0.4590	2.230	5.6940
Adjusted R2	0.2892		
Durbin-Watson	1.9786		
ln(Average Combination Truck lagging headway) (ft)			
Constant	3.645	8.399	
Average PC Speed (mph)	−0.009	−2.119	68.435
Average CT Speed (mph)	0.0190	6.497	64.982
ln(Average PC lagging headway) (ft)	0.3140	3.183	5.6950
Adjusted R2	0.6400		
Durbin-Watson	2.1480		
N	94		

else being equal, an increase in the flow rate of combination trucks increases the predicted lagging headway of passenger cars. This might be because when more combination trucks are added into the traffic stream passenger cars exercise caution by keeping more safety distance from combination trucks. The average passenger car speed was found to be a significant variable that increases headway. As explained in the previous model, this is somewhat intuitive as larger stopping distance is required at higher speeds, thus a driver is more likely to leave greater room between their vehicles and the vehicle ahead of them. Both endogenous variables have a significant positive relationship, meaning an increase in lagging headway of single or combination trucks increases passenger car lagging headway. This may be due to certain unaccounted similarities between the travel behaviors of these three vehicle classes. The combination truck coefficient which is slightly higher than that of single-unit truck coefficient suggests that the headway of passenger cars is more influenced by combination trucks.

6.3.2 Single-unit Truck Following

The adjusted R^2 for single-unit trucks is 0.2891, not trivial, but not as strong as that of passenger car. This is not unexpected as single-unit trucks are fewer in number in a traffic stream (on average single-unit trucks comprise 4.6% of the overall traffic stream). The speed of single-unit trucks has significant correlation with the single-unit trucks lagging headway. With an increase in speed of single-unit trucks, the lagging headway of single-unit truck increases. This suggests that when single-unit trucks travel faster, they exercise caution and keep more space between themselves and the leading vehicle. The average passenger car lagging headway (an endogenous variable) is significantly correlated with single-unit truck lagging headway and an increase in passenger lagging headway results in an increase in the lagging headway of single-unit truck.

6.3.3 Combination Truck Following

Combination trucks display model characteristics that are somewhat different from single-unit trucks. The adjusted R^2 of 0.6400 represents a reasonable strong correlation between observed and predicted headways of combination trucks. The speed of passenger cars and combination trucks are significantly correlated with the combination truck lagging headway. However, a higher speed of passenger cars decreases the lagging headway of combination trucks, while an increase in speed of combination trucks increases the combination trucks lagging headway. This suggests that when combination trucks 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 combination trucks more comfortable thus decreasing their headway. The endogenous variable (lagging headway of passenger car) is similar to single-unit trucks. An increase in passenger lagging headway is associated with an increase in combination truck lagging headway, which indicated that as passenger cars increase their headway combination trucks also behave similarly.

6.3.4 Model Accuracy

The developed models do not have an issue of serial correlation as the value of the Durbin-Watson statistics for all models falls between 1.7 and 2.3 which is a reasonable range (Washington et al., 2003). To evaluate the predicting accuracy of the developed models, the Mean Absolute Percent Error (MAPE) is estimated in a manner similar to that done for urban interstates.

Table 6.4 presents MAPE values for the 3-equation 3SLS models by model type. Values closer to zero signify better accuracy. Figure 6.4 through Figure 6.6 present the predicted over the actual values of the headways by vehicle class for the rural interstate and graphically illustrates that 3-equation 3SLS models predictive accuracy is reasonable.

6.4 Further Exploration of the Headway Models

In yet another extension of this study, the average spatial lagging headways are estimated on the basis of the class of vehicle that leads and the class that follows.

TABLE 6.4
MAPE Values by Model Type – Rural Interstate

Variable	MAPE Value for different Vehicle Classes
PC Average Headway	0.13
SUT Average Headway	0.402
CT Average Headway	0.13

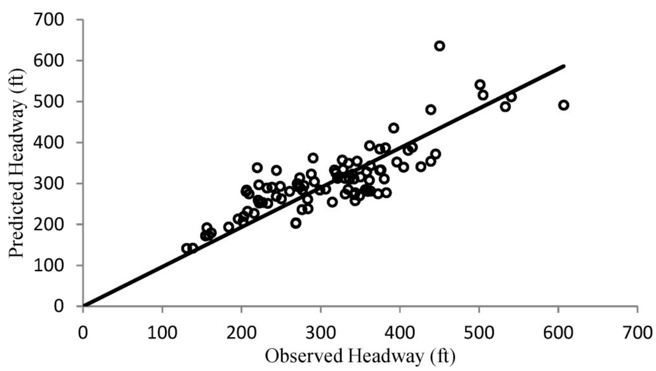


Figure 6.4 Predicted vs. Observed PC Headways (3-Equation 3SLS Model - Rural Interstate)

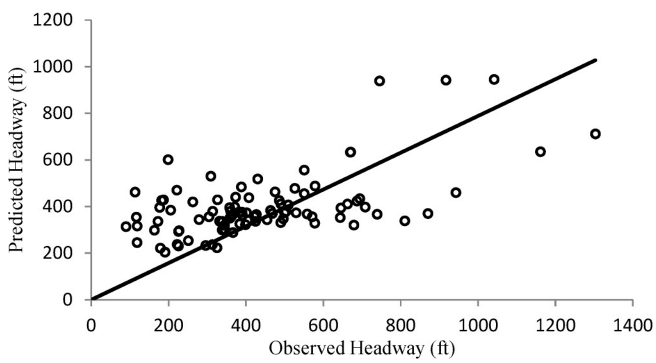


Figure 6.5 Predicted vs. Observed SUT Headways (3-Equation 3SLS Model - Rural Interstate)

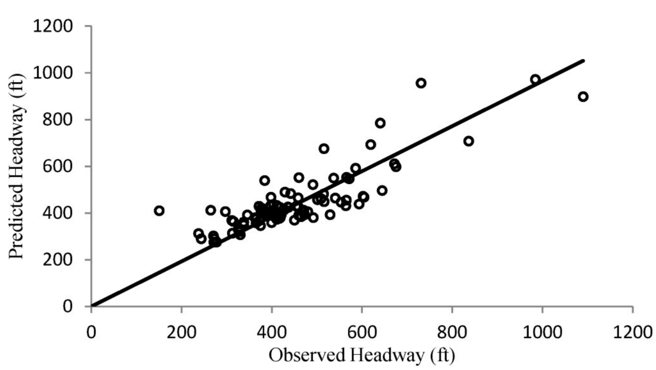


Figure 6.6 Predicted vs. Observed CT Headways (3-Equation 3SLS Model - Rural Interstate)

It is assumed that headways are expected to differ by class of vehicle that follows and/or leads. For example, a passenger car following another passenger car may generally prefer a different lagging headway than one following a single-unit truck or combination truck. This study seeks to develop a nine-equation 3SLS model for average spatial lagging headway and then ultimately find the average lagging headway for each vehicle class. The average lagging headways on the basis of class of vehicle leading and following are estimated using the following system of equations:

$$ln(H_{pc-pc}) = \beta_{pc-pc}X_{pc-pc} + \lambda_1 H_{pc-ct} + \tau_1 H_{sut-pc} + \phi_1 H_{ct-pc} + \varepsilon_{pc-pc} \quad (6.5)$$

$$ln(H_{pc-sut}) = \beta_{pc-sut}X_{pc-sut} + \vartheta_2 H_{ct-pc} + \varepsilon_{pc-sut} \quad (6.6)$$

$$ln(H_{pc-ct}) = \beta_{pc-ct}X_{pc-sut} + \varepsilon_{pc-ct} \quad (6.7)$$

$$ln(H_{sut-pc}) = \beta_{sut-pc}X_{sut-pc} + \phi_2 H_{ct-pc} + \phi_3 H_{ct-sut} + \varepsilon_{sut-pc} \quad (6.8)$$

$$ln(H_{sut-pc}) = \beta_{sut-pc}X_{sut-pc} + \tau_2 H_{sut-pc}\varepsilon_{sut-pc} \quad (6.9)$$

$$ln(H_{sut-ct}) = \beta_{sut-ct}X_{sut-ct} + \vartheta_4 H_{ct-sut}\varepsilon_{sut-ct} \quad (6.10)$$

$$ln(H_{ct-pc}) = \beta_{ct-pc}X_{ct-pc} + \tau_3 H_{sut-pc} + \varepsilon_{ct-pc} \quad (6.11)$$

$$ln\ (H_{ct-sut}) = \beta_{ct-sut}X_{ct-sut} + \tau_5 H_{sut-pc} + \tau_6 H_{sut-ct} + \phi_5 H_{ct-pc} + \varepsilon_{ct-sut} \quad (6.12)$$

$$ln(H_{ct-ct}) = \beta_{ct-ct}X_{ct-sut} + \lambda_7 H_{ct-pc} + \varepsilon_{ct-ct} \quad (6.13)$$

where

$ln(H_{m-k})$ is the natural logarithm of average "rear bumper to rear bumper" spacing of vehicle type m when following a vehicle type k

β_{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)

λ_m, τ_m, and φ_m are estimable scalars

ε_{m-k} is the disturbance term.

Having estimated the individual headways and knowing the percentage of vehicle of each class leading/following, the class average headway can be estimated as follow:

$$\overline{H}_{pc} = p_{pc-pc}H_{pc-pc} + p_{pc-sut}H_{pc-sut} + p_{pc-ct}H_{pc-ct} \quad (6.14)$$

$$\overline{H}_{sut} = p_{sut-pc}H_{sut-pc} + p_{sut-sut}H_{sut-sut} + p_{sut-ct}H_{sut-ct} \quad (6.15)$$

$$\overline{H}_{ct} = p_{ct-pc}H_{ct-pc} + p_{ct-sut}H_{ct-sut} + p_{ct-ct}H_{ct-ct} \quad (6.16)$$

where $\overline{H}_m$ is the class average lagging headway for class m, p_{m-kj} is the percentage of vehicle of class m following class k vehicles, and H_{m-k} is the average lagging headway of vehicle class m following vehicle class k.

The parameters used in the estimation are drawn from the same dataset as for the 3-equation headway models. The final PCE values are calculated, considering the ratio of class average lagging headways. This type of framework is far more computationally intensive and grows much more difficult with every vehicle class considered, but the payoff in accuracy may be worth the effort. By directly using rational data and robust analytical methods, it is expected to have a model that captures the complex reality of vehicle headway and passenger car equivalence. For this extension of the study the dataset consists of a total of 142 observations drawn from the urban interstate data. This dataset is limited due to the relatively small number of observations that comprise each of nine combinations of vehicle following pairs (car following car, car following single-unit truck, car following a combination truck, single-unit truck following car, single-unit truck following single-unit truck, single-unit truck following combination truck, combination truck following car, combination truck following single-unit truck, and combination truck following combination truck). Table 6.5 displays the results of the 9-equation 3SLS model estimated for urban interstates using 142 observations. There are total of nine model equations, three each for passenger cars, single-unit trucks, and combination trucks. 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.

6.4.1 Passenger Car Following

Each of the first three equations (Equation 6.5 – 6.7) estimates a passenger car following headway for each of the three vehicle classes. The three equations have a reasonable fit with adjusted R^2 values of 0.6405, 0.7650 and 0.4758 respectively. The percentages of passenger cars and single-unit trucks 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 due to the requirement of longer stopping sight distance that is generally required at higher speed.

The variables representing number of passenger cars, single-unit trucks, and combination trucks are all significant in one or more of the car following equations, albeit with different magnitudes (Table 6.5). 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.

6.4.2 Single-unit Truck Following

Equations 6.8 – 6.10 provide the three cases in which single-unit trucks follow other vehicles. The three equations have reasonable fit with adjusted R^2 values of 0.8710, 0.4549 and 0.5715, respectively. The percentages of passenger cars and single-unit trucks are significant variables with a positive influence in all three equations. This suggests that increasing the percentage of cars and single-unit trucks is associated with an increase in single-unit truck lagging headway regardless of what vehicle 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 single-unit trucks headway increases. This is due to the propensity of drivers to maintain a larger stopping sight distance at higher speeds to avoid rear-end crashes. The numbers of passenger cars, single-unit trucks and combination trucks are three other variables which are significant in these equations. Thus, the addition of passenger cars or single-unit trucks is observed to be associated with a reduction in available space, thus lowering the headway. On the other hand, the addition of combination trucks increases the headway as single-unit trucks maintain a longer safety distance. This is similar to the observation in the passenger car following equations, thus showing the similarity in the behavior of these classes of vehicles in the traffic stream. Endogenous variables appear in all three equations: these increase the headway in all types of vehicle interactions involved.

6.4.3 Combination Truck Following

Equations 6.11 – 6.13 represent the three cases where combination trucks follow other vehicles. The three equations have reasonable fit, with adjusted R^2 values of 0.6891, 0.5769 and 0.7993 respectively. The number of passenger cars, single-unit trucks and combination trucks are three variables that are significant in all three equations. An increase in the number of single-unit trucks or combination trucks affects the lagging headway of combination trucks differently depending on the class of vehicle being followed by the combination truck (Table 6.5). Furthermore, when the percentage of passenger cars or combination trucks increases, the

TABLE 6.5
Results of the Estimated 9-Equation 3SLS?Model

Variable	Coefficient	t-stat	Variable	Coefficient	t-stat
ln(Average PC-PC Lagging Headway) (ft)			*ln(Average PC-SUT Lagging Headway) (ft)*		
Speed of PC	0.0101	5.863	Percentage of PCs	0.063	21.213
Percentage of PCs	0.05	36.716	Percentage of SUTs	0.0306	3.291
Percentage of SUTs	0.0991	9.309	Headway MUT-PC	0.002	5.494
Headway PC-MUT	0.0017	6.842	No. of PCs	−0.0015	−7.723
Headway SUT-PC	−0.0002	−1.852	No. of CTs	0.0043	8.659
Headway MUT-PC	0.0006	3.353	Adjusted R-square	0.765	
No. of PCs	−0.0006	−6.105	*ln(Average SUT-PC Lagging Headway) (ft)*		
No. of SUTs	−0.006	−5.187	Speed of SUT	0.0068	2.599
No. of CTs	0.0041	22.545	Percentage of PCs	0.0539	20.358
Adjusted R-square	0.6405		Percentage of SUTs	0.1156	5.662
ln(Average PC-CT Lagging Headway) (ft)			Headway MUT-PC	0.0007	2.222
Speed of PC	0.0079	2.77	Headway MUT-SUT	0.0007	5.211
Percentage of PCs	0.0442	21.266	No. of PCs	−0.0005	−2.674
Percentage of SUTs	0.0812	4.945	No. of SUTs	−0.0063	−2.822
Headway PC-PC	0.0037	7.261	No. of CTs	0.0043	11.481
No. of PCs	−0.0005	−3.037	Adjusted R-square	0.871	
No. of SUTs	−0.0045	−2.489	*ln(Average ST-PC Lagging Headway) (ft)*		
No. of CTs	0.0041	14.216	Speed of SUT	0.0131	2.792
Adjusted R-square	0.4758		Percentage of PCs	0.0511	10.928
ln(Average ST-ST Lagging Headway) (ft)			Percentage of SUTs	0.0757	6.34
Speed of SUT	0.0224	2.516	Headway MUT-SUT	0.001	3.532
Speed of CT	−0.0209	−2.501	No. of PCs	−0.0011	−4.527
Percentage of PCs	0.0467	12.39	No. of CTs	0.0048	7.086
Percentage of SUTs	0.0865	5.917	Adjusted R-square	0.5715	
Headway SUT-PC	0.0021	3.041	*ln(Average CT-ST Lagging Headway) (ft)*		
No. of CTs	0.003	3.426	Speed of PC	−0.0193	−3.601
Adjusted R-square	0.4549		Percentage of PCs	0.0678	14.855
ln(Average CT-PC Lagging Headway) (ft)			Headway SUT-PC	0.002	4.131
Speed of PC	0.0259	7.621	Headway SUT-MUT	0.001	3.796
Percentage of CTs	0.2168	15.463	Headway MUT-PC	0.0017	2.913
Headway SUT-PC	0.0012	3.361	No. of PCs	−0.0013	−5.495
No. of PCs	0.0034	18.116	No. of SUTs	0.0059	4.442
No. of SUTs	0.004	3.185	No. of CTs	0.0055	8.315
No. of CTs	−0.0167	−11.166	Adjusted R-square	0.5305	
Adjusted R-square	0.6891		Number of Observations		142
ln(Average CT-CT Lagging Headway) (ft)			System Weighted Adjusted R-squared		0.6403
Percentage of PCs	0.0705	26.975			
Headway MUT-PC	0.0017	5.288			
No. of PCs	−0.0019	−12.174			
No. of SUTs	0.0056	6.647			
No. of CTs	0.005	12.102			
Adjusted R-square	0.7993				

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

lagging headway of combination trucks increases indicating that when these vehicles make up a larger portion of the traffic stream combination trucks exercise more caution. The speed of passenger cars is another significant variable that increases headway when combination trucks are following passenger cars but reduces headway when combination trucks are following single-unit trucks. In the former case, it appears that passenger cars "pull away" from combination trucks leading to larger headways, while an increase in passenger car speed may relegate combination trucks to the travel lane only where they fall closely in line with single-unit trucks. The endogenous variables appear in all three equations which always increase the headway in all types of vehicle interaction involved (Table 6.5).

6.4.4 Model Accuracy

To evaluate the predictive accuracy of the developed model, the Mean Absolute Percent Error (MAPE) was estimated. The resulting MAPEs are presented in Table 6.6 for 9-equation 3SLS models by vehicle class. Values closer to zero signify better accuracy. Figure 6.7 to Figure 6.9 presents the predicted over the actual values of the headways by vehicle class and graphically illustrates that 9-equation 3SLS models predictive accuracy is reasonable.

TABLE 6.6
MAPE Values by Vehicle Class and Model Type – 9-Eqautions 3SLS Model

Variable	9-Equation 3SLS Model
PC Average Headway	0.060*
PC-PC Average Headway	0.061
PC-ST Average Headway	0.052
PC-CT Average Headway	0.066
ST Average Headway	0.146†
ST-ST Average Headway	0.128
ST-PC Average Headway	0.160
ST-CT Average Headway	0.149
CT Average Headway	0.032‡
CT-CT Average Headway	0.033
CT-PC Average Headway	0.028
CT-ST Average Headway	0.035

*9-Equation 3SLS predicted headway averaged by PC
†9-Equation 3SLS predicted headway averaged by ST
‡9-Equation 3SLS predicted headway averaged by CT

6.5 Calculating PCE Values based on Headway Model Results

PCE values help to convert a mixed traffic stream into one comprised solely of pure passenger cars. Different methodologies can result in different PCE estimates leading to different traffic densities and

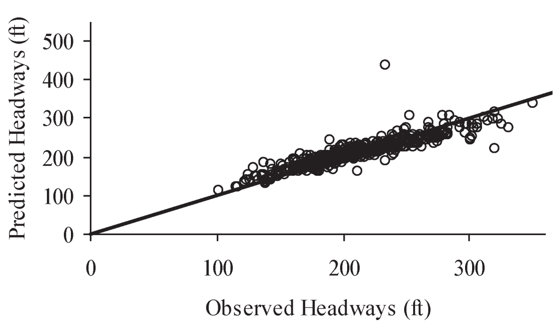


Figure 6.7 Predicted vs. Observed Passenger Car Headways (9-Equation 3SLS Model – Urban Interstate)

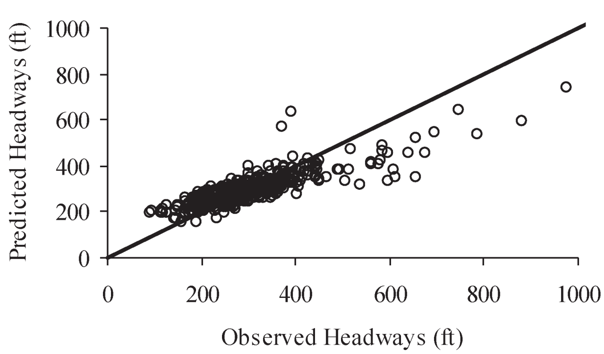


Figure 6.8 Predicted vs. Observed Single-unit Truck Headways (9-Equation 3SLS Model – Urban Interstate)

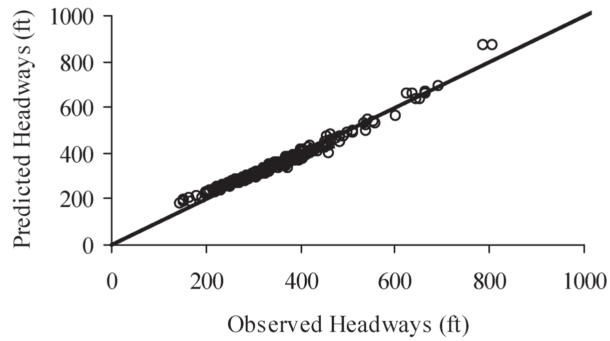


Figure 6.9 Predicted vs. Observed Combination Truck Headways (9-Equation 3SLS Model – Urban Interstate)

ultimately a different LOS. Table 6.7 presents the average condition at each site where data has been collected. Table 6.8 presents the comparison of actual observed headways and observation-based predicted headways estimated using a 3-equation 3SLS model for rural and urban interstate. It can be observed that generally the predicted values of lagging headways are reliable. In case of rural interstate the predicted values differ from observed values ranging from 6.32% to 11.66%. However, for individual rural interstate sites there could be larger differences between the observed and predicted headways as the selected sites (although located on similar freeways sections) might have different traffic conditions. In case of urban interstates, the difference between predicted and observed headways is less than 6% overall, which indicates that the model predictions are even more reliable. In the case of rural interstates, the difference between predicted and observed headways is less than 5% overall for passenger cars and combination truck which indicates that the model predictions are quite reliable. In the case of single-unit trucks, the predicted and observed headways differ by about 13% which might be due to the fact that on rural interstate single-unit trucks comprise just 3.5% of the overall traffic stream.

The ratio of single-unit or combination truck lagging headway to that of passenger car lagging headway provides a PCE value for each truck class. Table 6.9 presents these observation-based PCE values calculated at all data collection locations. Table 6.9 also presents average PCE values for rural and urban interstates estimated using headway models. The single-unit and combination truck PCE values estimated using the 3-equation 3SLS model for urban interstates are: 1.35 and 1.60 respectively. For the rural interstate estimated single-unit and combination truck PCE values are: 1.30 and 1.45 respectively. The PCE values estimated for the rural interstate are based on fewer number of observations as compared to urban interstate (94 observations used for rural headway model and 452 observations used for urban headway model), hence not recommended to replace the existing single PCE value of 1.5 for both single-unit and combination trucks. There is a further need

TABLE 6.7
Summary Statistics of the Data at Different Urban and Rural Locations

Variable	Rural Interstate Loc-1	Rural Interstate Loc-2	Rural Interstate Loc-3	Rural Interstate Mean	Urban Interstate Loc-1	Urban Interstate Loc-2	Urban Interstate Loc-3	Urban Interstate Loc-4	Urban Interstate Mean
Ave. PC lagging headway (ft)	294.44	357.01	300.19	311.295	196.136	220.905	232.090	208.640	213.062
Ave. SUT lagging headway (ft)	459.87	444.99	422.78	438.002	270.669	344.735	325.942	273.491	302.550
Ave. CT lagging headway (ft)	442.57	455.10	455.79	451.979	323.053	372.087	366.724	333.435	347.672
PC Flow (PC/15 min)	77.50	67.48	97.51	85.266	262.056	215.127	173.186	209.313	218.646
ST Flow (SUT/15 min)	3.42	2.81	6.04	4.596	12.088	8.913	18.163	14.870	13.066
CT Flow (CT/15 min)	41.92	31.48	34.55	35.904	19.144	16.762	40.884	40.939	28.162
Total Vehicles in 15 minutes	122.85	101.76	138.11	125.766	293.288	240.802	232.233	265.122	259.874
Ave. PC Speed (mph)	69.31	68.04	68.13	68.435	58.764	61.982	63.591	61.362	61.241
Ave. SUT Speed (mph)	68.69	62.84	68.40	67.238	58.392	61.807	63.725	59.336	60.599
Ave. CT Speed (mph)	65.88	60.93	66.30	64.982	58.565	61.240	61.333	58.963	59.939
Percent PC	64.15	67.27	70.88	68.212	89.689	89.561	73.852	78.301	83.742
Percent SUT	2.77	2.82	4.37	3.580	4.152	3.662	8.086	5.802	5.184
Percent CT	33.07	29.91	24.76	28.208	6.159	6.777	18.063	15.897	11.074

Rural Interstate Locations
Location 1 – I-65 (Lafayette)
Location 2 – I-74 (Crawfordville)
Location 3 – I-70 (SW of Indianapolis)
Urban Interstate Locations
Location 1 – I-465 North Indianapolis
Location 2 – I-465 North Indianapolis
Location 3 – I-465 South Indianapolis
Location 4 – I-465 South Indianapolis
See Appendix I and II for specific locations

TABLE 6.8
Comparisons of Measured and Predicted Headways

Location	Measured lagging Headway (ft) PC	Measured SUT	Measured CT	Predicted lagging Headway (ft) PC	Predicted SUT	Predicted CT	% Difference between measured and predicted headways PC	% Difference SUT	% Difference CT
Rural Interstate									
Point-1	294.441	459.865	442.571	284.992	379.381	438.760	3.21%	17.50%	0.86%
Point-2	357.014	444.995	455.104	304.565	366.546	403.865	14.69%	17.63%	11.26%
Point-3	300.190	422.781	455.787	314.541	398.350	444.060	−4.78%	5.78%	2.57%
Average	311.295	438.002	451.979	297.254	381.59	432.144	4.51%	12.88%	4.39%
Urban Interstate									
Point-1	196.136	270.669	323.053	192.115	261.987	318.245	2.050%	3.208%	1.488%
Point-2	220.905	344.735	372.087	215.373	293.793	341.39	2.504%	14.777%	8.250%
Point-3	232.09	325.942	366.724	223.464	310.778	360.054	3.717%	4.652%	1.819%
Point-4	208.64	273.491	333.435	209.496	280.655	336.024	−0.410%	−2.619%	−0.776%
Average	213.063	302.55	347.672	208.671	284.362	336.875	2.062%	6.011%	3.105%

of quality data collection from a number of different highway segments from different locations across the state to establish separate PCE values for rural interstate. Headway based PCEs values estimated for urban and rural interstate are different from the single PCE value of 1.5 provided by the HCM. This difference can be more prominent at locations having higher traffic volumes and larger numbers of single-unit or combination trucks, as a greater disparity may exist between the LOS using estimated PCEs (values based on actual traffic observations) and the LOS estimated using HCM's single PCE value.

6.6 Implications of Study Results

The present study developed a methodology through which separate PCE values can be estimated for single-unit and combination trucks. The separation of the PCE values for these two truck classes can influence the results of LOS estimation. To illustrate the implications of the study results, a number of hypothetical scenarios were examined. Table 6.10 presents three scenarios for an urban freeway. For all three scenarios, the percentage of single-unit trucks is maintained constant at 5% while

TABLE 6.9
Estimation of PCE Values using Study Methodology

Location	SUT PCE	CT PCE
Rural Interstate*		
Point-1(I-65) Lafayette	1.331	1.540
Point-2 (I-74) Crawfordsville	1.204	1.326
Point-3(I-70) SW of Indianapolis	1.266	1.412
Average PCE value for Rural Interstate	**1.30**	**1.45**
Urban Interstate**		
Point-1	1.364	1.657
Point-2	1.364	1.585
Point-3	1.391	1.611
Point-4	1.340	1.604
Average PCE value for Urban Interstate	**1.35**	**1.60**

*- PCE value based on a limited data set (94 Observations)
**- PCE value based on sufficient large data set (452 Observations)

the percentage of combination trucks is varied from 20% to 5%. The values of different traffic parameters used for comparison purposes are within the range of actual observed traffic as summarized in Table 5.2.

Scenario – 1 (5% Single-unit and 20% Combination Trucks): Consider a traffic stream composed of 713 passenger cars, 48 single-unit trucks and 190 combination trucks (Table 6.10). Using the PCE value of 1.6 for combination trucks and 1.35 for single-unit trucks estimated using headway models, and following an otherwise standard HCM procedure for a flat freeway section, a LOS C is obtained. However, under same traffic characteristics but with a single PCE value of 1.5 for all trucks yields LOS B.

Scenario – 2 (5% Single-unit and 10% Combination Trucks): Consider a traffic stream composed of 1335 passenger cars, 79 single-unit trucks and 157 combination trucks (Table 6.10). Using separate PCE values of 1.6 for combination trucks and 1.35 for single-unit trucks, for the same flat freeway section, a LOS D is obtained. However, the single PCE value of 1.5 yields LOS C.

Scenario – 3 (5% Single-unit and Combination Trucks): Consider a traffic stream composed of 585 passenger cars, 33 single-unit trucks and 33 combination trucks (Table 6.10). Using PCE values of 1.6 for combination trucks and 1.35 for single-unit trucks, for the same freeway section a LOS B is obtained. The single PCE value of 1.5 also yields LOS B.

As the percentage of combination trucks increases, difference in traffic densities increases with different assignments of PCE values, resulting in differences in LOS. When the percentage of combination trucks in a traffic stream is small (5%), the gap between the resulting LOS values from the two methodologies decreases with converging results.

A similar effect was observed for single-unit trucks. Table 6.11 presents three scenarios for an urban freeway. For all three scenarios, the percentage of combination trucks is maintained constant at 5% while the percentage of single-unit trucks is varied from 20% to 5%. The values of traffic parameters used for comparison purposes are within the range of actual traffic observed, as summarized in Table 5.2. Using a similar procedure as previously discussed, the LOS indices obtained for three scenarios using two different methodologies are as follows:

Scenario – 4 (20% Single-unit Trucks and 5% Combination Trucks):
- LOS using HCM PCE values C
- LOS using separate PCE values from the Headway Approach B

Scenario – 5 (10% Single-unit Trucks and 5 % Combination Trucks):
- LOS using HCM PCE values D
- LOS using separate PCE values from the Headway Approach C

Scenario – 6 (5% Single-unit and Combination Trucks):
- LOS using HCM PCE values A
- LOS using separate PCE values from the Headway Approach A

As observed in scenarios 1 through 3 involving combination trucks, scenarios 4 through 6 also indicate that as the percentage of single-unit trucks increases,

TABLE 6.10
Hypothetical LOS Comparison-1: Effect of Varying Percentage of Combination Trucks

	Scenario -1		Scenario -2		Scenario -3	
	Headway Approach	HCM	Headway Approach	HCM	Headway Approach	HCM
PC Flow (PC/hr)	713	713	1335	1335	585	585
ST Flow (SU/hr)	48	48	79	79	33	33
CT Flow (CT/hr)	190	190	157	157	33	33
Percent PC	75%	75%	85%	85%	90%	90%
Percent ST	5%	5%	5%	5%	5%	5%
Percent CT	20%	20%	10%	10%	5%	5%
Average PC Speed (mph)	60	60	65	65	60	60
PCE (ST)	1.35	1.5	1.35	1.5	1.35	1.5
PCE (CT)	1.60	1.5	1.60	1.5	1.60	1.5
Vp(PC/hr)	1081	1069	1692	1688	681	683
Density	18.01	17.81	26.03	25.97	11.35	11.38
LOS	**C**	**B**	**D**	**C**	**B**	**B**
Remarks	Different		Different		Similar	

the difference appears in LOS indices with different assignments of PCE values. When the percentage of single-unit trucks in a traffic stream is small (5%), the gap between the resulting LOS indices from the two methodologies decreases with converging results.

A change in LOS index by one level may not seem very significant, but the difference between an acceptable and unacceptable LOS can surely have significant impacts. One road section with a LOS of E may need immediate improvement while another with LOS D may be acceptable. This disparity in LOS is not likely to occur in all traffic conditions. However, there can be a number of different traffic conditions (depending upon percentage of combination trucks, percentage of single-unit trucks, total hourly volume and traffic speed) which can result into such situations. Since roadway design depends on estimated LOS, PCE values used may result in different design specifications and different conclusions from evaluation studies. Also, the alternative methodology is based on field traffic data at a particular location; therefore it has the advantage over the single PCE value based results which are developed through simulations. For the evaluation of traffic flow on existing roadway sections, it appears to be appropriate to use separate PCE values for accurate LOS estimation. It is therefore recommended that a PCE value of 1.6 for combination trucks and 1.35 for single-unit trucks be used for urban freeways. However, since the results of rural PCE estimation are not based on sufficient data, it is recommended that HCM's single PCE value of 1.5 be continued to be used for rural freeways, until sufficient quality data is collected for acceptable statistical analysis.

6.7 Chapter Conclusions

Two sets of 3SLS models were developed as functions of a number of traffic variables for rural and urban interstates that predict the lagging headway of each vehicle class. Also, a 9-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 was estimated. Models were calibrated on the basis of video data collected using a mobile traffic laboratory at four urban locations along I-465 in Indianapolis and three locations on different rural interstates in Indiana.

The study results revealed that predicted headways based on field data allow reliable calculation of separate PCE values for two truck classes. The results support the assertion that separate PCE values for single-unit and combination trucks provide a robust description of an equivalent traffic stream. The average observed lagging headways for passenger cars, single-unit trucks, and combination trucks across all study locations, both for rural and urban interstate, differed only marginally from predicted headways.

The single-unit and combination truck PCE values estimated using the 3-equation 3SLS model for urban interstates are: 1.35 and 1.60 respectively. For rural interstates the corresponding PCE values are: 1.30 and 1.45 respectively. The PCE values estimated for rural interstates are based on fewer numbers of observations as compared to urban interstates (94 observations used for rural headway model and 452 observations used for urban headway model). Therefore it is not recommended to replace the existing single PCE value of 1.5 for rural interstates recommended by HCM. There is a need for further quality data collection from a number of different highway segments from different locations to establish separate PCE values for rural interstates.

Depending upon traffic composition, the recommended PCE values of 1.6 for combination trucks and 1.35 for single unit trucks for urban freeways, may lead to different LOS indices compared to single HCM PCE value of 1.5 for all truck types. Separation of PCE values by truck type is supported when a traffic stream has high percentage of trucks of either or both types. The use of separate PCE values by truck types may result in a different characterization of LOS, thus having significant impact on roadway design or

TABLE 6.11
Hypothetical LOS Comparison-2: Effect of Varying Percentage of Single-unit Trucks

	Scenario - 4		Scenario -5		Scenario - 6	
	Headway Approach	HCM	Headway Approach	HCM	Headway Approach	HCM
PC Flow (PC/hr)	724	724	1347	1347	477	477
ST Flow (SU/ hr)	193	193	159	159	27	27
CT Flow (CT/hr)	48	48	79	79	27	27
Percent PC	75%	75%	85%	85%	90%	90%
Percent ST	20%	20%	10%	10%	5%	5%
Percent CT	5%	5%	5%	5%	5%	5%
Average PC Speed (mph)	60	60	65	65	55	55
PCE (ST)	1.35	1.5	1.35	1.5	1.35	1.5
PCE (CT)	1.60	1.5	1.60	1.5	1.60	1.5
Vp(PC/hr)	1062	1086	1688	1704	555	557
Density	17.69	18.09	25.97	26.21	10.09	10.12
LOS	**B**	**C**	**C**	**D**	**A**	**A**
Remarks	Different		Different		Similar	

operational studies. In addition, the proposed model allows for the prediction of site-specific PCE values. In the case of the 3-equations 3SLS model, one can accurately predict lagging headways, thus PCE values; using only 6 simple inputs items (the speed and number of vehicles for each class i.e., passenger cars, single-unit trucks and combination trucks). These items can be observed using existing traffic monitoring infrastructure/ procedures, and the output (lagging headways and PCE values) can be calculated using a simple Excel spreadsheet.

In order to refine the models in future studies, a large dataset covering multiple locations over an extended period of time is required. An expansion of the data to include more highway segments and more information per segment would allow for a more robust model. The addition of such data items would allow factors such as climatic and traffic conditions, highway geometric characteristics, and road functional class to be taken into account.

7 INVESTIGATION OF PCE VARIATIONS ACROSS DIFFERENT LOCATIONS

7.1 Introduction

The current edition of the HCM (TRB, 2000) makes no geographic distinctions in cal-culating PCEs, and thus is ill-suited for addressing regional variance. Elefteriadou et al. (1997) developed PCEs for the current HCM using the equivalent delay method established by Sumner et al. (1984). An issue occurs because this method uses calibrated microscopic simulations rather than field data. So, although one may calibrate to different freeways, the method cannot be used to represent geographic variations of different regions. While individual states may make their own adjustments, it may be constructive to account directly for regional variations. Doing so would help standardize calculations across regions. Regional variations may arise from many conditions. Climate may be a factor; recurring inclement or abrupt changes in weather may affect driving. Truck and passenger car behavior may also depend on driving culture or land use. Numerous disparities in geography may have different effects on PCE. Highways located close to agriculture farms need not experience traffic patterns similar to those near mines, logging camps or other land used.

Regional variation is not just an issue across state borders. Even within the state of Indiana, there are regions which might have distinct characteristics. Similarly, there may be different land use patterns in different parts of the state. The north central part of the state is quite flat while the south east portion has some rolling terrain. It is suitable to test intra-state variation. For this study, the urban data was collected from a single highway (I-465 Indianapolis) so it is not expected to have any significant variation in the northern and southern part of Indianapolis. On the other hand, the rural data was collected from three different highways located miles away representing different regions. Therefore, it is appropriate that investigation of PCE variation across different regions is checked using rural data only.

Alternative PCE methods may be able to consider these regional differences. One such method is the headway ratio established by Cunagin and Messer (1983) and further developed in Chapter 4 and Chapter 6. To consider different regions, one simply applies data from the areas of interest. Ideally, one would devise a headway model using data from multiple regions with local indicator modifiers. Such a model may account for geographic distinctness.

In considering data from different physical sources, one may wonder about the impact of using different electronic sources. That is, different types of data collection may result in different models. A good example may be to combine the Microloop and video data to check that whether these two data sets should be modeled together or separately.

7.2 Datasets

Datasets corresponding to two different perspectives were used to carry out the analysis. First, a comparison was carried out between two data collection techniques: video data from three locations (I-65 Lafayette, I-70 and I-74) and Microloop data from a single point (I-65 MM-128). In the second step, combined video data from all three rural locations (I-65 Lafayette, I-70 and I-74) is compared with data from individual sites to ascertain whether individual models should be estimated for all three locations or whether there should be one combined model for all three locations. Thus, differences in both geography and data collection methodology in addition to the obvious potential differences in traffic flow characteristics are addressed. The Microloop data is from a Microloop station at I-65 mile marker 128 northbound near Indianapolis. The video data comes from three different locations: I-65 outside Lafayette, I-70 south west of Indianapolis, and I-74 near Crawfordsville. All the datasets come from flat locations; however there might be slight variations in data recording techniques thus resulting into minor variations in recording the vehicle length or gap between vehicles. Noting these inherent differences, it is believed that these two datasets may offer statistically unique models.

The Microloop detector captured four days of two lanes of real-time vehicle information on all vehicle types (PC, SUT, and CT), comprising 494 aggregated observations of 15-minute periods. The video-recorded portion of the data came from three locations, comprising 94 observations of 15-minute periods for all vehicle types collected between January and March of 2010. Both the datasets were aggregated in a similar way.

Table 7.1 describes the significant variables of the individual datasets from two different data sources: Microloop and video data. The Microloop dataset seems different from the dataset collected at three other interstate locations. Apparently, the dataset from two

TABLE 7.1
Basic Statistics of the Datasets from Different Sources

	Rural Interstate –Microloop and Video Recorded Data		
Variable	Microloop	Video-recorded	Combined
Average PC lagging headway (ft)	542.44	311.295	505.49
Average SUT lagging headway (ft)	637.09	438.002	605.26
Average CT lagging headway (ft)	724.96	451.979	681.32
PC Flow (PC/15 min)	72.88	85.266	74.86
ST Flow (SUT/15 min)	3.77	4.596	3.90
CT Flow (CT/15 min)	19.74	35.904	22.32
Total Vehicles in 15 minutes	96.39	125.766	101.09
Average PC Speed (mph)	69.57	68.435	69.39
Average SUT Speed (mph)	64.47	67.238	64.92
Average CT Speed (mph)	65.18	64.982	65.15
Percent PC	72.38	68.212	71.71
Percent SUT	4.63	3.580	4.47
Percent CT	22.99	28.208	23.82

sources seemed to be different but initial indications did not reveal a need to combine the data or whether to use separately for the modeling.

Table 7.2 describes the significant variables of the individual video datasets from three rural interstate locations. The datasets apparently do not seem very different and it is only through an appropriate statistical test can it be established whether to model them together or separately.

7.3 Analysis Method

To ascertain the distinctness of the different datasets, one must estimate separate headways models using Equation 6.1 – 6.3. Since six different datasets were compared, therefore headways models were estimated six times using Equation 6.1 – 6.3 (total of 18 headway models). While the first run used all 588 observations (Microloop and video-recorded combined), the 2nd used Microloop data, 3rd used combined video recorded data and, 4th, 5th and 6th used the I-65 Lafayette, I-70 and I-74 data, respectively. The latter models, however, use exactly the same variables as the parent model. This provides the basic information for considering distinct models.

For evaluating the models of the combined data, the key parameter of each model is the log-likelihood (LL) at convergence. Although this study uses regression techniques rather than maximum likelihood (ML) methods, LL is still a valid statistic as 3SLS has the same asymptotic variance-covariance matrix as a ML simultaneous system method, Full Information Maximum Likelihood (Washington et al., 2003).

With the LL for each model, one can calculate the likelihood ratio test statistic (Washington et al., 2003) for each vehicle type model (Equation 7.1) using formula as follows:

$$\lambda^u = -2\left(LL\left(\beta^u_{all}\right) - LL\left(\beta^u_{ML}\right) - LL\left(\beta^u_{VD}\right)\right) \qquad (7.1)$$

Here, LL $\beta_g{}^u$ refers to the LL of the model for vehicle type u and data g. Λ is known to be χ^2 distributed with degrees of freedom equal to the number of coefficients estimated in the total model. The resulting χ^2 test returns the probability that the split models are the same as the parent for that vehicle type. Values that are less than 0.05 are sufficient to reject that hypothesis with 95% confidence. With this test, one can determine if the two datasets are truly distinct.

Table 7.3 displays the results of the final derived from the combined data from all the rural locations. Note that the β-coefficients are not of primary interest but are herein presented for reference purpose. The coefficient results from the other data are not tabulated here as only the LL values are relevant. This is a three-equation 3SLS model that was developed using 588 observations (each 15-minute video-clip constitutes one observation). The 588 observations were only those observations where at least one vehicle from each vehicle class was present (at least one passenger car,

TABLE 7.2
Basic Statistics of the Datasets from Different Locations

	Rural Interstate- Video-recorded Data			
Variable	Ponit-1	Ponit-2	Ponit-3	Combined
Average PC lagging headway (ft)	294.44	357.01	300.19	311.295
Average SUT lagging headway (ft)	459.87	444.99	422.78	438.002
Average CT lagging headway (ft)	442.57	455.10	455.79	451.979
PC Flow (PC/15 min)	77.50	67.48	97.51	85.266
ST Flow (SUT/15 min)	3.42	2.81	6.04	4.596
CT Flow (CT/15 min)	41.92	31.48	34.55	35.904
Total Vehicles in 15 minutes	122.85	101.76	138.11	125.766
Average PC Speed (mph)	69.31	68.04	68.13	68.435
Average SUT Speed (mph)	68.69	62.84	68.40	67.238
Average CT Speed (mph)	65.88	60.93	66.30	64.982
Percent PC	64.15	67.27	70.88	68.212
Percent SUT	2.77	2.82	4.37	3.580
Percent CT	33.07	29.91	24.76	28.208

TABLE 7.3
3SLS Model Estimation Results Using Combined Rural Data

Variable	Coefficient	t-stat	Mean
ln (Average PC lagging headway) (ft)			
Constant	0.354	2.369	
PC Flow (PC/15 min)	−0.001	−9.991	74.860
CT Flow (CT/15 min)	−0.001	−4.525	22.323
Average PC Speed (mph)	0.026	14.175	69.389
Average SUT Speed (mph)	−0.005	−6.354	64.916
Average CT Speed (mph)	−0.012	−8.243	65.149
ln(Average SUT lagging headway) (ft)	0.156	12.867	6.301
ln(Average CT lagging headway) (ft)	0.660	30.177	6.479
Adjusted R2	0.7328		
Durbin-Watson	1.8540		
ln(Average Single-unit Truck lagging headway) (ft)			
Constant	1.074	2.906	
Average PC Speed (mph)	−0.024	−5.564	69.388
Average SUT Speed (mph)	0.019	8.319	64.916
Ln(Average PC lagging headway) (ft)	1.141	13.929	6.179
ln(Average CT lagging headway) (ft)	−0.222	−2.749	6.479
Adjusted R2	0.2778		
Durbin-Watson	1.9338		
ln(Average Combination Truck lagging headway) (ft)			
Constant	1.269	7.919	
Average PC Speed (mph)	−0.022	−8.751	69.388
Average CT Speed (mph)	0.018	9.023	65.149
ln(Average PC lagging headway) (ft)	0.900	33.521	6.179
Adjusted R2	0.5692		
Durbin-Watson	1.9517		
N	588		

single-unit truck or combination truck following any other vehicle). The first column is a descriptive list of the significant variables. The next column hosts the estimated exploratory factors. The third column shows the significance of each variable; a |t-stat| $\geq$ 1.96 indicates the 95% confidence interval.

The adjusted R^2 value of 0.7328 indicates a rather strong correlation between the predicted and measured passenger car headways. The sign of the variables PC Flow (PC/15 minutes) and CT Flow (CT/15 minutes) indicates that, all else being equal, an increase in flow rate of passenger cars or combination trucks decreases the predicted lagging headway of passenger cars. This is an intuitive result; as more vehicles are added on the traffic stream, the spatial constraints increase, resulting in a decrease in headway. Average passenger car speed is another significant variable, though it increases headway. This is somewhat intuitive as larger stopping distance is required at higher speeds, thus a driver is more likely to give greater room between their vehicles and the vehicle ahead of them. Conversely, as single-unit and combination trucks increase their speed, passenger car headway decreases. This suggests that passenger cars are more comfortable with faster moving single-unit and combination trucks. Both of the endogenous variables have a significant positive relationship, meaning an increase in lagging headway of single or combination trucks increases passenger car lagging headway. This may be due to certain unaccounted similarities between the travel behaviors of these three vehicle classes. The combination truck coefficient which is slightly higher than that of single-unit truck coefficient suggests that the headway of passenger cars is more influenced by combination trucks.

The adjusted R^2 for single-unit trucks is just 0.2777, not trivial, but not as strong as that of passenger car. This is not unexpected as single-unit trucks are fewer in number in a traffic stream (on average single-unit trucks are 4.5% of the overall traffic stream). Both, the speed of passenger cars and single-unit trucks have significant correlation with the single-unit truck lagging headway. However, increasing the speed of passenger cars decreases the lagging headway of single-unit truck, while an increase in speed of single-unit trucks increases the single-unit truck lagging headway. This suggests that when single-unit trucks increase their speed they exercise caution and leave more space between themselves and the leading vehicle, while an increase in passenger car speed actually makes the single-unit trucks more comfortable thus decreasing their headway.

Both of the endogenous variables (average passenger car lagging headway and average combination truck lagging headway) are significantly correlated with single-unit truck lagging headway. An increase in passenger lagging headway is associated with an increase in that of single-unit trucks while and increase in combination truck lagging headway results into decrease in lagging headway of single-unit truck.

Combination trucks display somewhat different model characteristics than single-unit trucks. The adjusted R^2 of 0.5692 represents a reasonable strong correlation between observed and predicted headways of combination trucks. Both the speed of passenger cars and combination trucks have significant correlation with the combination truck lagging headway. However, increasing the speed of passenger cars decreases the lagging headway of combination trucks, while an increase in speed of combination trucks increases the combination trucks lagging headway. This suggests that when combination trucks 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 combination trucks more comfortable thus decreasing their headway. A similar phenomenon was observed in case of the single-unit truck model. The endogenous variable (lagging headway of passenger car) is similar to single-unit trucks. An increase in passenger lagging headway is associated with an increase in combination truck lagging headway, which indicated that as passenger car increase their headways, the combination trucks behave similarly.

Likelihood ratio tests presented in Table 7.4 and 7.5, indicated that either the two datasets from two different sources/locations should be modeled together or separately. Each row of these tables is a particular vehicle type, and each "LL" column is a particular dataset. The Λ column is the test statistic proposed in Equation 7.1 while the next column, df, is the degrees of

TABLE 7.4
Likelihood Ratio Tests for Headway Models Estimated Using Data from Different Sources

Model	Total LL	Microloop LL	Video Data LL	Λ	df	Prob
PC	−171.113	23.3189	−23.2717	342.3204	7	0.0000
SUT	−405.3399	−293.3404	−75.7936	72.4118	4	0.0000
CT	−152.3627	−14.4799	−19.4522	236.8612	3	0.0000

TABLE 7.5
Likelihood Ratio Tests for Headway Models Estimated Using Data from Different Locations

		Individual Locations					
Model	Total LL	I-70	I-74	I-65	Λ	df	Prob
PC	−23.2717	−19.2113	8.954	0.4321	26.893	5	0.005
SUT	−75.7936	−37.1265	−19.5003	−18.1772	1.9792	2	>0.1
CT	−19.4522	−16.6299	−3.0242	4.3626	8.3214	3	>0.1

the freedom (representing the number of variables in one model). The final column lists results of the χ^2 distribution test using the Λ value and degrees of freedom, df.

In case where two datasets from two different sources are being compared (Table 7.1). For both trucks and passenger cars, this test provides evidence that each dataset is distinct. The test statistic is conclusive because a positive Λ is acceptable in the argument for the χ^2 distribution test. This would seem to imply that the combined-data passenger models are inferior to the models developed for the more specific individual datasets. This is intuitive because apparently the video recorded data and WIM data are two quite different datasets. Thus there is enough statistical evidence to reject the argument that there is insignificant variation in the two datasets.

Likelihood ratio tests, shown in Table 7.5, indicate that either the two datasets from two different regions (three different interstates) should be modeled together or separately. For both truck types, this test provides evidence that datasets are not distinct and hence a combined dataset will provide superior results as compared to individual datasets. In the case of passenger cars, the test results seem to imply that the combined-data passenger models are inferior to the models developed from the more specific individual datasets. As a whole, there is inadequate statistical evidence to reject the argument that there is significant variation in the datasets from different locations. Thus, if data is collected from similar freeway segments from different locations across the state than it is more appropriate to have a combined model instead of different individual models for different regions.

7.4 Chapter Conclusions

This chapter used six distinct datasets to build a 3SLS headway model with the basic aim to test whether the data obtained from different locations (regions) and different sources should be modeled together or separately. Based on the likelihood ratio test, there is statistical evidence against combining the datasets from the different sources. It would appear then that there is a significant difference in headways between the Microloop station and video data. The differences, however, may arise from other sources that are not inherently regional. It is also evident, based on the likelihood ratio test, that it is more appropriate to have a combined model if data is collected from similar freeway segments from different locations across the state, instead of different individual models for different regions.

8 CONCLUSIONS AND FUTURE WORK

8.1 Study Summary

The current Highway Capacity Manual provides a single PCE value to be used for one general class of trucks (TRB, 2000). However, a specific PCE value for different truck classes is more appropriate for determining the impact of trucks on traffic characteristics on a road segment. The present study used data from three rural freeways and four locations on a single urban freeway in Indiana to build 3SLS models to predict PCEs separately for single-unit and combination truck classes. The present study estimated a PCE value of 1.6 for combination trucks and 1.35 for single unit trucks for basic urban freeways (level terrain). For basic rural freeways, using a limited data-set, the study estimated a PCE value of 1.45 for combination trucks and 1.30 for single-unit trucks. However the PCE values estimated for rural freeways, having been based on a limited data-set, are not recommended for LOS estimation. For rural freeway PCE estimation, there is a need to collect quality data from a number of different highway segments from different locations across the state to establish separate PCE values. In the meantime, it is recommended that the HCM PCE value of 1.5 for all truck classes should be continued to be used for rural freeways.

The current PCE estimation methods, such as the one using equivalent delay, have a refined analytic background, but alternative methods such as the headway ratio method using field data, appear to be promising. As it can be expected, traffic variables such as vehicle flow rates and speed have significant impacts on vehicle headways. Furthermore, the study results indicate that not only do different vehicle classes have different headways, but they directly depend on headways of other vehicle classes. The study further examined the impact of headway models on predicted LOS indices.

The study also explored the regional variation of PCE values by developing headway models using data from different sources and from different geographical locations. The likelihood ratio test indicated that one must exercise due caution before combining data from different sources. The likelihood ratio test revealed that it is more appropriate to combine data from similar regions (freeway sections having different geographical locations) to estimate a 3SLS model. Furthermore, this study developed 9-equation 3SLS models based on type of vehicle leading using a limited dataset. The predicted headway differed marginally from observed headways and results proved superior to 3-equations 3SLS models.

8.2 Future Research

Although the study established that PCE values based on headway ratios could be used as a realistic alternative to the current method used for the HCM, further efforts are necessary to refine the study results. An effort should be made to collect an expanded data base, particularly for rural interstates. In order to obtain a robust model for rural interstates, future studies may need to include additional periods of congestion to properly model such conditions using data from several different roadways.

If information on items such as grade, number of lanes, lane width, climatic conditions, and day of week / month and segment length is available for each section, then the resulting model can account for varying geometry, climate and traffic. Having more sites also reduces the data collection burden per site; with adequate sites, one might only need the peak period data rather than all periods from each site. Also, data could be acquired from acceptable sources such as weigh-in-motion stations. WiM sites provide more detailed data having precise time stamps, and length and speed of individual vehicles and hence would provide more reliable estimation of vehicle headways. Furthermore, the axle-based classification used by WiM station algorithms provides a robust criterion for vehicle classification; this could be employed to expand the developed models for a larger number of truck classes (instead of just two classes as in the present study). Also, the 9-equation 3SLS model as developed for urban interstates using 142 observations could be further improved with additional observations.

Determining the specific cause and effect of regional variation may also involve future research. To examine the regional differences, the existing WiM network across Indiana could be used for collecting the required data. Non-traditional data collection methods such as aerial photography may prove relatively more accurate, as they could be easily processed to yield more precise vehicle lengths and lagging headways.

REFERENCES

AASHTO. Policy on Geometric Design of highways and Streets. American Association of State Highway and Transportation Officials, Washington, DC, 4th edition, 2001.

Al-Kaisy, A., Jung, Y, and Rakha, H. Developing Passenger Car Equivalency Factors for Heavy Vehicles During Congestion. ASCE Journal of Transportation Engineering, 131: 514, 2005.

Al-Kaisy, A., Hall, F. L., and Reisman E. S. Developing Passenger Car Equivalents for Heavy Vehicles on Freeways during Queue Discharge Flow. Transportation Research Part A, Vol. 36, No.8, pp. 725–742, 2002.

Cunagin, W. D., and Messer, C. J. Passenger Car Equivalents for Rural Highways. Transportation Research Record 905, 61–68, 1983.

Demarchi, S. H., and Setti, J. R. Limitations of Passenger-Car Equivalent Derivation for Traffic Streams with More Than One Truck Type. Transportation Research Record, 1852, 96–104, 2003.

Durbin, J. and Watson, G. S. Testing for serial correlation in least squares regression. Biometrika, 38(1–2), 159–178, 1951.

Elefteriadou, L., Torbic, D., and Webster, N. Development of Passenger Car Equivalents for Freeways, Two-Lane Highways, and Arterials. Transportation Research Record, 1572, 51–58, 1997.

Highway Research Board. Highway Capacity Manual: Practical Applications for Research, Department of Traffic and Operations, Committee on Highway Capacity, United States Government Printing Office, Washington, DC, 1950.

Highway Research Board. Special Report 87, Highway Capacity Manual, National Research Council, Department of Traffic and Operations, Committee on Highway Capacity, Washington, DC, 1965.

Highway Capacity Manual 2000. TRB, National Research Council, Washington, DC. 2000.

Highway Capacity Manual 2010. TRB, National Research Council, Washington, DC. 2010.

Hu, Y., and Johnson, R. Passenger Car Equivalents of Trucks in Composite Traffic. Report DTFH-61-80-C-00127, FHWA, U.S. Department of Transportation, 1981.

Keller, E. L. and Saklas, J. G. Passenger car equivalents from network simulation. Journal of Transportation Engineering, 110(4):397–411, 1984.

Krammes, R., and Crowley, K. Passenger Car Equivalents for Trucks on Level Freeway Segments. In Transportation Research Record 1091, pp. 10–17, 1986.

Linzer, E., Roess, R, and McShane, W. Effect of Trucks, Buses, and Recreational Vehicles on Freeway Capacity and Service Volume. In Transportation Research Record 699, pp. 17–24, 1979.

McShane, W. R. and Roess, R. P. Traffic Engineering. Prentice Hall polytechnic series in traffic engineering. Englewood Cliffs, NJ: Prentice-Hall, 1990.

Rakha, H., Ingle, A., Hancock, K., and Al-Kaisy, A. Estimating Truck Equivalencies for Freeway Sections. In Transportation Research Record, 73–84, 2007.

Seguin, E., Crowley, K., and Zweig, W. Passenger Car Equivalents on Urban Freeways. Report DTFH61-80-C-00106, Institute for Research State College, Pennsylvania, 1982.

Sumner, R., Hill, D., and Shapiro, S. Segment Passenger Car Equivalent Values for Cost Allocation on Urban Arterial Roads. Transportation Research Part A, 18(5–6): 399–406, 1984.

Tobin, J. Estimation of Relationships for Limited Dependent Variables. Econometrica, 26(1):24–36, 1958.

Van Boxel D. P. An Exploratory Study of Vehicle Class Headway Ratios as Passenger Car Equivalence Values Using Three Stage Least Squares Estimation. MS Dissertation, Purdue University, W. Lafayette, IN, 2009.

Van Aerde, M., and Yagar, S. Capacity, Speed, and Platooning Vehicle Equivalents For Two-Lane Rural Highways. Traffic Capacity and Characteristics, 1984.

Werner, A., and Morrall, J. Passenger Car Equivalencies of Trucks, Buses, and Recreational Vehicles for Two-Lane Rural Highways. In Transportation Research Record 615, pp. 10–17, 1976.

Washington, S., Karlaftis, M., and Mannering, F. Statistical and Econometric Methods for Transportation Data Analysis. CRC Press, 2003.

Webster, N. and Elefteriadou, L. A. Simulation Study of Truck Passenger Car Equivalents (PCE) on Basic Freeway Sections. Transportation Research Part B, 33(5), pp. 323–336, 1999.

APPENDIX I: DATA COLLECTION LOCATIONS - URBAN INTERSTATES

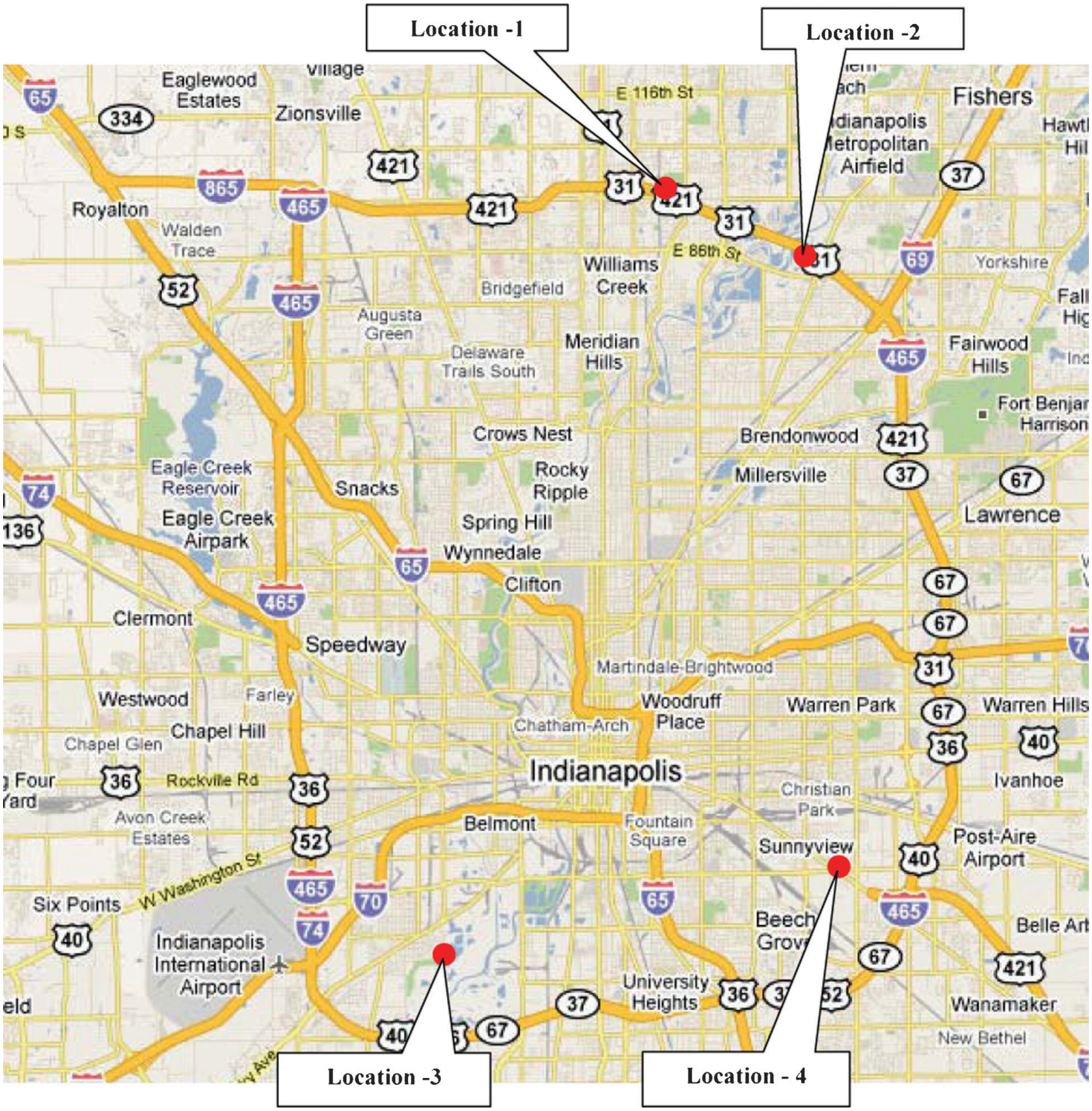


Figure A1 Data Collection Locations - Urban Interstates

Figure A2 Video Data Collection, Urban Interstate –Location-1 (I-465 Near 3939 Priority Way South Drive Suite 400, Indianapolis)

Figure A3 Video Data Collection, Urban Interstate – Locatio-2 (I-465 Near 7951 Knue Road, Indianapolis)

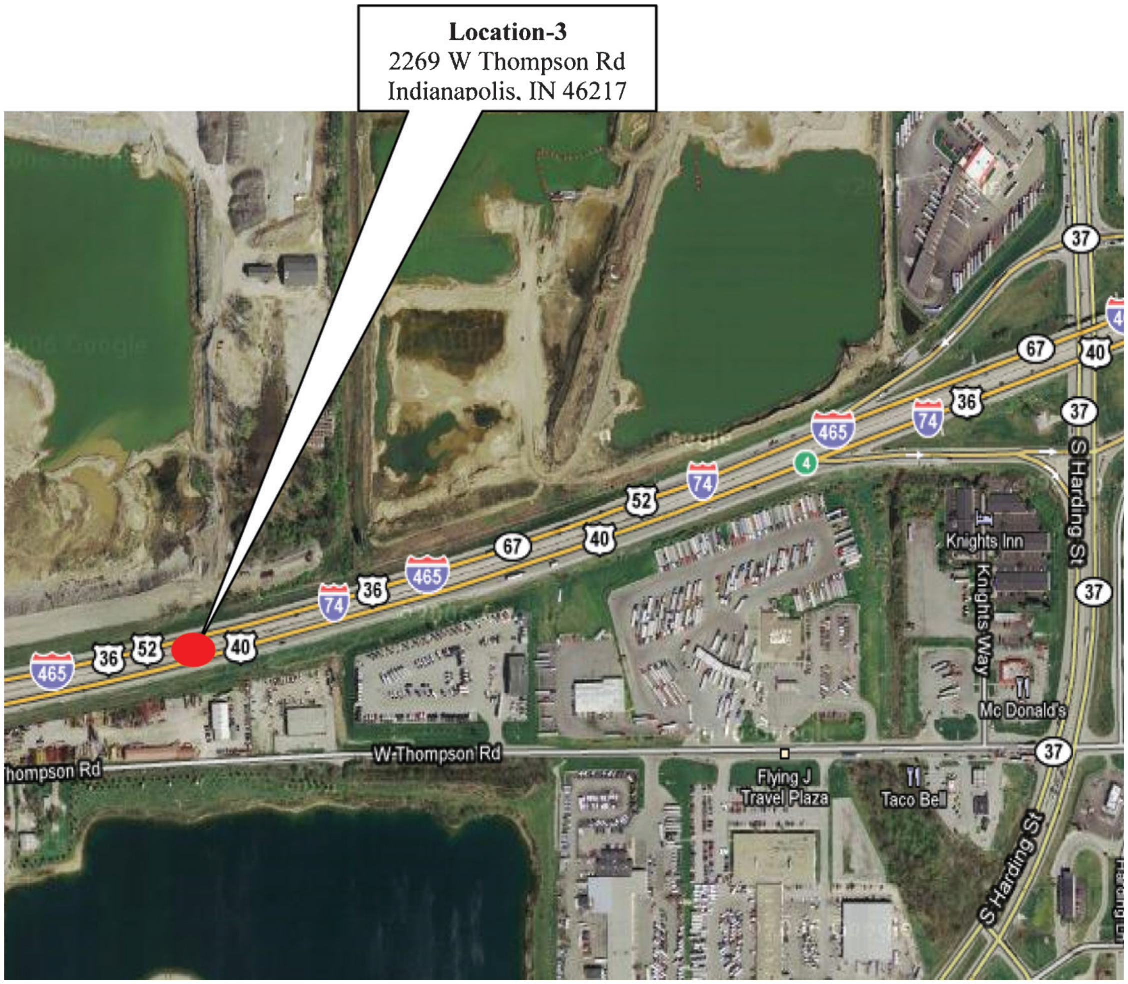


Figure A4 Video Data Collection, Urban Interstate – Location-3 (I-465 Near 2269 West Thompson Road, Indianapolis)

Figure A5 Video Data Collection, Urban Interstate – Location-4 (I- 465 Near South hunter Road, Indianapolis)

Figure A6 Data Collection Locations - Rural Interstates

Figure A7 Video Data Collection, Rural Interstate – Point-1 (I-65, Lafayette, Indiana)

Figure A8 Video Data Collection, Rural Interstate – Point-2 (I-74 Near County Road 450 N Crawfordsville, Indiana)

Figure A9 Video Data Collection, Rural Interstate – Point- 3 (I-70 Near E County Rd 600, Hendricks, Indiana)

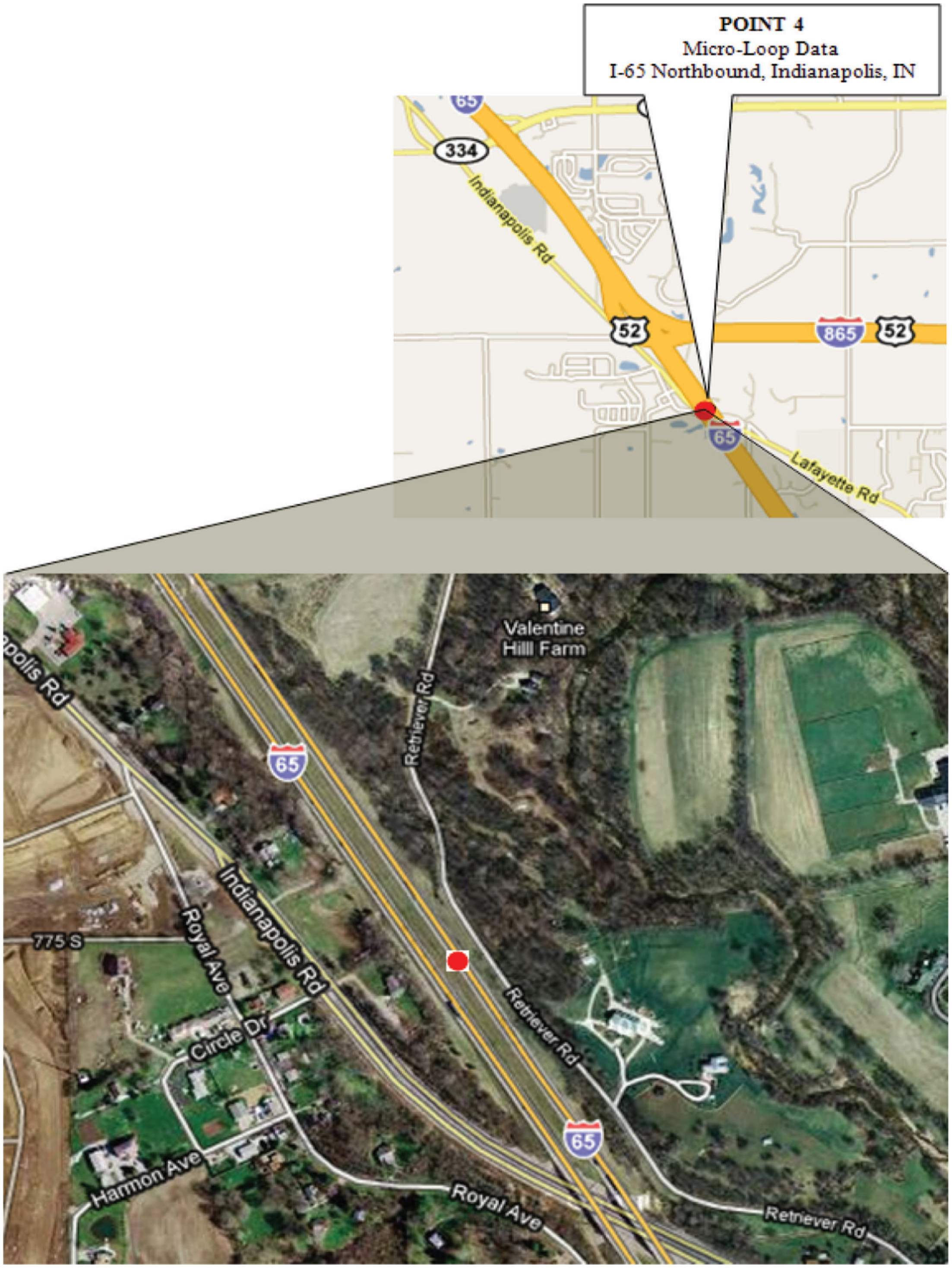


Figure A10 Video Data Collection, Rural Intersate – Point-4 (I-65, Near MM-128, Indiana)

APPENDIX III: SUMMARY STATISTICS, VIDEO DATA -URBAN INTERSTATES LOCATIONS

Summary Statistics of the Video Recorded Data – Urban Interstate Locations

Variable	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	213.062	42.459	101.214	350.311
Average ST lagging headway (ft)	302.550	127.446	92	1707.273
Average CT lagging headway (ft)	347.672	101.701	145	1482.143
PC Flow (PC/15 min)	218.646	74.452	12	461
ST Flow (SU/15 min)	13.066	7.370	1	45
CT Flow (CT/15 min)	28.162	16.259	1	75
Total Vehicles in 15 minutes	259.874	77.791	19	485
Average PC Speed (mph)	61.241	7.314	29.535	111.393
Average ST Speed (mph)	60.599	8.810	19.180	145.533
Average CT Speed (mph)	59.939	7.993	33.333	115.758
Percent PC	83.742	9.200	51.397	99.216
Percent ST	5.184	3.200	0.392	19.186
Percent CT	11.074	6.895	0.322	30.928

Summary Statistics of the Video Recorded Data,Urban Interstate - Location-1

Variable/Point-1	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	196.136	45.622	101.214	350.311
Average ST lagging headway (ft)	270.669	94.782	118	677.857
Average CT lagging headway (ft)	323.053	82.848	145	692.143
PC Flow (PC/15 min)	262.056	79.313	130	438
ST Flow (SU/15 min)	12.088	5.578	1	24
CT Flow (CT/15 min)	19.144	11.546	1	45
Total Vehicles in 15 minutes	293.288	89.820	139	472
Average PC Speed (mph)	58.764	10.443	29.535	111.393
Average ST Speed (mph)	58.392	12.453	19.180	145.533
Average CT Speed (mph)	58.565	10.530	33.333	115.758
Percent PC	89.689	3.670	81.557	98.947
Percent ST	4.152	1.819	0.526	9.412
Percent CT	6.159	3.273	0.446	14.286

Summary Statistics of the Video Recorded Data,Urban Interstate - Location -2

Variable/Point-2	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	220.905	42.185	123.872	318.847
Average ST lagging headway (ft)	344.735	185.916	92	1707.273
Average CT lagging headway (ft)	372.087	150.999	181	1482.143
PC Flow (PC/15 min)	215.127	79.419	81	461
ST Flow (SU/15 min)	8.913	5.232	1	24
CT Flow (CT/15 min)	16.762	8.814	1	40
Total Vehicles in 15 minutes	240.802	87.874	84	485
Average PC Speed (mph)	61.982	4.574	46.417	72.556
Average ST Speed (mph)	61.807	6.574	34.963	81.476
Average CT Speed (mph)	61.240	6.053	45.409	89.709
Percent PC	89.561	3.737	79.397	99.216
Percent ST	3.662	1.743	0.392	9.045
Percent CT	6.777	2.750	0.322	14.800

Summary Statistics of the Video Recorded Data, Urban Interstate - Location -3

Variable/Point-3	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	232.090	36.424	122.614	326.281
Average ST lagging headway (ft)	325.942	85.019	182	655.272
Average CT lagging headway (ft)	366.724	68.351	200	637.239
PC Flow (PC/15 min)	173.186	50.469	69	291
ST Flow (SU/15 min)	18.163	9.866	3	45
CT Flow (CT/15 min)	40.884	11.519	1	71
Total Vehicles in 15 minutes	232.233	52.512	109	379
Average PC Speed (mph)	63.591	5.833	38.167	73.467
Average ST Speed (mph)	63.725	6.358	50.724	96.303
Average CT Speed (mph)	61.333	6.227	41.718	77.178
Percent PC	73.852	9.289	51.397	96.364
Percent ST	8.086	4.758	1.493	19.186
Percent CT	18.063	5.763	0.909	30.928

Summary Statistics of the Video Recorded Data,Urban Interstate - Location -4

Variable/Point-4	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	208.640	35.393	135.585	322.787
Average ST lagging headway (ft)	273.491	82.771	94	786.729
Average CT lagging headway (ft)	333.435	56.279	222	664.240
PC Flow (PC/15 min)	209.313	50.447	12	326
ST Flow (SU/15 min)	14.870	5.952	1	32
CT Flow (CT/15 min)	40.939	14.042	1	75
Total Vehicles in 15 minutes	265.122	49.105	19	377
Average PC Speed (mph)	61.362	5.760	46.199	76.680
Average ST Speed (mph)	59.336	6.701	41.172	87.012
Average CT Speed (mph)	58.963	7.531	43.510	93.095
Percent PC	78.301	7.792	63.158	98.507
Percent ST	5.802	2.497	0.746	15.789
Percent CT	15.897	6.011	0.746	29.911

APPENDIX IV: SUMMARY STATISTICS, VIDEO DATA -RURAL INTERSTATE LOCATIONS

Summary Statistics of the Video Recorded Data – Rural Interstate Locations

Variable	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	311.29	93.34	130.52	606.66
Average ST lagging headway (ft)	438.00	231.86	89.46	1303.13
Average CT lagging headway (ft)	451.98	144.12	150.34	1089.94
PC Flow (PC/15 min)	85.27	31.36	30	174
ST Flow (SU/15 min)	4.60	3.35	1	15
CT Flow (CT/15 min)	35.90	19.70	4	88
Total Vehicles in 15 minutes	125.77	36.64	39	215
Average PC Speed (mph)	68.43	11.99	42.30	104.27
Average ST Speed (mph)	67.24	15.97	38.76	125.00
Average CT Speed (mph)	64.98	14.04	39.22	110.86
Percent PC	68.21	14.38	29.70	91.18
Percent ST	3.58	2.38	0.61	11.88
Percent CT	28.21	13.59	6.35	66.67

Summary Statistics of the Video Recorded Data, Rural Interstate - I-65 Location

Variable/I-65 Lafayette	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	294.44	77.87	205.66	540.47
Average ST lagging headway (ft)	459.87	239.32	112.94	1303.13
Average CT lagging headway (ft)	442.57	108.40	296.97	836.21
PC Flow (PC/15 min)	77.50	28.33	30	141
ST Flow (SU/15 min)	3.42	2.34	1	9
CT Flow (CT/15 min)	41.92	27.13	6	88
Total Vehicles in 15 minutes	122.85	25.38	64	165
Average PC Speed (mph)	69.31	7.75	59.70	90.48
Average ST Speed (mph)	68.69	10.14	59.74	99.43
Average CT Speed (mph)	65.88	8.63	53.35	89.98
Percent PC	64.15	21.15	29.70	89.06
Percent ST	2.77	1.95	0.61	8.91
Percent CT	33.07	19.89	9.38	66.67

Summary Statistics of the Video Recorded Data, Rural Interstate - I-74 Location

Variable/I-74	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	357.01	51.71	219.71	444.91
Average ST lagging headway (ft)	444.99	210.56	89.46	870.00
Average CT lagging headway (ft)	455.10	97.89	150.34	602.05
PC Flow (PC/15 min)	67.48	14.22	33	89
ST Flow (SU/15 min)	2.81	1.72	1	8
CT Flow (CT/15 min)	31.48	10.45	4	45
Total Vehicles in 15 minutes	101.76	21.81	39	124
Average PC Speed (mph)	68.04	4.77	62.51	75.78
Average ST Speed (mph)	62.84	7.02	53.50	80.21
Average CT Speed (mph)	60.93	4.69	56.03	69.16
Percent PC	67.27	7.98	53.27	87.18
Percent ST	2.82	1.55	0.89	6.45
Percent CT	29.91	7.98	10.26	43.75

Summary Statistics of the Video Recorded Data, Rural Interstate - I-70 Location

Variable/I-70	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	300.19	109.17	130.52	606.66
Average ST lagging headway (ft)	422.78	240.32	118.13	1160.98
Average CT lagging headway (ft)	455.79	177.12	237.45	1089.94
PC Flow (PC/15 min)	97.51	33.66	39	174
ST Flow (SU/15 min)	6.04	3.74	1	15
CT Flow (CT/15 min)	34.55	17.49	5	78
Total Vehicles in 15 minutes	138.11	41.65	45	215
Average PC Speed (mph)	68.13	15.73	42.30	104.27
Average ST Speed (mph)	68.40	20.66	38.76	125.00
Average CT Speed (mph)	66.30	18.41	39.22	110.86
Percent PC	70.88	11.42	50.53	91.18
Percent ST	4.37	2.66	0.91	11.88
Percent CT	24.76	10.18	6.35	46.32

APPENDIX V: SUMMARY STATISTICS - MICROLOOP DATA AT MM-128

Variable/I-70	Mean	Std. Dev.	Min	Max
Average PC lagging headway (ft)	542.44	115.79	97.17	854.45
Average ST lagging headway (ft)	637.09	259.57	127.26	2019.68
Average CT lagging headway (ft)	724.96	171.63	202.74	1504.86
PC Flow (PC/15 min)	72.88	46.57	3	266
ST Flow (SU/15 min)	3.77	3.21	1	17
CT Flow (CT/15 min)	19.74	14.57	1	62
Total Vehicles in 15 minutes	96.39	53.03	5	285
Average PC Speed (mph)	69.57	2.95	23.26	74.37
Average ST Speed (mph)	64.47	6.97	27.83	113.00
Average CT Speed (mph)	65.18	3.82	26.47	89.60
Percent PC	72.38	18.45	7.32	98.04
Percent ST	4.63	3.50	0.39	20.00
Percent CT	22.99	16.71	0.88	87.80

APPENDIX VI: PROCESSING SCRIPT

Microloop processing script

```
Shell code: micro.sh
# /bin/sh
for lane in $ (seq 1 -6)
do
touch I65"-"$lane".veh" done
rm I65-*.veh #Remove all previous data files awk -v road=I65 -f
roadmicro.awk< I65.log
for lane in $(seq 16)
do
touch I65"-"$lane".veh" done
awk code: roadmicro.awk
#! /usr/bin/awk
#spaceh = front bumper to front bumper dist
#laghead = lagging headway
#timeh = fa to fa time
#ivs = intervehicle spacing
#lengl[n] = length of leading vehicle in lane n
#lastt[n] = timestamp of leading vehicle in lane n
#tt = timestamp (sec)
#n = lane, need to determine which are going which direction
#hour = a[1]; minute = a[2]; sec = b[1]; am/pm is b[2];
month = d[1]; day = d[2]; year = d[3]
#Specify lane channel (4 = lane 2, 2 = lane 1
#86400 s = 1 day
B E G I N
{lastt[""]=495739;lengl[""]=19;frontl=4;FS=",";g=0;a=7}
{n = $3/2;if (n == 1 || n == 2){ if ($8 > 0 && $8 != "N/A")
{split($5,d,"/");#split date field split($6,aa,":");split(aa[3],b,"
[[:space:]+]");
if (aa[1] == 12) { aa[1] = 0 };#if time is 12 am/pm, set to zero if
(b[2] == "PM") {aa[1] += 12};
#add 12 hours to hr if in PM
tt = $9 + b[1] + 60*(aa[2] + 60*(aa[1] + 24*d[2]));
class = 2; if ($8 > 29) {class=6}; if ($8 > 49) {class=9};
speed = $7;leng = $8;if ($7>135) {speed=135};if ($8>120) {leng
= 120};
if (class > 4) {a = 4.5}; f = a*1.46667/32.2;
ssd = 1.46667*speed*2.5 + speed*speed/(30*(f+g)); trunc = 0;
timeh = (tt-lastt[n]); spaceh = timeh*speed*1.46667;
ivs = spaceh - lengl[n];laghead = ivs + leng;
if (ivs > ssd) { ivs = ssd; spaceh = ivs + lengl[n] ;
timeh = spaceh/(speed*1.46667);
laghead = ivs + leng; trunc = 1};
if (ivs>0) {print tt, n, speed, class, leng, timeh, spaceh, ivs, laghead
>> road "-" n ".veh"; lengl[n]=leng;a=7;lastt[n]=tt}}}}
```

WiM processing script

```
Shell code: ohio.sh
#! /bin/sh
for lane in $(seq 1 4)
do
touch O779"-"$lane".veh" done
rm O779-*.veh #Remove all previous data files
630 640 650 660
awk -v road=O779 -f roadohio.awk < ohio-4.dat for lane in $(seq
1 4)
do
touch O779"-"$lane".veh" done
awk code: roadohio.awk
#! /usr/bin/awk
#shell command to use this file
# awk -f road.awk < 350.TXT and other input files
#spaceh = front axle to front axle distance
#timeh = fa to fa time
#ivs = intervehicle spacing (Actually intervehicular axle spacing)
#lengl = length of leading vehicle
#lastt = timestamp of leading vehicle
#tt = timestamp (sec)
#n = lane, need to determine which are going which direction
#build array of std vehicle lengthvs, for class 0, use rec. lengthv
#Also array of standard lengthv of front overhand {lastt[""]=0;le-
ngl[""]=19;frontl[""]=4;g=0;a=7; lengthv[""]=0;lengthv[2]=19;
lengthv[3]=19;lengthv[4]=45; lengthv[5]=30;lengthv[6]=30;
lengthv[7]=30; lengthv[8]=55;lengthv[9]=68.5;lengthv[10]=73.5;
lengthv[11]=73.3; lengthv[12]=73.3;lengthv[13]=104.8;
fronto[""]=3;fronto[1]=0;fronto[2]=3;fronto[3]=3;fronto[4]=6;
fronto[5]=4;fronto[6]=4;fronto[7]=4;fronto[8]=3;fronto[9]=4;
fronto[10]=4;fronto[11]=2.33; fronto[12]=2.33;fronto[13]=2.33}
{n = $6+$7;if (n == 8) {lane=1};if (n == 9) {lane=2}; if (n == 5)
{lane=3};if (n == 4) {lane=4};class = $8; leng = lengthv[class];
if ($14 > lengthv[class] || class > 13 || class == 1)
{leng=$14*1.06}; split($2,d,"/");#splitdatefield
split($3,aa,":");#split(aa[3],b,"[[:space:]+]");
tt = aa[3] + aa[4]/1000 + 60*(aa[2] + 60*(aa[1] + 24*d[2]))-1123200;
speed = $9;if (speed>135) {speed=135};if (leng>120) {leng =
120};
if (class > 3) {a = 4.5}; f = a*1.46667/32.2;
ssd = 1.46667*speed*2.5 + speed*speed/(30*(f+g)); trunc = 0;
timeh = (tt-lastt[n]); spaceh = timeh*speed*1.46667;
ivs = spaceh - lengl[n];laghead = ivs + leng;
spaceh = spaceh+(frontl[n]-fronto[class]);ivs = spaceh-lengl[n];
lastt[n]=tt; timeh = spaceh/(speed*1.46667);laghead=ivs+leng;
if (ivs > ssd) { ivs = ssd; spaceh = ivs + lengl[n] ;
timeh = spaceh/(speed*1.46667); laghead = ivs + leng; trunc = 1}
```

```
if (class > 13) {class = 0};
if (ivs>0) {print tt, lane, speed, class, leng, timeh,
spaceh, ivs, laghead >> road "-" lane ".veh"};
frontl[n]=fronto[class];lengl[n]=leng;a=7;lastt[n]=tt}
```

Aggregation scripts

Typical shell code

```
#! /bin/bash
touch headway15o.dat rm headway15o.dat
#for ii in I65 for ii in O779
do
for ((lane=1; lane<5;lane++));do #do each lane as a separate file
for ((nn=0; nn<768; nn++)); do
awk -f avg15.awk -v road=$ii laneno=$lane incr=$nn
< $ii-$lane.veh >> headway15o.dat done
done done
awk -f peak15.awk < headway15o.dat > headmaxo.dat
```

A.3.2 awk code: avg15.awk

```
#! /usr/bin/awk
BEGIN {headway[""]=0; laghead[""]=0; timehe[""]=0;
speed[""]=0;
vehleng[""]=0;
intervs[""]=0; vehcount[""]=0; avg_head[""]=0; avg_lagh[""]=0;
avg_timeh[""]=0; avg_speed[""]=0; avg_leng[""]=0;
avg_ivs[""]=0; vehtot=0}
{if (int(($1-432000)/900) == incr)
{speed[$4] += $3; vehleng[$4] += $5;
timehe[$4] += $6; headway[$4] += $7;
intervs[$4] += $8; laghead[$4] += $9; vehcount[$4]++}} END
{printf "%s,%s,%s,",road,laneno,incr;
for (kk=0; kk<=13; kk++) {if (vehcount[kk]>0)
{avg_head[kk] = headway[kk] / vehcount[kk]; avg_timeh[kk] =
timehe[kk] / vehcount[kk]; avg_speed[kk] = speed[kk] / veh-
count[kk]; avg_ivs[kk] = intervs[kk] / vehcount[kk]; avg_leng[kk]
= vehleng[kk] / vehcount[kk]; avg_lagh[kk] = laghead[kk] /
vehcount[kk]; vehtot += vehcount[kk]}
printf "%6.2f,%6.2f,%6.2f,%5.2f,%5.2f,%6.2f,%4.0f,",
avg_head[kk], avg_lagh[kk], avg_ivs[kk], avg_timeh[kk], avg_
speed[kk], avg_leng[kk], vehcount[kk]}
```