Final report of ITS Center project: Rubbernecking impact of incidents

A Research Project Report

For the National ITS Implementation Research Center

A U.S. DOT University Transportation Center

An Analysis on the Impact of Rubbernecking on Urban Freeway Traffic

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A Research Project Report for the ITS Implementation Center

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Abstract

An incident influences traffic not only in the incident direction but also in the opposite direction. There has been research on the influence of incidents on the traffic in the incident direction. However, research relating to the influence on the opposite direction of traffic is rare. Previous research has shown that congestion due to incidents account for 60% of the total congestion on a freeway system. These incidents cause the freeway system to operate inefficiently. By determining which variables contribute to the "non-recurrent" congestion and also the impact on traffic, mitigation techniques may be applied to minimize these effects.

In this study the impact of incidents on the traffic in the opposite direction was investigated with focus on rubbernecking likelihood, delay, and capacity reduction. To achieve this study certain objectives were met. First, a database consisting of incident information, traffic and other related variables was developed. The next step was to determine whether the rubbernecking impact on the opposite direction traffic was significant. Factors that influence the impacts of rubbernecking likelihood were identified. Recommendations of effective countermeasures were developed to possibly reduce rubbernecking impacts. Traffic data was investigated while congestion delay as well as capacity reduction calculations were performed. This study is the first attempt to evaluate the rubbernecking impact of accidents on traffic in the opposite direction based on archived traffic and accident data.

Acknowledgements

There are many individuals who I would like to thank for helping me along with this study. First, I would like to thank my thesis advisor, Dr. Hualiang (Harry) Teng. The advice and support you have given me throughout this study is immeasurable. Thank you for being for guiding, encouraging, and challenging me during this process.

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Chapter 1: Introduction

Freeway incidents cause major congestion throughout the United States every year. These incidents are often vehicle-vehicle crashes, which many times cause major backups, sometimes for miles, along freeways. These overcrowded situations are costly gridlocks, costing the travelers time and money. Other costs incurred especially due to an incident include increased potential for secondary accidents, additional wear and tear on vehicles, and environmental pollution. Historical statistics show that more than 50% of urban freeway congestion is caused by incidents (Lindley, 1989). Reducing the amount of congestion with various Intelligent Transportation Systems (ITS) or other methods is an important area of research. Through the research and implementation, time and money and even lives can be saved. In the past, research has been focused on determining and modeling the impacts of incidents in the direction of traffic of the incidents. The results from the research can be used to determine system performance measures such as delay, capacity reduction and travel times.

Although the modeling of incident traffic in the same direction is important, it deals with only half of the traffic problem. Accidents also have an impact on the opposite direction of traffic. Even though there are no lane blockages in the opposite direction of an accident, there are reasons to believe that an impact exists on traffic. This impact is due to rubbernecking. According to the Webster Dictionary “rubbernecking” means to look about, stare, or listen with exaggerated curiosity. Individuals driving in the opposite direction of an accident are often distracted by the incident. It is the curiosity of the event that leads to distraction, and then causes a reduction in vehicle speeds. This reduction in vehicle speeds begins to create congestion. Although a significant part of rubbernecking is attributed to various human factors, there are other factors such as presence of barriers that influence the form of rubbernecking.

This thesis investigates the impact of traffic in the opposite direction of travel from a vehicle accident. To accomplish this investigation, there are certain objectives to accomplish.

1. Determine whether the rubbernecking impact on the opposite direction traffic is significant.
2. Investigate traffic data and calculate traffic delay and capacity reduction in the opposite direction of travel.
3. Identify the factors that influence the impacts in terms of rubbernecking likelihood, traffic delay and capacity reduction.
4. Recommend effective countermeasure on rubbernecking in the opposite direction.

To determine whether rubbernecking impact is significant, occupancy vs. time plots are created for each incident. Significant changes in occupancy are observed visually and documented. Once these significant impacts were documented the rubbernecking likelihood (a probability of rubbernecking occurrence), delay (veh*hr) and capacity reduction (percentage of capacity loss) are derived using various methods. These results for delay and capacity reduction for the Hampton Roads area are then compared with the delay and capacity reduction in other comparative studies. To identify the influencing factors, linear and binary regression models are developed. The variables that are statistically significant in these models are identified as outstanding. Based on the identification of the influencing factors, mitigation measures are recommended.

The area focused in this study is the freeway system in the Hampton Roads area in Virginia. This freeway system consists of approximately 10 miles of Interstate 64 from I-564 down south to Indian River Road and also Interstate 264 eastbound from the I-64 interchange. Incident and associated accident data has been collected by the Hampton Roads Smart Traffic Center and archived by the University of Virginia's Smart Travel Lab. The incident type and year examined in this study are limited to vehicle accidents in the year 2000.

The remaining parts of this thesis include background information, previous research on incident delays and modeling, methodology explanation, results, analysis and findings, and finally conclusions and recommendations.

Chapter Two consists of background information and previous research done on the various measures this study investigated.

Chapter Three consists of the methodology used in this study. A detailed list of different techniques attempted and used in this study is laid out.

Chapter Four contains the results and evaluation of the different measures described in the methodology.

Chapter Five documents the analysis of the results section, including regression models, prediction models, and summary.

Chapter Six includes conclusions and recommendations.

Chapter 2: Background Review

An incident is a traffic event that has an impact on traffic conditions. Incidents come in many forms, including disabled vehicles, abandoned vehicles, various spills and debris, environmental events (weather), and probably the most influential, vehicle accidents. These incidents decrease flow and add additional congestion to the already crowded urban freeways. This causes the Level of Service (LOS) to decrease and also adds to causes of additional incidents. Previous research has been done on traffic impacts of incidents, incident management, incident prediction, and other topics pertaining to these random events. Although the information gathered for these studies is typically for traffic in the same direction as the incident, it is still valuable for this study.

2.1 Flow / Occupancy (Density) Relationships

The flow and density relationship has been explored since the publication of the L-W-R theory Lighthill and Whitman in 1955 and Richards in 1956. In general, flow is defined as the number of vehicles to pass a point during a certain time. Density is referred to as the number of vehicles per roadway length. Many models have been developed in an attempt to determine the correlation between flow and density. Some models such as the Greenshield model use single regime non-linear approach (see Figure 1), while others use multi-regime complex models.

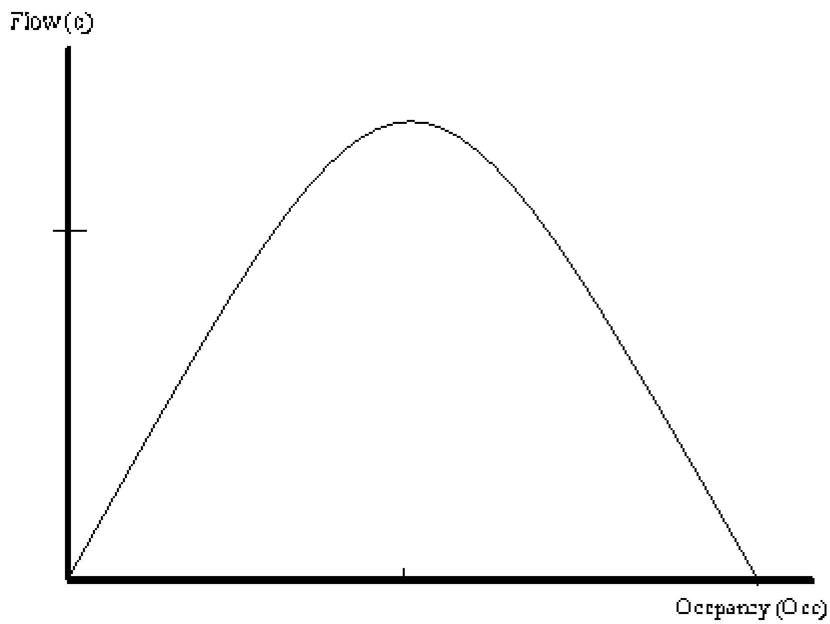

Figure (2-1): Greenshield's Flow vs. Density Model

The model developed by a Northwestern University research team, takes into consideration a two-regime linear model. The first regime considers a positive slope linear relation of flow and occupancy during non-congested conditions.

$$OCC \leq OCC_{capacity}$$

The other regime considers a negative slope linear relation of flow and occupancy for congested conditions.

$$OCC > OCC_{capacity}$$

Note that occupancy measures the percentage of time vehicles occupy a section of roadway where a loop detector is installed. It is often used in place of density because it is directly proportional to density based on a factor of average vehicle length. This two-regime linear model is diagramed below.

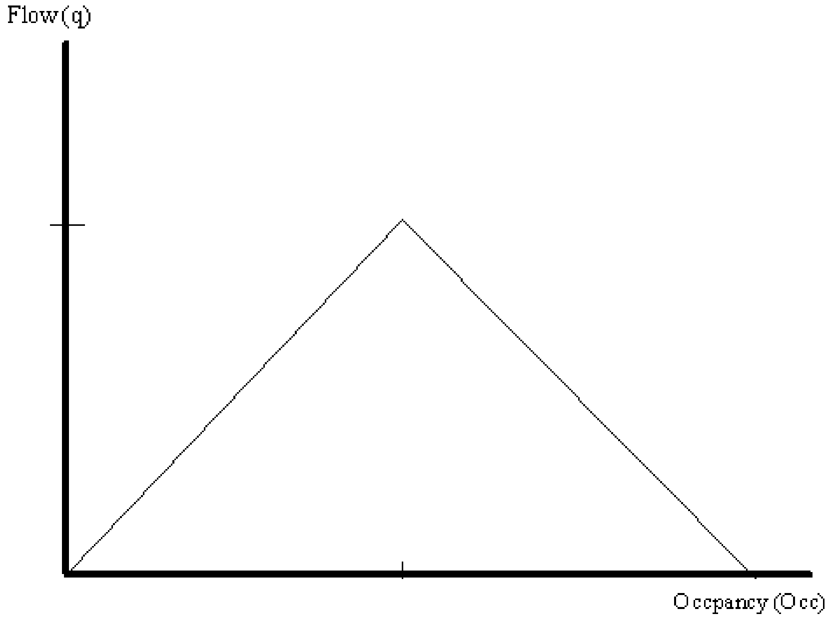

Figure (2-2): Two-Regime Flow vs. Occupancy Model

2.2 Traffic Delay

Congestion delay is referred to as the difference between actual travel time and the free-flow time on a section of freeway (Hall, 1992). It can be determined for a wide variety of traffic situations such as freeway and arterial systems. In freeway systems, delay is often thought about in terms of "recurrent" and "non-recurrent" delays. Recurrent delays are delays experienced in everyday travel based on historical data. Non-recurrent delays are delays caused by an event or an incident and it can be broken up into two periods, immediate delay and residual delay. Immediate delay is the part of the delay incurred during the duration of the incident. The residual delay is the delay sustained after the incident has cleared. It is estimated that 60% of all freeway delay is attributed to incident producing non-recurrent delay (Lindley, 1989).

Incident-induced delays have been calculated using a variety of methods. Morales (1986) developed a cumulative volume approach to calculating freeway delays. In this approach, two cumulative volume curves (one for arrival and the other for departure at an incident site) are plotted on a time axis. The area between these two curves represents the extra delay due to an incident. This is shown below in Figure 2-3.

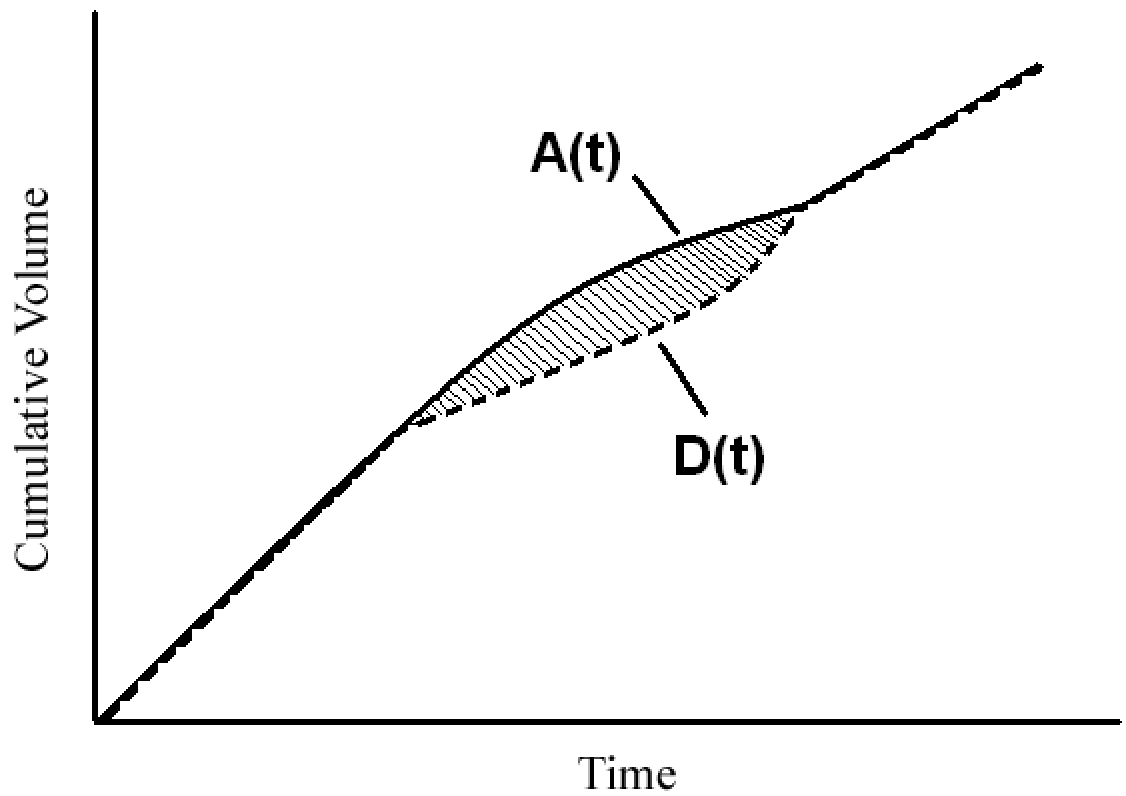

Figure (2-3): Cumulative Volume Diagram - Delay due to an Incident

In addition to this delay calculation based on the cumulative curves, it has been suggested to adjust one or both of these curves. Daganzo (1997) proposes a 'virtual' arrival curve be used to determine delays. This virtual arrival curve is a translation of the actual arrival curve based on the "number of items that would have been seen directly upstream of the restriction" by the beginning of the incident duration. The actual arrival curve is translated to the right by a value of τ, representing the travel time between observers, or stations. This new method of determining delays is just one of the recent methods used.

Al-Deek et al (1994) developed a new method and made improvement to Morales' approach by looking at delays in time slices. They incorporated vehicle speeds in conjunction with traffic volumes to develop a delay formula. Assumptions they made include:

- Traffic speed and volume data are determined from the loop stations on a roadway segment and these data are homogeneous throughout the segment
- Incident delay is calculated with respect to a reference (or base) average speed which reflects normal conditions that may or may not be congested. The reference speed represents a historical speed profile which may be used to segregate (distinguish between) incident and non-incident (recurring) congestion.

A drawback to this approach is that it required one-minute speed averages. Smaller interval averages (less than one minute) could lead to "noisy" data, while larger intervals (greater than one minute) do not allow for accurate estimation of queue boundaries. The delay was then calculated using the formulas shown below. Different from the queuing diagram approach where incident duration, capacities before and after an incident and traffic demand are used to calculate delay, the incident delay is determined using the time-slice method by Al-Deek (1994). The individual slices are summed up to form the total delay shown at the bottom of the reference below.

$$D_k^i = L_{\partial k} \frac{\Delta T}{60} F_k^i \left(\frac{1}{V_k^i} - \frac{1}{V_k^{i,r}} \right) \text{ for } 0 < V_k^i < V_k^{i,r} \tag{1}$$

$$D_k^i = F_k^i \left(\frac{\Delta T}{60} \right)^2 \text{ for } V_k^i = 0 \tag{2}$$

$$D_k^i = 0 \text{ for } V_k^i > V_k^{i,r} \tag{3}$$

where

D_k^i = Delay on freeway segment "k" during time slice "i" (vehicle-hours)

L_k = Length of segment k (miles)

ΔT = Length of time slice "i" (minutes)

F_k^i = Flow (from loops) on segment "k" during time slice "i" (vehicles per hour)

V_k^i = Speed (from loops) on segment "k" during time slice "i" (miles per hour)

$V_k^{i,r}$ = Reference average speed on segment "k" during time slice "i" (miles per hour).

The total delay on the freeway section that is caused by the incident is given by:

$$TD = \sum_{i=1}^{m} \sum_{k=1}^{n} D_k^i \tag{4}$$

In addition to the queuing diagram and real-time traffic data based approach computer simulation is another effective way in modeling traffic delays during incidents.

2.3 Capacity Reduction

The Highway Capacity Manual (HCM) defines freeway capacity as "the maximum hourly rate at which persons or vehicles can reasonably transverse a point or uniform section of a lane or roadway during a given time period." During this time period, typically 15 minutes, the freeway must be operating under 'ideal conditions'. When these ideal situations are not present, typically during an incident, the capacity is reduced. The HCM provides an equation for capacity reduction caused by basic non-ideal conditions (lane width, heavy vehicle factor, number of lanes, etc), but not for incident situations. The HCM states that a capacity reduction of 10-20 percent is characteristic of rainy weather. A separate study by Jones and Goolsby (1970) revealed a 14 percent loss of capacity due to rain. This capacity loss is based on the maximum number of vehicles able to pass a section of roadway in a given time. Although the maximum possible flow should not change, the actual amount of vehicles passing a section of roadway would be reduced.

The reduced capacity used in incident modeling is called the 'effective capacity' and is referred to the "expected roadway capacity, over time, after accounting for the occurrence of incidents." (Hall, 1992) Having an effective capacity formula based on incident characteristics would be an ideal solution of calculating capacity reduction. However, such a formula would not hold for situations for which more than one incident is present. It has been proposed that in the case of multiple incidents, the incident that has the largest impact on capacity should be used in the analysis. This is to say that the capacity reduction "is not the sum of their magnitudes, but their maximum." The research by Goolsby in 1971 and Lindley in 1986 developed capacity reductions for certain lane and shoulder blockages. It was concluded that "the effective capacity loss due to incidents is far less than the effective loss due to removing a single lane on a four-lane roadway."

2.4 Rubbernecking Effects

It is a result of a human response to the surroundings such as freeway signs, scenery, billboard ads, and many other visual "eye-candy". From a traffic operations standpoint, rubbernecking is a serious issue that can sometimes create traffic congestion and even traffic incidents. On the other hand, the attention of the driver is focused on these surroundings and less attention is on the roadway, making rubbernecking a safety issue as well as a traffic congestion issue.

A 2003 study by the Virginia Commonwealth University's Transportation Safety Training Center (TSTC) revealed that rubbernecking was the leading cause of vehicle crashes. These rubbernecking accidents were not caused by landmarks or other scenery; they were caused by drivers looking at other vehicle crashes and other roadside traffic incidents. Rubbernecking caused by vehicle crashes and other incidents accounted for sixteen-percent of all vehicle crashes, while the total number of outside the car distractions accounted for 35-percent. There has been research performed on calculating rubbernecking effects of traffic in the same direction of travel as the incident, including studies by. These effects are due to rubbernecking of adjacent lanes and shoulders. Although preliminary findings of this suggest significant rubbernecking effects on the opposite direction of travel, there is no documentation available on this topic.

2.5 Physical Factors

Drivers cannot be distracted by events or objects they cannot see. To mitigate rubbernecking in the opposite direction, this statement calls for barriers that block vision to opposite direction traffic conditions. The Hampton Roads freeway system, consisting of I-64 and I-264, implements a variety of different barrier techniques. Certain segments along the freeway system have only guardrails and a grass median dividing the freeway traffic. Certain sections of the Hampton Roads freeway are implemented with standard 42" concrete barriers, while other sections have double stacked concrete barriers. Below are pictures from the Hampton Roads freeway system and the median barriers associated with it. By having the data on the availability of the different types of barriers on roadway segments, it is possible to investigate its relationship with the rubbernecking impact on opposite traffic conditions. The derived information could help develop mitigations to reduce rubbernecking impacts on opposite direction traffic conditions.

Figure (2-5): Barrier Guardrail System on a Section of Roadway on I-64

Figure (2-5): A Standard Concrete Barrier on I-264

Figure (2-6): A Double Stacked Concrete Barrier on I-64

2.6 Summary

This chapter provided an overview of previous work done related to this study. From the initial research in the 1950's to the complex traffic modeling of the 21st century, traffic studies attempt to provide a safer and more efficient roadway. Previous research in Flow vs. Density modeling, delay calculations, capacity reduction, and rubbernecking have all contributed as background information for this study. The next chapter will show the procedure taken to complete this study.

Chapter 3: Methodology

In this study, the following procedure is adopted:

1. Extract incident data from Hampton Roads freeway system
2. Filter data by limiting type of incidents to "accidents"
3. Determine appropriate traffic data to collect for given incidents.
4. Plot occupancy each vehicle accident
5. Determine significant impacts on both the same and opposite direction of accidents
6. Determine location of incidents at station level
7. Use Binary Logit Model for determining incident impact modeling
7. Plot cumulative volume for identified significant impact accidents
8. Calculate delay for identified significant impact accidents
9. Determine capacity by retrieving historical data
10. Plot Flow rate vs. Density (Occupancy) for incidents
11. Compare of historical capacity and incident capacity
12. Calculate capacity reduction
13. Use Linear Regression Modeling for delay and capacity reduction results
15. Evaluation of results and recommendations based on analysis

3.1 Data Source

Data for the Hampton Roads freeway system operated by Hampton Roads Smart Traffic Center (HRSTC) were collected for this study. This freeway system consists of approximately 20 miles of Interstate 64 from I-564 down south to Indian River Road and Interstate 264 eastbound from the I-64 interchange (See Figure 3-1).

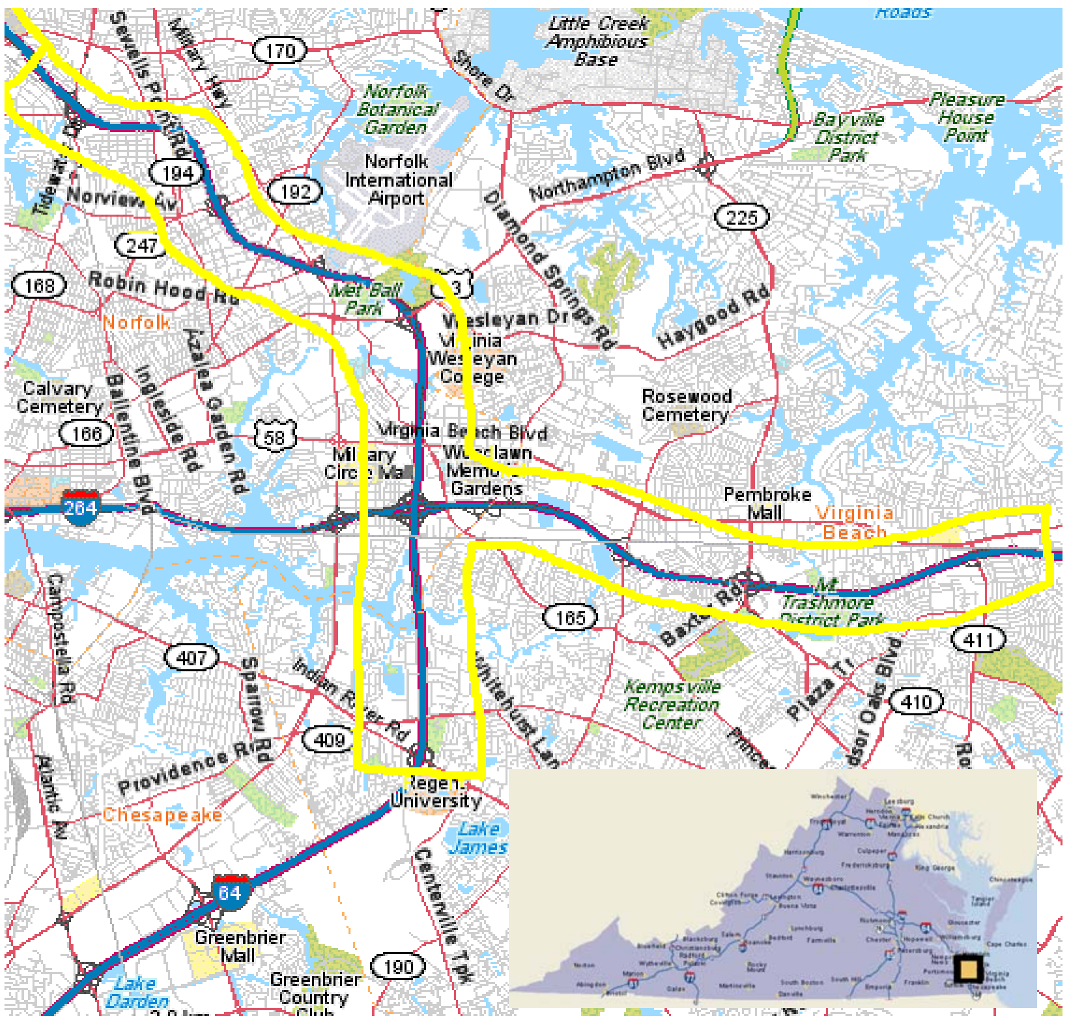

Figure (3-1): Area Map of Hampton Roads Freeway System

The HRSTC uses technology to improve motorist safety and convenience, reduce area traffic congestion and decrease motorist travel time in the Hampton Roads area. There are closed circuit television cameras overlooking the 20 miles of freeway traffic. These cameras assist in incident management as well as any other traffic tie up. These incidents are then documented into a database with a variety of information regarding the incident. In addition to the cameras loop detectors are installed along freeway system. From these detectors, real-time traffic data are collected and sent to the Center. These loop detector data is accessible through the Smart Travel Lab at the University of Virginia, in Charlottesville.

3.2 Incident Data

Specifically, the incident database was retrieved from the Smart Travel Lab's **hr.incident** table in the Oracle 8i database. This table contains information on each incident and includes sub-tables with additional information. The information on incidents include incident identification number, incident begin time (including date/time in MM/DD/YYYY HH24:MI format), incident duration (in minutes), incident type, weather, detection source, and a brief description of the incident. Sub-tables include information such as the roadway of occurrence, direction, location, number of lanes and shoulders blocked, and information about the vehicle(s) involved (make/model/color/etc). The incident identification number is listed as a TMS Call Number including a year and a identification number (Example, '2000-00001'). The duration of the incident is defined as the time from when the incident is detected until the clearance of the incident. The weather during the incident is documented and includes conditions such as rain, snow, sleet, clear, cloudy and even ice. A complete layout of the hr.incident table can be viewed below. A brief description of the incident is sometimes given. This brief description may include the number of personal injuries or a more accurate location of the incident. A summary of the database can be seen below.

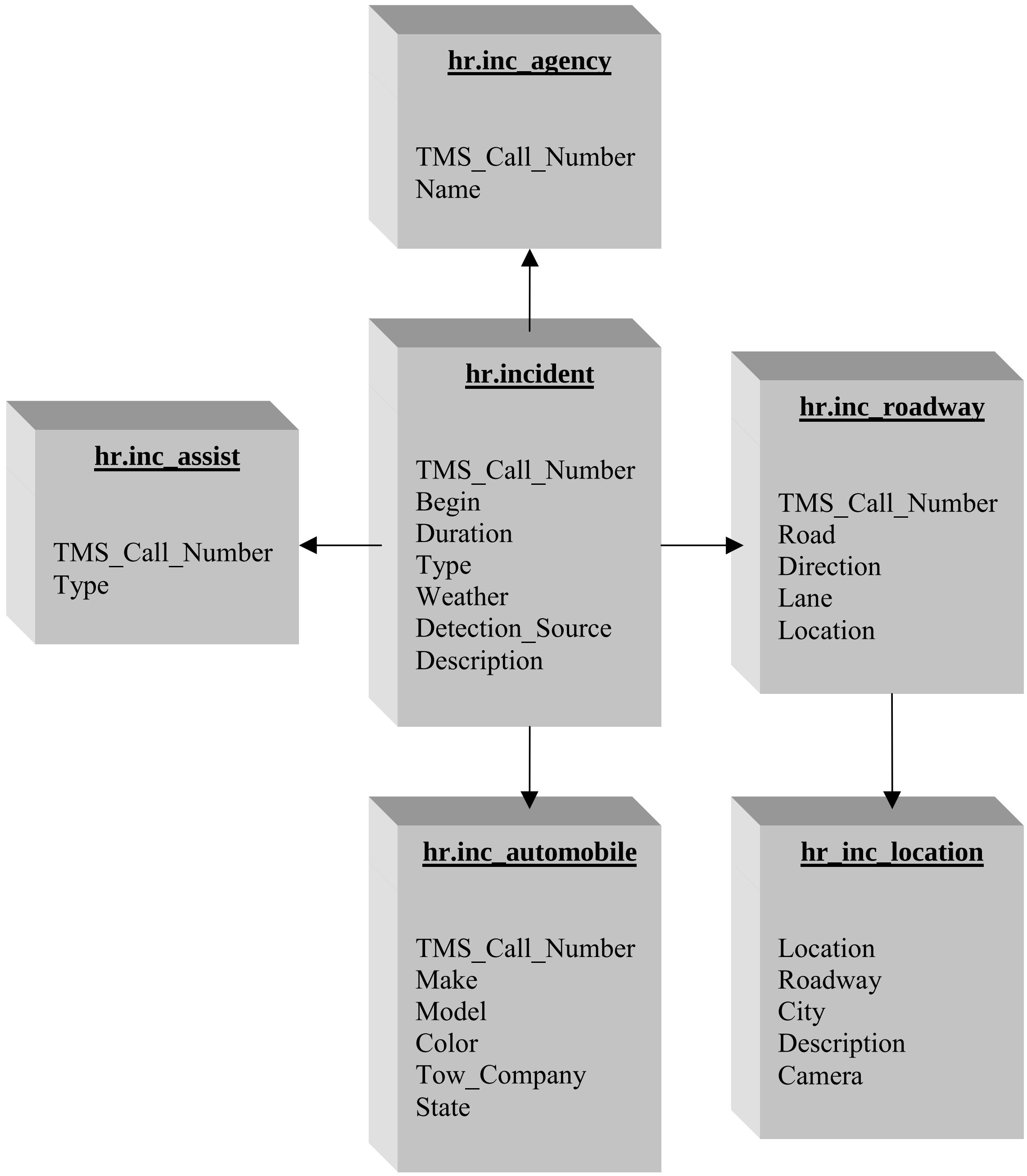

Figure (3-2): The hr.incident Table Available from the University of Virginia STL (Smith, 2001)

Though, useful in other studies, some of this information is not pertinent. The relevant information used in this included the incident identification number, incident begin time, roadway, direction, location, duration of incident, weather, number of lanes and shoulders blocked, and description. Incidents of the year 2000 were pulled from the hr.incident table. During this time period, available incident types included the following:

- Abandoned Vehicles
- Vehicle Accidents
- Bridge Incidents
- Debris
- Disabled Vehicles
- Severe Weather Conditions
- Other

It was decided that impacts due to rubbernecking would most likely only occur during vehicle accidents. The acquired incidents were then filtered to only include incident whose type was ‘accident’. Information about each accident is given in the database.

3.3 Traffic Data

Traffic data were collected based on the date, time, and location of each incident that are included in the database. Note that the exact sites of the incidents cannot be readily known from the location code of the incident in the the hr.incident database. Each location code is a section of roadway typically 2 miles long and having three or four detector stations within. Thus, traffic data had to be collected for all stations within the location code of the incident. Total volumes, average speeds, and average occupancy were collected for an extended period, starting from one hour before the incident beginning time and ending one hr after the duration of the incident. This period accounts for the time period where traffic is operating normally before the incident and where traffic is recovering and once again operating normally after the duration of the incident. By collecting data for this extended period of time it is ensured that the full effects of the incident are captured. A working SQL code was developed to expedite this long process. A copy of this code can be found in Appendix A.

3.4 Determination of Incident Location and Significance of Rubbernecking Impacts

After the traffic and incident information for each incident had been collected, the incidents were grouped together into a single spreadsheet. The next step was to determine whether each incident had significant impacts on traffic in the same and opposite direction as the incident. This is determined based on visual observations of occupancy vs. time plots of the incidents. An example is shown in Figure 3-3.

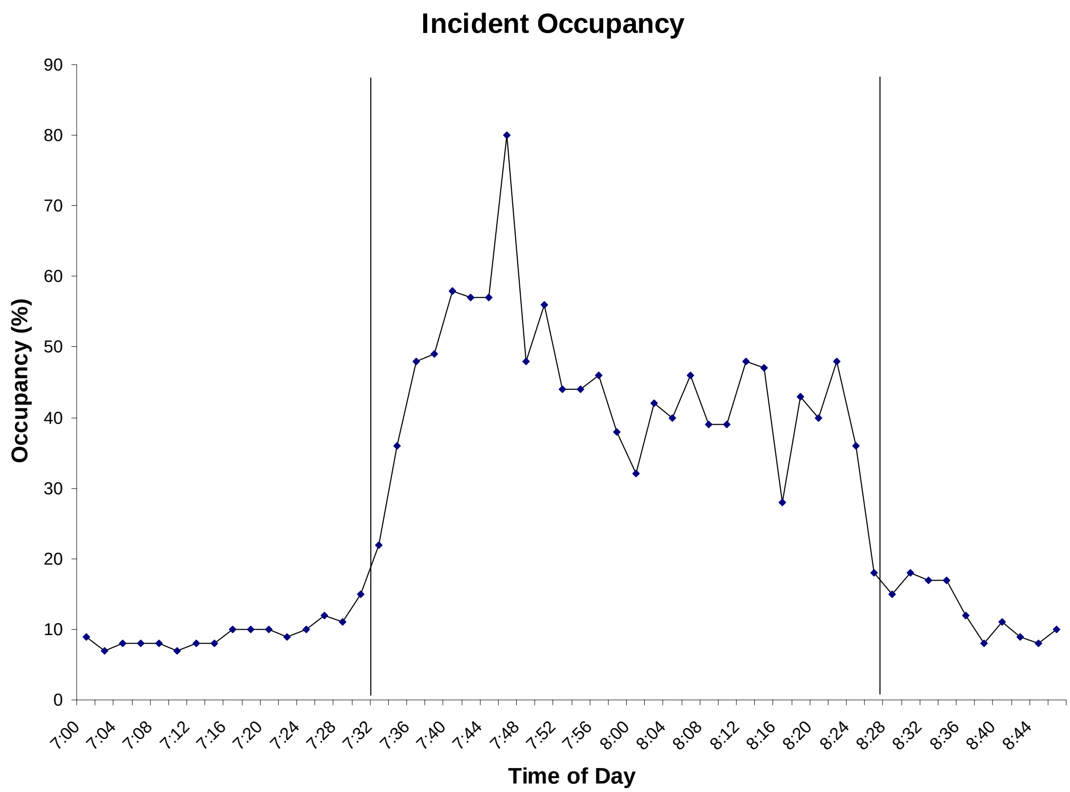

Figure (3-3): Example of Incident Occupancy

In this study, such a plot was created for both the incident direction and the opposite direction. The plots show whether a significant increase or decrease in occupancy was present in both travel directions. This beginning and ending points were visually determined for each incident. These cutoffs represent the effective duration of the incident. The effective duration observed does not factor in the time required for the shockwave of the traffic to reach the immediate upstream station. This would cause the duration to be shifted by the shockwave travel time. This incident duration assumes a station detection technique rather than a point detection approach. The visual observations used to determine occupancy change significance is an arbitrary process. One person's visual significance may be different from another person's. The duration of each incident was observed and documented accurately.

As mentioned before, the HRSTC incident database only gives a vague location as to where the incident took place. The 'location code' given is a section of roadway consisting of multiple stations. There is no documentation as to which stations between which the incident happened. Using Figure 3-4, the exact location of each accident can be determined based on observing the patterns of the changes in occupancies. Specifically, it was perceived that the immediate upstream station from each accident would have the earliest and largest occupancy impact. Subsequent upstream stations should also show an impact, but at a later time due to the backward moving shockwave.

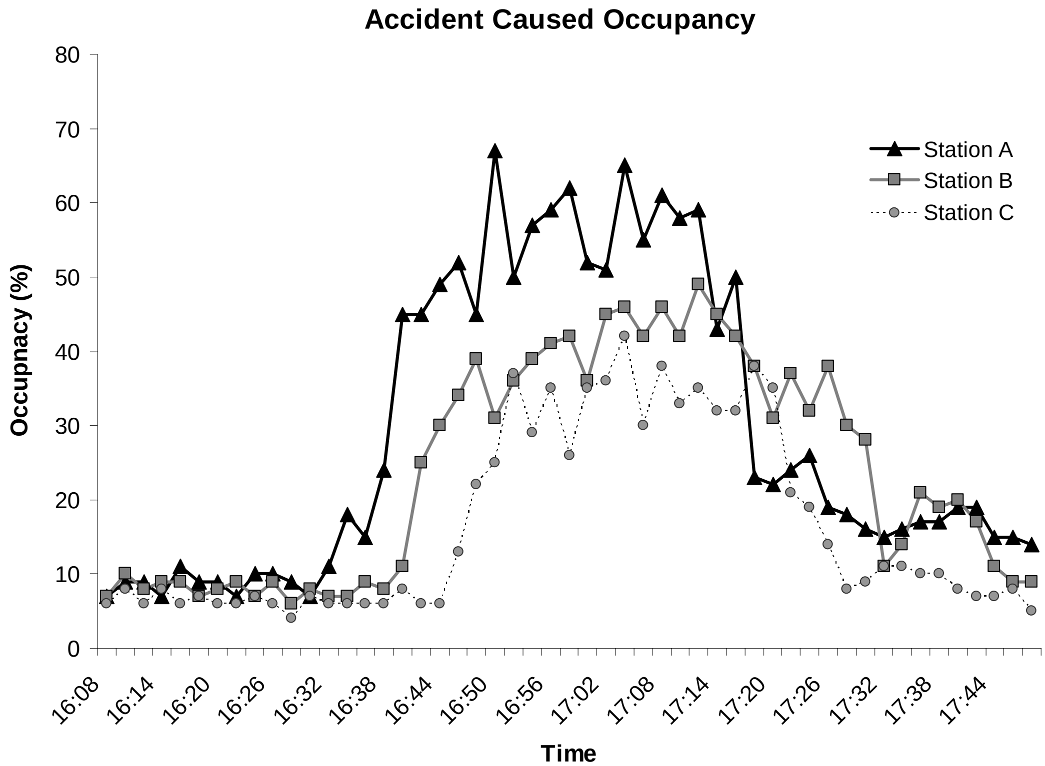

Figure (3-4): Incident-caused Occupancy at Multiple Stations

Note that the occupancy plot of multiple stations in Figure 3-4 indicates the immediate upstream station of the incident. It can be seen that the impacts of occupancy increase reach Station A prior to reaching Station B and Station C. This pattern shows that Station A is the immediate upstream station of the accident. Precautions have been made in dealing with this traffic data. Multiple incident periods can give misleading results. Once the accident database was developed and traffic data was collected, it was checked whether the accidents were isolated events with no other incidents affecting the target area. Queries were run to determine whether additional incidents were involved during the time period and location of the incidents. Multiple incidents occurring during these accident times were not used in the analysis.

It is possible to use other traffic data to determine these traffic impacts. Vehicle speed data could be used to replace occupancy. As occupancy increases due to an incident, vehicle speeds would decrease. The observation of a significant decrease in speeds may indicate the presence of an incident or rubbernecking. Speeds are collected and averaged from loop detectors. These speeds have maximum limits and often do not capture an accurate display of actual vehicle speeds. In addition to occupancy and speed data, vehicle volumes could also be used. The vehicle flow during an accident tends to decrease. This is evident in any traffic jam. A visual observation of a decrease in flow could possibly be due to an accident. Although speed and volumes (flow) may be possible variables to use, occupancy was chosen to be the significant impact variable in this study.

3.5 Congestion Delay Calculations

In this study, incident delay is derived based on the cumulative volume plots (mentioned earlier), where upstream and downstream station volumes are used. As shown in a previous graph, the area between the two curves represents the increased delay due to an accident. In this study, this area is measured by taking the integral of the difference of the curves over the duration of the impact of the accident. This duration should not be confused with the database documented ‘duration’. The database duration is the time between the arrivals of service vehicles and the complete clean up of the incident. The duration used in the integral should be looked at as the duration of the impact and recovery of the incident. The integral can be written as follows:

$$\int_{T_1}^{T_2} [A(T) - D(T)]dT \tag{5}$$

Note that using the integral to calculate delays requires the functions of the cumulative curves, which are unavailable in this case of traffic delay calculation. This problem was solved by using the properties of the area function. This is a routine used to estimate areas under complex functions. In order to find the area under a curve, smaller rectangles can be made. These smaller rectangles are added together to determine the area under the curve. An example of this procedure is show below.

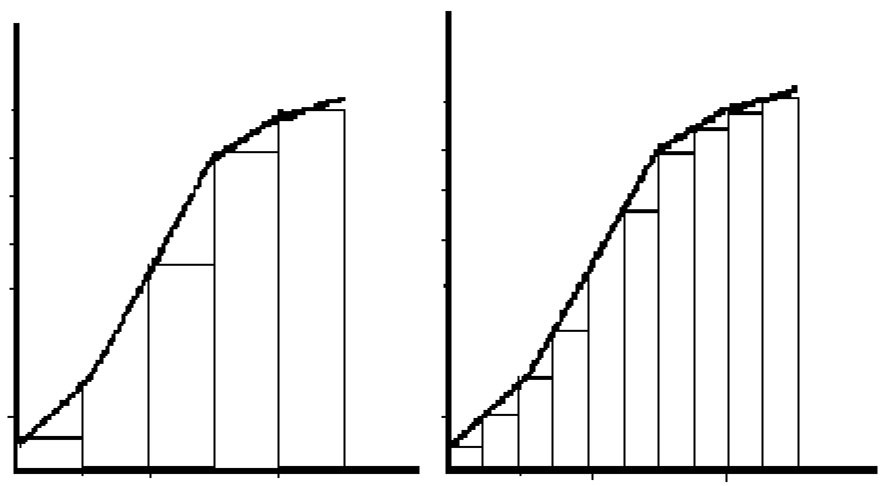

Figure (3-5): Example of Rectangular Area Approach

The figure on the left is using the rectangle area approach with a certain Δx value. The area under the curve is better approximated as the Δx value decreases. This is shown by the figure on the right. The application of this principle is quite simple. The difference between the arrival curve and the departure curve for each time slice of data represents the number of vehicles unable to pass through the bottleneck, or in this case, the ‘rubberneck’. The time-step used in this corresponds to the quality of data collected. Since the study used one-minute aggregate data, the respective time-step for the delay integral is one-minute. The y-axis direction represents the difference in the arrival and departure curves of the incident. The x-axis represents the time-step or data collection interval. An example of applying the rectangular area approach to this is shown below in Figures 3-6 and 3-7.

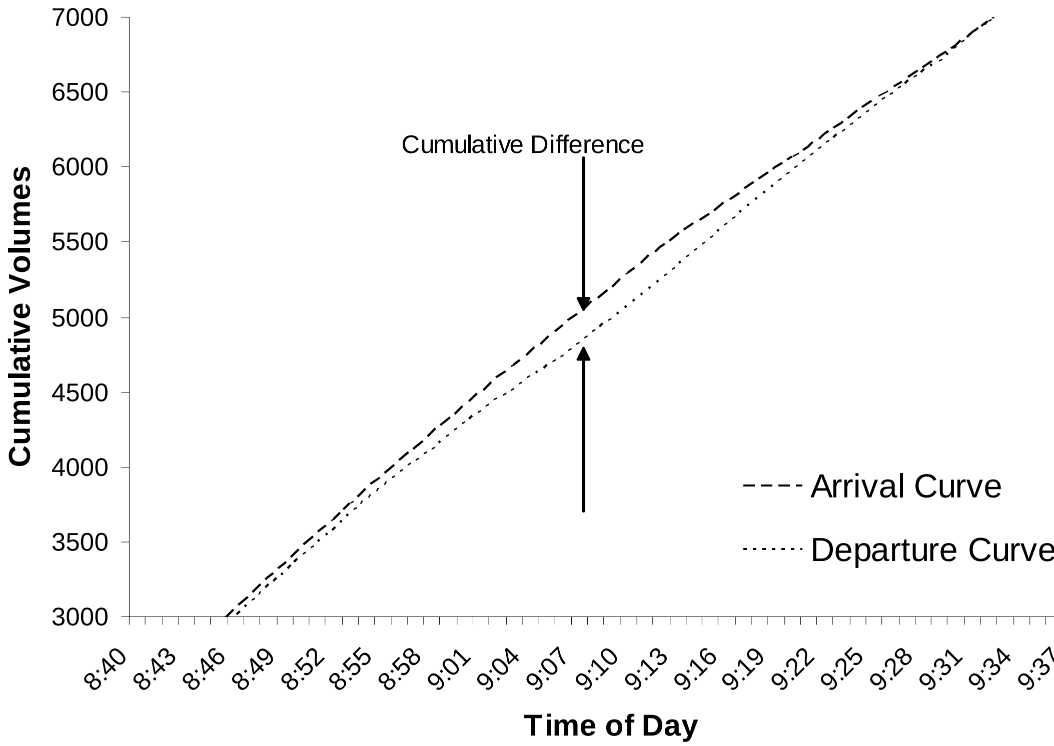

Figure (3-6): Example of Cumulative Arrival and Departure Curves

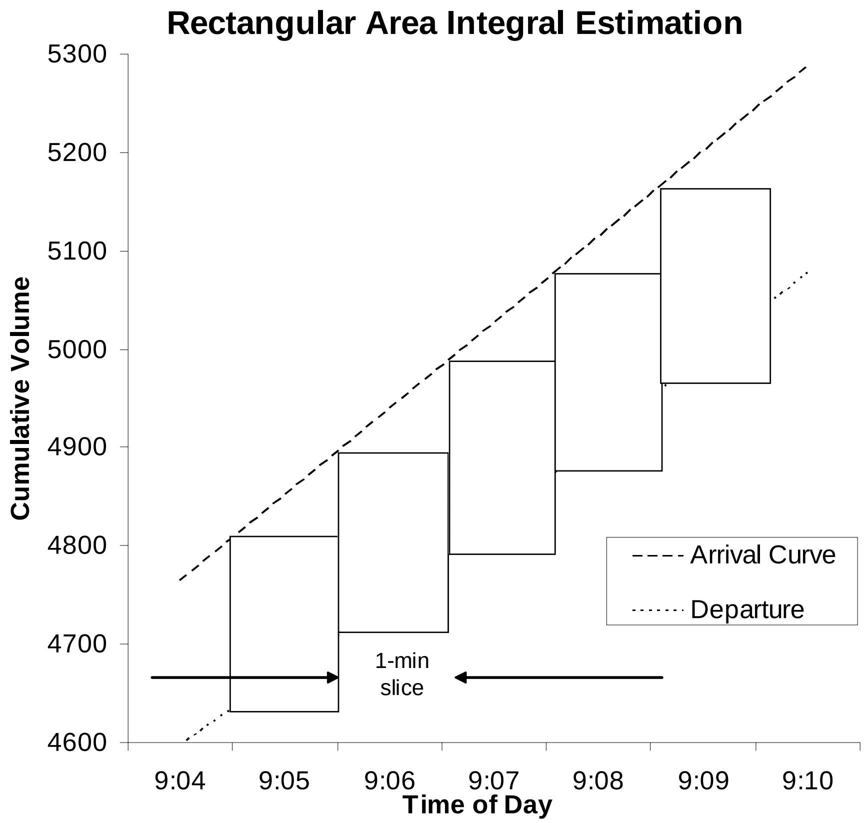

Figure (3-7): Application of Integral Estimation on Delay Calculation

By multiplying the cumulative volume difference and time-step dimensions, the area of a time slice is formed. This time slice area represents the delay due of the time slice. Summing all of the time slice delays represents a close estimate of the total delay due to the accident. This total delay calculation is shown below.

$$Delay = \left[Cum.Vol_{Arrival} - Cum.Vol_{Departure} \right] \left[TimeSlice \right] \quad (6)$$

The additional development of a 'virtual arrival curve' (Daganzo, 1997) is not appropriate in this study. The travel time τ between ¼ or 1/3 mile station gaps based on 60 mph free flow speeds would be approximately 15-20 seconds. A 20-second lateral translation of the arrival curve would not be a significant change to the curves.

3.6 Capacity Reduction

Reduction of capacity due to incidents was derived based on the two-regime linear model. After accurate locations were established for the accidents, historical volume data was collected for the corresponding detector stations. In order to determine capacity of the freeway sections five days worth of historical data were retrieved for each accident's respective upstream station. Due to the presence of incident(s) during the day of interest, other incident-free days were selected to act as historical periods. This historical data came from surrounding days and weeks depending on weekday/weekend information from the accident. From these data, flow vs. occupancy graphs were created from which the data points for non-congested situation and the congested situation can be distinguished using visual inspection. Regression analysis was performed on the two sets of data (non-congested/congested). This regression developed two intersecting lines, one from each of the regimes. Freeway capacity of the location was determined by the intersection of the two regression lines.

Once a historical capacity of the area was established, the accident traffic data was evaluated using the same two-regime linear regression analysis. The accident traffic data was plotted on flow vs. occupancy graphs and similar regression was performed on the data. The capacity of the accident is determined from this analysis.

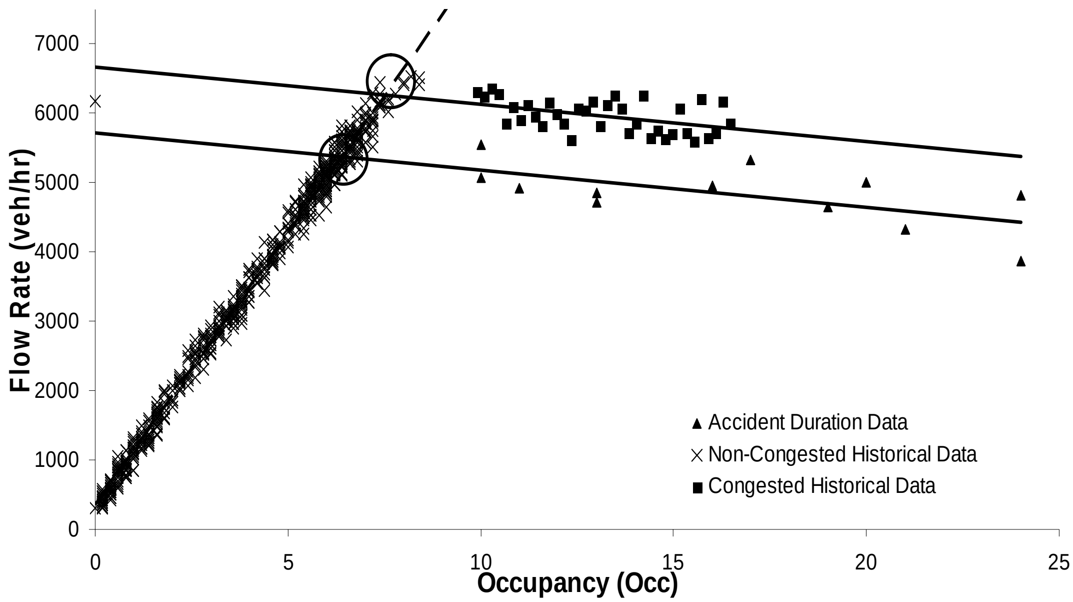

Figure (3-8): Example of Capacity Reduction Calculation

Each accident in the database has a historical capacity and an accident (or actual) capacity associated with it. Capacity reduction is commonly viewed as a percentage of reduction from the actual capacity. By dividing the difference between historical capacity and accident capacity by the historical capacity, the result is the percentage of capacity reduced by the accident:

$$Capred = [Cap_{hist} - Cap_{acc}]/[Cap_{hist}]\% \quad (7)$$

3.7 Binary Logit Model

Whether an accident causes impacts of rubbernecking is a binary variable. To identify the factors that are associated with such a binary variable, binary logit model is usually adopted.

According to the binary logit model, the "utility" for an accident to cause rubbernecking impact on the opposite direction traffic can be written as:

$$U_{in} = \beta' \mathbf{x}_{in} + \varepsilon_{in} \tag{8}$$

where $\mathbf{x}_{in}$ represents the independent variable, ε_{in} represents the error in the model and β represents a vector of coefficients for explanatory variables included in the vector $\mathbf{x}_{in}$ and ε_{in} is denoted as the error of the "utility", U_{in}. The maximum likelihood estimation method can be used to determine the coefficients of the model.

The rubbernecking likelihood for an accident can be calculated as follows:

$$P(i=1) = \frac{e^{U_{1n}}}{e^{U_{1n}} + e^{U_{0n}}} \tag{9}$$

where 1 represents rubbernecking, and 0 denotes not.

3.8 Linear Regression

In this study, linear regression models were used to identify the factors that significantly determine the amount of traffic delay and capacity reduction to the opposite direction traffic. In the modeling, the measures of traffic delay and capacity reduction serve as response variables; while the characteristics that may lead to delay and capacity reduction are the independent or predictor variables. These variables include v/c ratios prior to an incident, duration of the incident, weather, number of lanes and shoulders blocked, peak hour/non-peak, day/night, weekend/weekday, and visual barriers. In general, the linear regression model takes the form of:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \tag{10}$$

where y denote delay or capacity reduction ratio, X represents influencing variables, and β is the coefficients.

Chapter 4: Results and Analysis

4.1 Incident Data

Initially, incident data were collected for the years 2000 and 2001. These incidents were filtered to only include 'accident' type incidents. It was soon brought the attention of this study that traffic data from the Hampton Roads Smart Traffic Center were missing for a good part of the 2001 year. Thus, 2001 accident and traffic data was removed from the database, leaving only year 2000 accident and traffic data. In summary, 36769 total incidents occurred in the Hampton Roads freeway system in the year 2000, with 2175 being accidents. During that year, accidents accounted for 5.9% of the total incidents. Many of these accidents do not provide any location data, so they were thrown out. The analysis conducted in this study was based on the 840 accidents with sufficient incident data information.

4.2 Significant Impacts

By visually observing occupancy behaviors in all 840+ documented accidents, significant impacts could be distinguished. Significant impacts due to accidents are fairly easy to make out. Typically a sharp increase of occupancy occurs soon after the accident begins. This increased occupancy is usually held fairly constant for the duration of the incident. After the incident has cleared the occupancy returns to its normal values. This process of distinguishing significant impacts was described in the methodology. Out of the 840 accidents in the year 2000, the results of significant impacts can be seen in Table 4-1.

Table 4.1: Statistics of Significant Impacts of Occupancy due to Accidents

	Number of significant impacts	**Percentage (%)**
Total Accidents	*840*	*100*
Same Direction as Accident	**201**	**23.9**
Opposite Direction as Accident	**102**	**12.1**
Significant Impact in both SAME *and* OPPOSITE Directions	**84**	**10.0**

This table shows that 201 out of the 840 accidents had an impact on traffic occupancy in the same direction as the accident. 102 out of the 840 showed significant changes in occupancy for the opposing traffic. Out of these accidents, 84 showed a significant impact in *both* directions. These 84 cases are the most important accidents, where there are significant impacts in both the same and opposite directions based on visual observations of occupancy. As seen in the table, this situation makes up 10% of the total number of incidents. An interesting statistic in the table is the number of incidents which showed a significant impact of opposite direction traffic, but showed no impact in the same direction. Only eighteen of the 840 total accidents showed this phenomenon. Different factors could lead to this dilemma. Greater volumes in opposite direction of the accident could possibly have a greater impact. Different geometric designs of the freeway could possibly have an effect on traffic in the opposite direction and not in the same direction. Whatever the case may be, only a very small proportion of the total number of accidents showed this occurrence.

Statistical analysis was performed on the 840 total incidents. This analysis uses a binary logit model to determine the rubbernecking likelihood of an accident and also to determine outstanding variables that cause rubbernecking. Table 4.2 lists the results of binary logit model. Table 4.3 shows the quality of the fitted binary logit model. It can be seen that four variables significantly influence whether an accident impacted the traffic in the opposite direction: peak, weather, presence of barriers, and weekend. The t-statistic is a significance test used to determine whether a certain variable is significant or not. Critical t-stat values with percentiles used in this study are shown below.

# observations	80th	85th	90th	95th
84	0.847	1.044	1.294	1.668
840	0.842	1.036	1.282	1.645

The coefficient for variable Peak is negative, which implies that an incident occurred in peak periods was less likely to cause rubbernecking impact to the opposite direction. It might be reasonable because motorists are in the rushes of homeward bound or work bound travel. Under this condition, the curiosity of the motorists to know the accidents in the other direction may be under certain control. The coefficient for weather (rain/snow/ice) is negative. It indicates that an accident occurred in rain might be less likely to cause the attentions of motorists traveling in the other direction. It might be reasonable to expect that the bad weather demanded more attention of motorists on their travels and left lesser chances for them to care about the events happening in the other direction. The coefficient for Weekday is positive. It suggests that an accident occurred in a weekday would be more likely to cause rubbernecking in the opposite direction than it occurred in weekends. It may be due to the high volume of traffic in weekdays than weekends. Under high volume condition, the potential number of motorists to rubberneck would be more than that under the low volume condition. As far as the factor of barrier is concerned, the coefficient is negative. It implies that the presence of barriers on an accident scene decreased the likelihood of rubbernecking in the opposite direction. This may be due to blocking of the barriers for the motorists to view the accidents in the other direction. Note that this variable is significant only on 70% level, not as significant as the other variables. Retrospect the fact that the data on the presence of barriers were collected in 2004 while accident occurred in 2000. The barriers exist in 2004 may not presence in 2000. Considering this possible error, the result is accepted as reasonable.

Table 4.2 Results of a Binary Logit Model

Variable	Coefficient	Standard Error	t-stat
Constant	-4.39220546	.65932825	-6.662
PEAK	-3.27492185	.49187300	-6.658
WEATHER	-.97968397	.42100950	-2.327
BARRIER	-.47736199	.43069356	-1.108
WEEKDAY	5.17244375	.60798673	8.507

Log likelihood function	-130.1868
Restricted log likelihood	-281.3884
Chi squared	302.4033
Degrees of freedom	4
Number of observations	840

The frequencies of the actual and predicted outcomes of the discrete choice model are located below. Additional analysis is also provided.

Table 4.3 Discrete Choice Model Results

	Predicted		*Total*
Actual	0	1	
0	713	43	*756*
1	14	70	*84*
Total	*727*	*113*	*840*

0 = no significant impact
1 = significant impact present

Based on 840 accidents, the discrete choice modeling predicted which accidents would impact opposing traffic. Out of the 84 accidents that showed significant impacts on opposing traffic, 70 (or 83.3%) were selected by the discrete choice model to have such an impact. The remaining 14 accidents were deemed insignificant. The success of the model is also evaluated by the complete number of significant and insignificant impacts predicted. The impacts of 783 (93.214%) out of the total number of accidents had been successfully predicted using this choice model.

4.3 Rubbernecking Delay Calculations

Delays were calculated for the 84 accidents which showed significant impact on traffic in both the same and opposite directions. These calculations were possible using cumulative volume plots as described in the methodology. While individual vehicle delays are typically measured with units in **[veh*min]**, delays of freeway systems are typically measured in **[veh*hr].** Delay calculations resulted in a range of 3.6 veh*hr to 590.0 veh*hr. A histogram of the delay is presented in Figure 4-1.

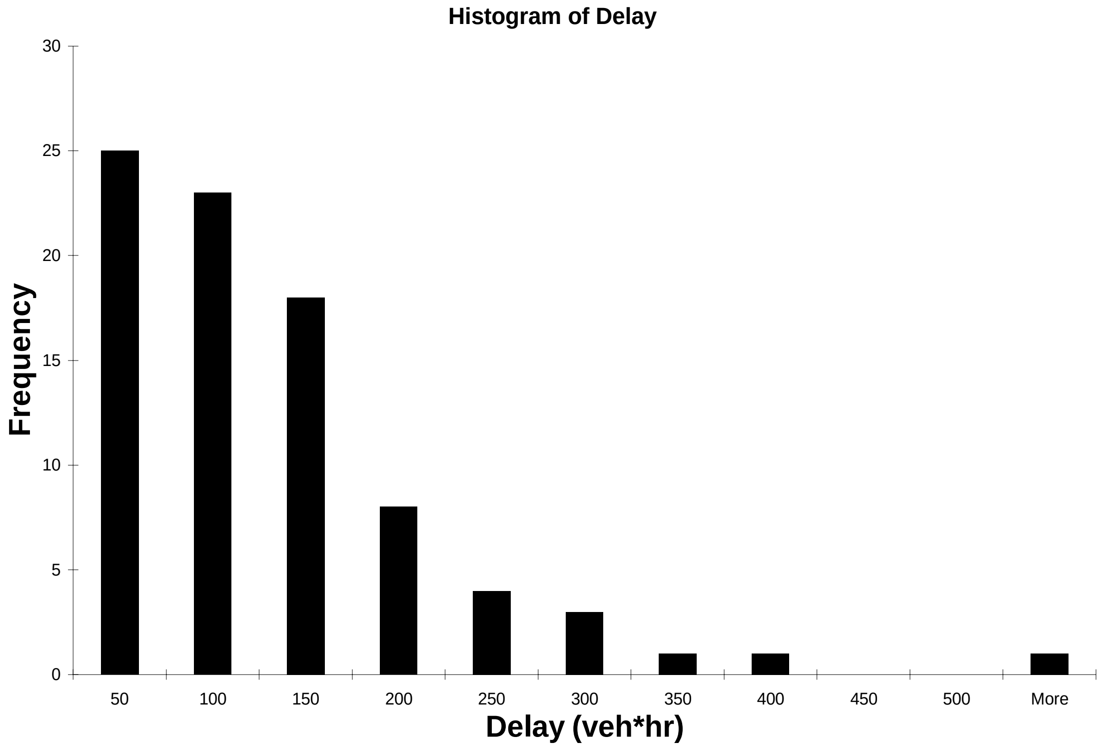

Figure (4-1): Histogram of the Frequency of Delay

The figure shows that lower delays are prevalent. Specifically, 78.5 percent of traffic delays fall between 0 and 150 veh*hr. This indicates that major congestion delay is not common. Only 12 percent of the delays are over 200 veh*hr.

In modeling the delay using linear regression model, it was realized that delay cannot be used directly as the dependent variable. It is because the calibrated linear regression model cannot guarantee to produce a delay with a positive value, which would not be convenient if the model is used for forecasting. A regular approach to dealing with this situation is to use a natural log transformation of delay as the dependent variable in regression. Figure 4-2 presents the histogram of Ln(Delay).

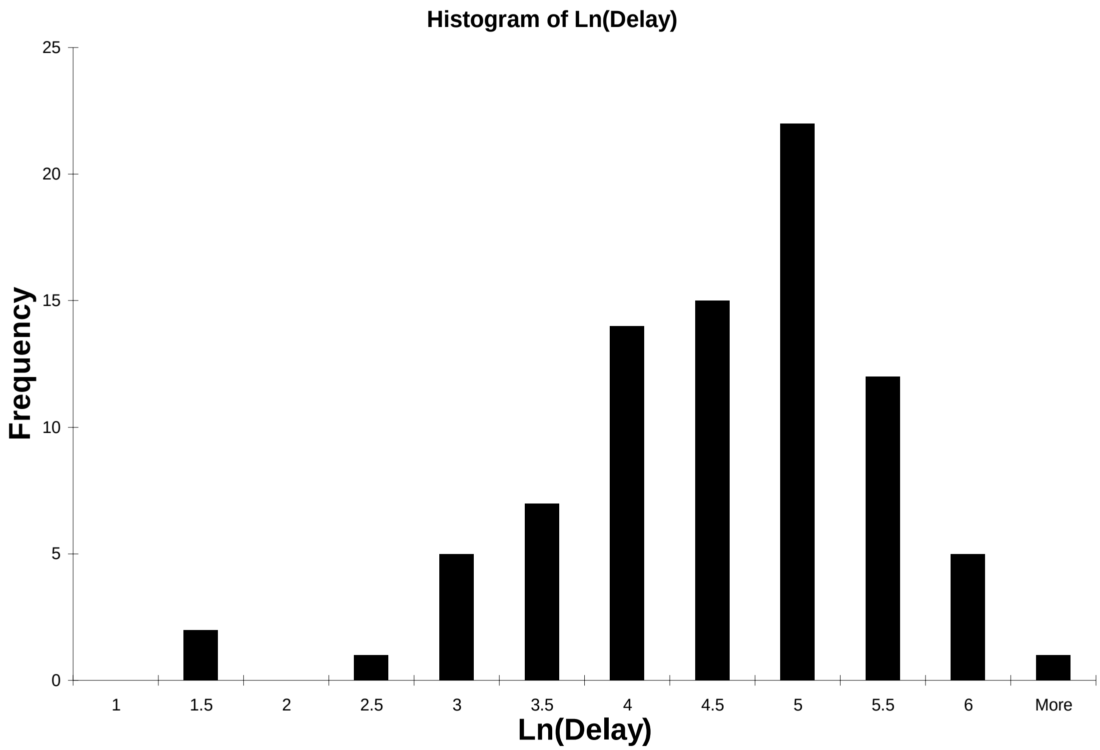

Figure (4-2): Histogram of the Frequency of the Natural Log of Delay

It can be seen that the natural log transformation of the delays is better distributed for normal distribution than that without the transformation. Therefore, the regression analysis was performed on this newly adopted transformation.

In the calibration of the linear regression model, predictor variable used in this analysis include:

- Duration – time period required to clear an incident
- Weekday/Weekend – whether an accident happened during a weekday or weekend
- Peak – whether an accident happened during an AM or PM peak rush

- Weather – inclement or clear weather
- Barrier – presence of barriers
- Day/Night – whether the accident happened during the day or at night
- Lanes Blocked – number of lanes blocked by accident
- Shoulders Blocked – number of shoulders blocked by accident
- Volume/Accident Capacity Ratio – volumes before the accident are compared to the reduced capacity of the accident
- Volume/Historical Capacity Ratio - volumes before the accident are compared to the reduced capacity of the accident

Correlation matrix was developed for these variables, and the results are presented in Table 4.4. From this matrix, it can be seen that the following pairs of variables are highly correlated.

Table 4.4: Correlation Coefficient Matrix

Predictor Variable 1	Predictor Variable 2	Correlation Coefficient
Weekday/Weekend	Peak Period	0.494
V/C Accident	V/C Historical	0.797

Table 4.4 lists the correlation coefficient matrix. It indicates that the following pairs of variables are highly correlated: (Weekday, Peak), and (V/C Accident, V/C Historical). This correlation does make sense. Weekday traffic experiences a peak period of

congestion that weekend traffic does not. The correlation shows that the significant accidents that happened during the weekday also happened during the AM or PM peak period. The V/C value during the accident should be similar to the V/C value for historical data. The capacity of opposite traffic due to the accident may be similar to the historical capacity of the same location. Some predictor variable may be correlated with others on a case by case basis. This correlation analysis only deals with the accidents that showed significant traffic impacts in both the same and opposite direction of the incident.

After a correlation analysis, a model was calibrated with results presented in Table 4.5.

Table 4.5: Congestion Delay Model Results

Variable	Coefficient	Standard Error	t-stat
Constant	7.24118149	.46588171	15.543
DURATION	.01963081	.00218229	8.995
BARRIERS	-.25688358	.18161164	-1.414
VOLCAP	.72782444	.56328168	1.292

Degrees of freedom = 80
R-squared = .5301680
Adjusted R-squared = .5125493
Number of observs. = 84

It can be seen from the table that the coefficient of the variable incident duration is positive. It implies accidents with greater duration lengths will have a greater delay associated with it. This result is consistent with our expectation. The variable Barrier is a binary variable where “0” means no barrier presented at an accident site while “1” the presence. The table indicates that the coefficient of Barrier is negative. It means that less delay would be incurred to the traffic in the opposite direction if barriers presented at an accident site. In the Hampton Road area, there are two types of barriers, each with different heights. Each of them can only block the views of a certain portion of motorists. Thus, the variable of barrier cannot be shown as strong as expected. Finally, the coefficient of V/C ratio (volumes before the incident vs. the capacity at incident site) is positive. It indicates that Higher V/C values account for greater delay.

4.3 Capacity Reduction Modeling

For the 80+ accident, capacity reduction ratios were derived. The histogram for these ratios is presented in Figure 4-4.

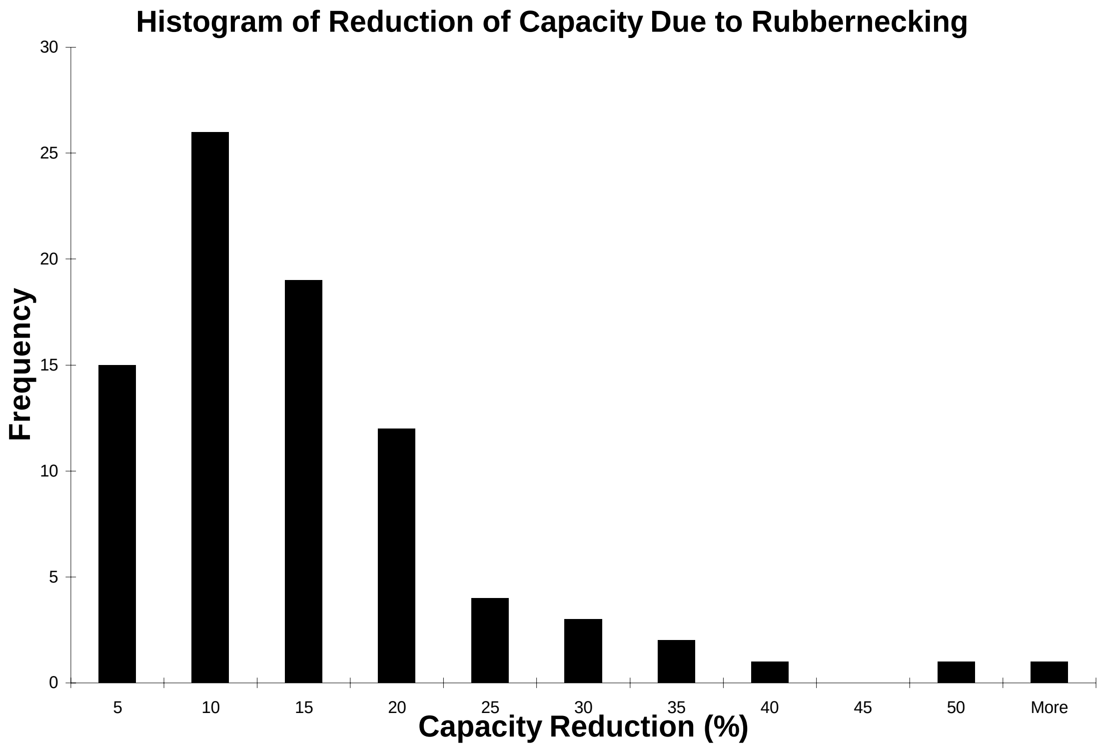

Figure (4-4): Histogram of Capacity Reduction Percentage

Similarly to histogram for delay, the majority of the results are skewed to the lower end. In other words, 72 out of the 84 (86%) accidents have capacity reductions of 20 percent or less. For the same reason as that for delay, this variable was transformed into a log form. The histogram of the capacity reduction ratio after the natural log transformation is presented in Figure 4-5.

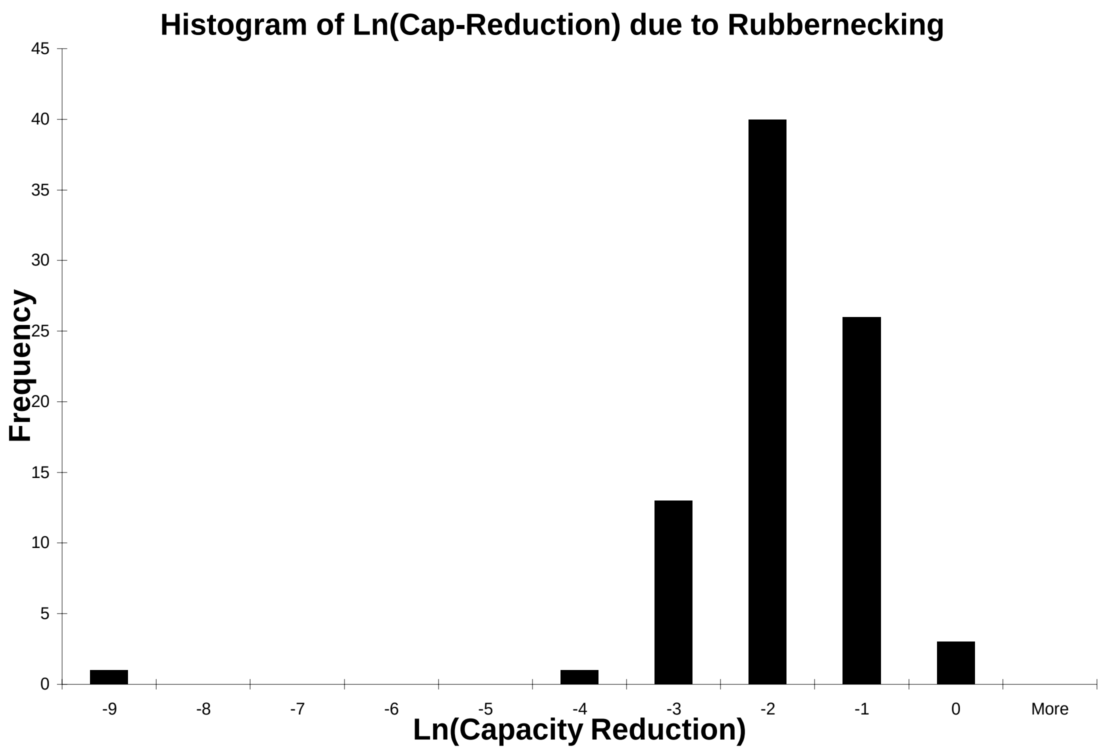

Figure (4-5): Histogram of Ln(Capacity Reduction) due to Rubbernecking

A linear regression model was calibrated. The results of the calibration are presented in Table 4.6. It can be seen that the three variables: peak, duration and day are statistically significant.   It can be found that the coefficient for peak is positive. It means that relatively more capacity would be reduced if an accident occurred in a peak period. This result is understandable because the traffic in peak is vulnerable. A minor disturbance such as slowdown by rubbernecking could cause traffic stall. It can also be seen from the table that the coefficient for duration is positive. It implies that accidents with longer duration would cause more capacity reduced relatively. This result can be understood from the perspective of chance that motorists are exposed with different duration an accident exists on a roadway. The longer an accident stay on a roadway, the higher likely motorists were attracted to the accident in the other direction. The slowdown effect of traffic can be cumulated to have a high capacity reduction ratio. Table 4.6 shows that the coefficient of Day is negative. It implies that higher capacity reduction ratio can be resulted in the opposite direction. Intuitively, motorists need more slowdown in a low visibility condition to observe accidents in the other direction than in a high visibility condition such as day time.

Table 4.6 Capacity Reduction Model Outcome

Variable	Coefficient	Standard Error	t-stat
Constant	-2.6042853	.19724509	-13.203
PEAK	.94004556	.47265573	1.989
DURATION	.00617251	.00337886	1.827
DAY	-.39697424	.25537293	-1.554

Number of observs.	=	84
Degrees of freedom	=	80
R-squared	=	.1155236
Adjusted R-squared	=	.8235576E-01

The capacity reduction model was developed to attempt to predict capacity reduction due to rubbernecking. This model is a result of the data used in this study for the given scope. Although this model may be used in other freeway systems, it is not guaranteed. The variables used in this models may vary from freeway to freeway.

Chapter 5: Conclusions

5.1 Conclusions

This study is the first attempt to evaluate the rubbernecking impact of accidents on traffic in the opposite direction based on archived traffic and accident data. Three models were developed for determining the likelihood of occurrence of rubbernecking, traffic delay and capacity reduction caused by rubbernecking. The data indicate that about 10 percent of accidents caused rubbernecking, average delay caused by rubbernecking is 107 veh*hr, and the average capacity reduction is 12.7 percent. These statistics indicate that the rubbernecking impact is significant. Certain mitigation measures have to be taken into consideration.

One of the variables used throughout this study is the duration time of the incident. This duration time has no actual meaning in the models described. The duration used in these models acts as a surrogate to the severity of the incident. Typically, a more severe incident would require a longer clearance process, making the duration of the incident longer. Using the documented duration of each incident based on severity of the incident should be noticed.

Based on the interpretation of the results of the regression models, it can be concluded that the rubbernecking likelihood is influenced by peak periods, weather, presence of barriers, and weekday travel; the delay is influenced by duration, presence of barriers, and V/C ratios of traffic before the occurrence of an incident; and the capacity reduction ratio is influenced by peak periods, duration, and day/night travel. Based on these identified factors, countermeasures can be developed targeting the time period and locations specified by these variables.

Barriers are an effective way to reduce the likelihood of rubbernecking in the opposite direction and the delay caused by the rubbernecking. This conclusion is drawn upon the coefficients of the variable barrier in the models for the likelihood of rubbernecking occurrence and traffic delay. The statistical significance of these coefficients in these models implies that barrier presence is a significant contributor to the occurrence of rubbernecking and the delay caused by the rubbernecking. Intuitively, installation of barriers can be thought of as a direct way to mitigate the occurrence of rubbernecking. Because it is costly if concrete barriers are installed along all the highway systems, cost-effective barriers can be investigated.

All the three models can be applied to data in other areas to evaluate the rubbernecking impacts. It is reasonably to perceive that the required data for these two models can be collected for each incident in an area. By plugging the values of the data into these three models, the likelihood of rubbernecking can be determined first, and then the delay and capacity reduction can be calculated correspondingly.

5.2 Future Research

Rubbernecking is a major problem in highway systems throughout the United States. The methodology and results can act as a basis of research on rubbernecking in future. This research could be used to spark interest in issues related to rubbernecking and their impacts. The following issues have been identified for research in future: incident and traffic data quality, statistical modeling and human factor characteristics.

First, more accurate information about incidents should be collected. In order to successfully utilize the incident data, locations of incidents must be exact. A more accurate location of the incident would aid in determining upstream and downstream stations, required for many traffic measures. In addition to the total duration times of incidents, it would beneficial to have detection times, response times, duration times, and recovery times. The descriptions of incidents in the database are often short and do not contain useful information. A detailed description would help by providing useful information. Another problem encountered was the number of lanes and shoulders blocked. There were accidents that had more than one shoulder blocked. This number cannot be correct. A more detailed description could help solve this problem.

More information about accidents such as types and number of vehicle involved should be collected. By having this information available, it is possible to identify whether this information contributes to the rubbernecking in the opposite direction. As a result, it can be identified exactly the items in accident scenes that attract motorists to slowdown causing rubbernecking.

An effort should be made to model the impact of barrier height on rubbernecking likelihood, traffic delay and capacity reduction. The results in the likelihood model indicate that barrier is not as significant as other variables. Also, the variable barrier is set as binary by which the height of barrier cannot be investigated. To derive information that is more helpful in practice on installing barriers, it would be beneficial to have a clear understanding of the relationship between barrier's height and rubbernecking impact.

It is also necessary to investigate the role of human factor on rubbernecking. As indicated in the analysis of this study, motorists in peak period tended to create less rubbernecking than in other periods. It seems that human factors were playing roles in the causes of rubbernecking impacts. By understanding the impact of human factors, the rubbernecking issue may be better addressed.

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Appendix A: SQL+ Code

```
alter session set nls_date_format = 'DD-MON-YYYY HH24:MI';

set termout off;
set linesize 220;
set trimspool on;
set wrap off;
set pagesize 0;
column type format a10;
column weather format a16;
column direction format a4;
column location_code format a8;

set serveroutput on;
DECLARE
  CURSOR my_cur IS
    select a.tms_call_number, a.inc_begin, a.inc_type, a.duration, a.weather, b.direction,
        b.location_code
    from incident a, inc_roadway b  where a.tms_call_number=b.tms_call_number and
        a.inc_type='ACCIDENT'
    and to_char(a.inc_begin,'DD-MON-YYYY')='07-JAN-2000' and
        b.location_code='E264-02' and b.direction='EB';

  c_rec my_cur%rowtype;
  t1 hr.incident.inc_begin%TYPE;
  t2 hr.incident.inc_begin%TYPE;
  t3 hr.incident.inc_begin%TYPE;
  t4 hr.incident.inc_begin%TYPE;
  d1 hr.incident.duration%TYPE;
  i number(4);

        d date;
        datex date;
        t char(5);
        ck number(7);

BEGIN
  FOR c_rec IN my_cur LOOP
     d1 := c_rec.duration;
     t1 := c_rec.inc_begin;
        select calendar_key into ck from calendar where datex = to_char(to_date(t1,'DD-
MON-YYYY HH24:MI'),'DD-MON-YYYY');
```

```
          select count(*) into i from station_flow where stationid=154 and calendar_key =
ck;
      Declare
         CURSOR test_cur IS
             select calendar_key, time_key,stationid,volume,speed,occupancy from
station_flow
             where stationid=154 and calendar_key = ck;
         t_rec test_cur%ROWTYPE;

      begin
        for t_rec in test_cur loop

                   select datex into d from calendar where calendar_key=ck;
                   select time_string into t from timex where time_key = t_rec.time_key;

                   datex := to_date(concat(concat(to_char(d, 'DD-MON-YYYY'), ' '), t));
            insert into table4john values
(c_rec.tms_call_number,c_rec.inc_begin,c_rec.inc_type,
            c_rec.duration,
c_rec.weather,c_rec.direction,c_rec.location_code,datex,t_rec.stationid,
            t_rec.volume,t_rec.occupancy,t_rec.speed);
        end loop;
      end;

       dbms_output.put_line(c_rec.tms_call_number ||  ' ' || i );
  END LOOP;
  commit;
END;
/

spool z:\users\jpm7a\auto\new.txt

select
tms_call_number,inc_begin,inc_type,duration,weather,direction,location_code,datex,stati
onid,
volume,speed,occupancy from table4john;

truncate table table4john;
spool off;
```

Appendix B: Coefficient Correlation Matrix

	peak	duration	weather	barriers	day	weekday	Lane	shoulder	Delay	Hcap	Acap	CapRed	Volumn	lndelay	LnCapred	volhcap	volacap
peak	1																
duration	-0.007	1															
weather	0.0629	-9E-04	1														
barriers	-0.031	0.0204	-0.045	1													
day	-0.035	-0.09	-0.052	-0.073	1												
weekday	-0.494	-0.113	-0.325	0.1186	-0.031	1											
Lane	0.154	0.1939	0.084	0.0957	0.0322	-0.167	1										
shoulder	0.0424	0.1523	0.1054	0.0208	-0.027	-0.032	-0.335	1									
Delay	-0.064	0.8847	-0.052	0.0055	-0.072	-0.056	0.1327	0.1304	1								
Hcap	-0.071	0.0747	0.0812	0.2069	-0.181	0.2158	-0.051	0.0221	0.1352	1							
Acap	-0.282	-0.021	0.1268	0.1532	-0.132	0.2552	-0.144	0.1149	0.029	0.8794	1						
CapRed	0.4625	0.2291	-0.095	0.1009	-0.033	-0.231	0.1844	-0.178	0.2074	0.062	-0.395	1					
Volumn	-0.214	0.0834	0.2006	0.0697	-0.037	0.1616	-0.152	0.2152	0.15	0.7301	0.8281	-0.306	1				
lndelay	-0.003	0.7132	-0.074	-0.144	0.0199	-0.108	0.0802	0.077	0.8274	0.0024	-0.118	0.2579	0.0136	1			
LnCapred	0.2138	0.2062	0.008	-0.029	-0.189	-0.135	0.1465	-0.041	0.2017	0.1087	-0.205	0.7134	-0.114	0.2011	1		
volhcap	-0.222	0.0125	0.1777	-0.138	0.1327	0.029	-0.121	0.263	0.0662	-0.061	0.1872	-0.518	0.6132	0.0387	-0.292	1	
volacap	0.0711	0.1787	0.1426	-0.058	0.1295	-0.113	-0.004	0.1804	0.2257	-0.04	-0.071	0.0989	0.4871	0.2246	0.1478	0.7973	1

Appendix C: Table of Results

TMS Call Number	Delay (veh*hr)	Cap-Red (%)
2000-00234	18.45	9.146341
2000-00429	56.86667	2.777778
2000-00738	242.7333	13.29114
2000-03167	45.81667	8.666667
2000-03279	191.85	11.14583
2000-03639	90.18333	11.53846
2000-04115	47.73333	14.361
2000-04310	96.88333	9.452736
2000-04726	18.73333	0.769231
2000-04986	48.98333	5.851064
2000-05210	35.3	11.29032
2000-05248	61.56667	5.662983
2000-06043	50.55	17.94872
2000-06483	62.35	2.941176
2000-06634	217.2667	20
2000-06688	31.65	2.158273
2000-06870	32.91667	16.47727
2000-07814	18.76667	2.733119
2000-07815	19.4	3.453689
2000-07893	75.08333	2.96875
2000-08184	66.8	5.806452
2000-08185	79.46667	50
2000-08622	98.08333	26.2069
2000-08788	71.08333	7.843137
2000-08794	51.86667	10.46512
2000-09005	52.81667	33.07692
2000-09006	128.2	20.3125
2000-09217	38.11667	3.08642
2000-09915	3.6	8.93617
2000-09968	269.0333	14.05405
2000-10516	226.9333	13.88889
2000-10565	99.9	8.382353
2000-10578	135.7833	19.09091
2000-10586	41.13333	7.756813
2000-10592	43.15	5.967742
2000-11268	3.85	8.974359
2000-11932	82.36667	15.24249
2000-12395	107.25	7.153729
2000-13610	44.6	4.936709
2000-13662	119.0833	0.01
2000-13838	44.78333	11.96721
2000-13844	53.58333	19.81132
2000-14813	135.9167	3.90625

2000-15422	61.53333	6.666667
2000-15825	136.5833	10.41667
2000-16126	306.4667	12.17949
2000-16421	74.93333	55.66038
2000-18006	124.05	17.16418
2000-19137	112.5833	12
2000-19144	124.3167	7.692308
2000-19670	140.5833	11.53846
2000-19786	33.4	8.928571
2000-20082	254.6167	39.83333
2000-21471	82.45	12.58065
2000-21496	83.63333	17.88235
2000-22418	33.06667	16.61017
2000-22602	146.8667	6.428571
2000-22956	84.66667	14.38849
2000-23318	359.0167	11.22449
2000-24855	232.9667	6.842105
2000-25055	20.41667	7.692308
2000-25399	85.45	23.33333
2000-25400	130.8667	4.090909
2000-26246	169.0667	10.29703
2000-26475	113.0667	9.384615
2000-26555	152.1833	13.65079
2000-26871	24.08333	8.90411
2000-27134	174.2167	24.10714
2000-27201	26.96667	6.103896
2000-27685	133.9833	25.94595
2000-28243	9.016667	6.153846
2000-30216	114.25	15.94203
2000-31038	589.9833	19.89247
2000-31449	153.05	2.933333
2000-31496	16.25	9.166667
2000-31564	126.0833	13.39286
2000-31681	262.9333	21.69014
2000-31764	30.11667	3.960396
2000-32419	85.81667	26.47059
2000-33923	116.9667	2.380952
2000-34239	175.4333	15.45455
2000-34535	118.0333	34.05797
2000-34888	153.9333	5.928854
2000-35297	166.7667	8.461538

Appendix D: Barrier Height Location Results

Barrier Type	Avg. Duration	Avg. Delay	Avg. Cap-Red
None	**36.875**	**6299.938**	**0.108882**
Standard	**43.22222**	**6483.689**	**0.12724**
Double	**39.82609**	**6413.217**	**0.139197**