Final report for ITS Center project: Incident capacity estimation

UVA Center for Transportation Studies

A Research Project Report

For the National ITS Implementation Research Center

A U.S. DOT University Transportation Center

Characterization of Accident Capacity Reduction

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ABSTRACT

ABSTRACT

Incidents are a major cause of urban highway congestion. Incidents include any event that temporarily reduces roadway capacity, such as accidents, debris, disabled vehicles, and hazardous material spills. Incident capacity reduction will be used in the incident management systems, advanced traveler information systems, queuing analysis, and computer simulation models. A study conducted in 1970 estimated that an accident or disabled vehicle blocking one lane out of three lanes will reduce traffic flow by an average of 50 percent, an accident blocking two lanes out of three lanes will reduce traffic flow by an average of 79 percent, and an accident or disabled vehicle blocking shoulder lane(s) out of three lanes will reduce traffic flow by an average of 33 percent. However, very little other research has comprehensively addressed the impact of incidents on capacity. The premise of this project is that the incident capacity reduction is best modeled as a random variable, not a deterministic value, as is the current practice.

Extensive traffic flow and incident data for the Hampton Roads region of Virginia in the Smart Travel Laboratory provides us the opportunity to model incident capacity reduction as a random variable. Capacity under prevailing conditions can be estimated by calibrating a speed-flow and /or density-flow curve for a given highway. The peak of this curve defines capacity. When an incident occurs and a bottleneck is formed, the reduced capacity of the roadway is reached and can be measured directly as incident capacity. Incident capacity reduction can be computed as the difference between these two values over the capacity under prevailing conditions, and then modeled as a random variable.

This research focuses on estimating accident capacity reductions with one lane and two lanes out of three lanes blocked, and modeling them as random variables based on the traffic flow and accident data for the Hampton Roads region. The results indicate that accident capacity reduction with one lane out of three lanes blocked can be modeled as Beta distribution with an average of 63 percent, which is fairly higher than the result of previous research (50 percent), and accident capacity reduction with two lanes out of three lanes blocked can be modeled as Beta distribution with an average of 77 percent which is slightly lower than the result of previous research (79 percent).

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GLOSSARY

Incident: any non-recurrent event that causes reduction of roadway capacity, such as accidents, debris, disabled vehicles, and hazardous material spills.
Capacity: the maximum hourly rate at which persons or vehicles can reasonably be expected to traverse a point or uniform section of a lane or roadway during a given time period under prevailing roadway, traffic, and control conditions.
Volume: the total number of vehicles that cross a point on the highway during a period of time, normally one hour
Flow: the number of vehicles passing a specific point or short section in a given period of time in a single lane. It is expressed as vehicle per hour per lane.
Speed: is defined as the average rate of motion and is expressed in miles per hour (mi/hr).
Time mean speed: the arithmetic mean of the speeds of vehicles passing a point on a highway during an interval of time.
Density: the number of vehicles occupying a section of roadway in a single lane. It is expressed as vehicle per mile per lane.
Occupancy: measure of the percentage of time for which a vehicle is detected over a detector on a highway during an interval of time.
Optimum Speed: the speed at which the flow reaches the maximum value (i.e. capacity)
Optimum Density: the density at which the flow reaches the maximum value (i.e. capacity)

CHAPTER 1: INTRODUCTION

1.1 Motivation

1.1.1 Overview

Incidents include any event that temporarily reduces roadway capacity, such as accidents, debris, disabled vehicles, and hazardous material spills (Faradyne, 2000). Incidents are a major cause of urban highway congestion. It is estimated that incidents account for 60 percent of the vehicle-hours lost to congestion (Cambridge Systematic, Inc, 1990). Incident management systems are in place in many cities to reduce the time lost due to incidents. Advanced traveler information systems are also used to provide travelers with important traffic information concerning incident congestion.

Queuing analysis and computer simulation models are important analysis techniques used in incident management systems and advanced traveler information systems. Queuing analysis can be used to estimate traffic characteristics under incident situations, including the estimation of the maximum queue length, average queue length, maximum individual delay, average individual delay, and total delay. Computer simulation models can be used to study transportation systems, transportation plans, and management strategies and evaluate the performances in the laboratory rather than in the field. Queuing analysis can be regarded as a simplified simulation model.

Remaining incident capacity is a key input of queuing analysis and computer simulation models. It is estimated that an accident or disabled vehicle blocking one out of three lanes will reduce traffic flow by an average of 50 percent, an accident blocking two out of three lanes will reduce traffic flow by an average of 79 percent, and an accident or disabled vehicle blocking shoulder lane out of three lanes will reduce traffic flow by 33 percent (Goolsby, 1970). This result is widely used by practitioners. However, very little other research has comprehensively addressed the impact of incidents on capacity. Furthermore, the stochastic characteristics of incident capacity reduction have not been investigated thoroughly. The premise of this project is that the capacity reduction caused by incidents is best modeled as a random variable, not a deterministic value, as is the current practice.

Capacity can logically be considered as a random variable rather than a deterministic value due to the variations in traffic control, weather, and other conditions. Even under ideal conditions, capacity is not a constant due to the variations in driver and vehicle characteristics. Also, incident capacity reduction is a random variable rather than a deterministic value due to the variations in incident characteristics (e.g., duration, extent, time of day, and background volume). Modeling incident capacity reduction as a random variable should provide for a more realistic estimation of incident characteristics.

1.1.2 Importance for Queuing Analysis

"Queuing analysis involves the mathematical study of queue that is a common phenomenon that occurs whenever the current demand for a service exceeds the current capacity to provide that service" (Hillier and Lieberman, 1986). The basic queuing process is shown in Figure 1.1.

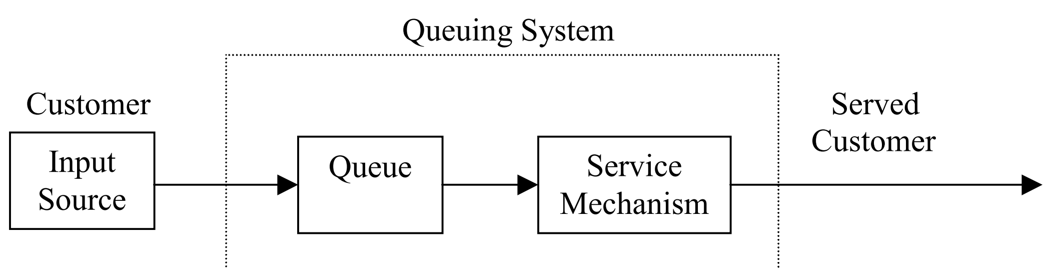


Figure 1.1: The Bas *Hillier and Gerald J. Lieberman, Introduc*

Queuing analys stics under the incident situation, including the estimation of the maximum queue length, average queue length, maximum individual delay, average individual delay, and total delay. The inputs include normal capacity (μ), the traffic demand (λ) when the incident occurred, the incident capacity (μ_R) and the duration (t_R). It can be seen that incident capacity is one of the key inputs. Table 1.1 is an example of estimated traffic characteristics under the incident situation based on the deterministic queuing analysis.

Table 1.1: Estimated Traffic Characteristics under the Incident Situation

Estimated Traffic characteristics		Equations
Time Duration in Queue (hours)	t_Q	$t_R(\mu - \mu_R)/ (\mu - \lambda)$
Number of Vehicles Queued (vehicles)	N_Q	λt_Q
Maximum Queue Length (vehicles)	Q_M	$t_R(\lambda - \mu_R)$
Average Queue Length (vehicles)	Q_Q	$t_R(\lambda - \mu_R)/2$
Maximum Individual Delay (minutes)	d_M	$60t_R(\lambda - \mu_R)/ \lambda$
Average Individual Delay (minutes)	d_Q	$30t_R(\lambda - \mu_R)/ \lambda$
Total Delay (vehicles)	T_D	$t_R\, t_Q(\lambda - \mu_R)/2$

Source: Adolf D. May, Traffic Flow Fundamentals, 1990

A sensitivity analysis study can be undertaken to assess the effect of the estimation of incident capacity reduction on the estimated traffic characteristics under the incident situation. “Sensitivity analysis involves investigating the effect on the model estimation caused by making changes in the values of the model parameters” (Hillier and Lieberman, 1986). For example, consider a three-lane directional freeway with a total capacity of 6000 vehicles per hour. Then, assume that during the middle of the day, the traffic demand is at 80 percent of capacity. Assume an incident blocks one out of three lanes and reduces traffic flow by 46, 48, 50, 52 and 54 percent, and the reduction in capacity lasts for about 45 minutes. Table 1.2 shows the results of sensitivity analysis.

The results of sensitivity analysis indicate that the estimation of incident capacity reduction affects the estimated traffic characteristics under the incident situation significantly. Small changes in incident capacity reduction (two percent) modify the estimation of total delay significantly (11 or more percent), and thus, affect the estimation of total system performance. It is very important, therefore, to estimate incident capacity reduction accurately.

Table 1.2: Sensitivity Analysis of Estimated Traffic Characteristics Under the Incident Situation

Estimated Traffic Characteristics	Incident Capacity Reduction (%)				
	46%	48%	50%	52%	54%
Time Duration in Queue (hours)	1.73	1.80	1.88	1.95	2.03
Number of Vehicles Queued (vehicles)	8280	8640	9000	9360	9720
Maximum Queue Length (vehicles)	1170	1260	1350	1440	1530
Average Queue Length (vehicles)	585	630	675	720	765
Maximum Individual Delay (minutes)	14.63	15.75	16.88	18.00	19.13
Average Individual Delay (minutes)	7.31	7.88	8.44	9.00	9.56
Total Delay (vehicles)	1009.13	1134.00	1265.63	1404.00	1549.13

1.1.3 Importance for Computer Simulation Models

"Computer simulation models incorporate queuing analysis, car-following theory, shock wave analysis, and other analytical techniques into a framework for simulating complex components or systems of interactive components" (May, 1990). CORSIM, a widely used microscopic simulation model, models the "rubbernecking" phenomenon in addition to the physical blockage on traffic flow by incidents. Drivers of vehicles in adjacent lanes tend to slow down to see what is happening as they pass an incident. This phenomenon, namely "Rubbernecking" phenomenon, results in lower speeds and then lower capacity, and explains the additional capacity reduction beyond the corresponding physical loss.

The rubberneck factor indicates the percentage of capacity reduction of each remaining lane that is not blocked during the incident. For example, if one lane out of three lanes was completely blocked and each of the remaining two lanes was influenced by a rubberneck factor of 10 percent, the capacity of the link would be reduced as shown in the following equation:

$$RC = (100\%)(1/3) + (10\%)(1/3) + (10\%)(1/3)$$
$$RC = 40\%$$

1/3 indicates the portion of volume normally carried in each lane and 10% indicates the capacity reduction in each remaining lane that is not blocked during the incident. In this example, the roadway's capacity would be reduced by 40% during an incident.

This is a somewhat simplified model of incident capacity reduction. The calculated result, 40 percent, is less than Goolsby 's commonly accepted value of 50 percent capacity reduced by an accident blocking one lane out of three lanes. If analysts want to decide on an appropriate rubberneck factor, they need to collect data and perform simulations to test several alternative rubberneck factors, just as Cragg (1994) did in simulation analysis of route diversion strategies for freeway incident management. Furthermore, incident capacity reduction is modeled as a deterministic value, not a random variable in CORSIM.

As for the necessity of modeling incident capacity reduction as a random variable instead of a deterministic value in simulation models, here is an example to illustrate the danger of replacing the probability distribution of a random variable by its mean in simulation models. This example is derived from the book of simulation modeling and analysis (Law and Kelton, 2000). This example considers an incident that creates a bottleneck. It is assumed that the vehicle arrives at the bottleneck every one minute, and the vehicle departs the bottleneck every 0.99 minute. Furthermore, the interarrival times and departing times are assumed to be random variables with exponential distributions. Then based on the M/M/1 queuing analysis model, the average number of vehicles waiting in the queue can be calculated as $(\lambda/\mu)^2/[1-(\lambda/\mu)]$, where λ is the mean interarrival rate (vehicles per time interval), and μ is the mean departing rate (vehicles per time interval). The result indicates that the long-run average number of vehicles in the queue is approximately 98.

If we replace the probability distributions of the interarrival times and departing times by its mean, that is, we assume that each interarrival time is exactly one minute and each departing time is exactly 0.99 minutes, then no vehicle ever waits in the queue. The comparison of the results indicates that the variability of the probability distributions, rather than just their means, has a significant impact on the estimation of the congestion level under the incident situation.

1.2 Research Objective, Tasks and Scope

The objective of this research is to conduct a comprehensive study on the impact of incidents on capacity, based on the traffic flow and incident data for the Hampton Roads region of Virginia in the Smart Travel Laboratory of the University of Virginia. This objective is fulfilled through the following tasks:

1. Estimate capacities under prevailing conditions by calibrating speed-flow curves for several segments of Hampton Roads to provide a frame-of-reference.
2. Measure Incident capacity as the 10-minute minimum oversaturated flow in the bottleneck created by an incident.
3. Calculate the absolute value of incident capacity reduction as the difference of incident capacity and the capacity under prevailing conditions and then, calculate the percentage value of incident capacity reduction as the absolute value of incident capacity reduction over the capacity under prevailing conditions and model it as a random variable following a probability distribution.

A preliminary study indicated that few cases with measurable capacity reduction for disabled vehicles could be found based on the incident and traffic flow data for the Hampton Roads region in the Smart Travel Laboratory. It is probably because that most disabled vehicle event occurred on shoulder lanes with short durations. The statistics of durations and number of lanes blocked by different types of incidents are given in Chapter Four. The preliminary study also indicates that most cases with measurable capacity reduction are one lane, two lanes and shoulder lanes out of three lanes blocked by accidents. Based on the preliminary study, this research focuses on estimating accident capacity reduction for one lane, two lanes or shoulder lanes out of three lanes blocked and modeling it as a random variable.

One thing needs to be mentioned here is that, the percentage value of accident capacity reduction is modeled as a random variable and presented as the result in this research instead of the absolute value of accident capacity reduction. The advantage of modeling and presenting the percentage value instead of the absolute value of the accident capacity reduction is that, the accident capacity can be estimated for the other study sites given the capacity under prevailing conditions.

1.3 Organization of the Thesis

The remainder of this thesis includes a literature review, the description of methodology, data analysis and results, and the conclusions of this work.

Chapter Two describes a literature review about incident management systems, previous work on this topic, and related contents in the Highway Capacity Manual (2000).

Chapter Three first describes the existing definition of capacity and capacity estimation methods. After that, our efforts to clarify the definition of accident capacity and to develop the methodology of accident capacity estimation are discussed. Then, the methodology of modeling the accident capacity reduction as a random variable is presented.

Chapter Four describes the study site, data collection, process of calculation and modeling, and the results. This chapter discusses the methodology in more detail.

Chapter Five summarizes the conclusions and contributions of the thesis and discusses suggested further research based on this work.

1.4 Summary

This chapter describes the motivation, objective, tasks, scope and organization of this thesis. First, the importance of estimating incident capacity reduction accurately and modeling it as a random variable is discussed. Then, the objectives, main tasks, and scope of this research are described. Finally, the organization of the thesis is presented.

CHAPTER 2: LITERATURE REVIEW

2.1 Incident Management Systems

As discussed in Chapter One, incidents are a major cause of urban highway congestion. Additional fuel consumption and air pollution are commonly associated with congestion caused by incidents. The other serious problems caused by incidents include the risk of secondary crashes, and the danger of incident responders working at the scene. According to a study conducted by Minnesota Department of Transportation (1982), secondary crashes accounts for 13 percent of all crashes occurred during peak hours. Furthermore, incident responders are vulnerable and exposed to injury. According to the statistics of the IACP (1998), in 1997, nearly 40 percent of all law enforcement officers who died on duty died in traffic.

Incident management systems are now in place in many cities to minimize the congestion caused by incidents, and improve the safety of motorists, crash victims, and incident responders. For these purposes, agencies responding to incidents, such as the Police, the Fire, 911 Dispatch, the Towing and Recovery, the Emergency Medical Service (EMS), and transportation agencies, need to coordinate effectively and efficiently. In addition, the main activities of incident management systems, including detection, verification, motorist information, response, site management, traffic management and clearance, need to be performed in a systematic way. The good performance of an individual activity cannot guarantee the good performance of the whole system, which is actually the objective of an incident management system.

Some benefits of an effective incident management system can be quantified, such as improved response time, reduced delay, improved air quality, reduced occurrence of secondary incidents, and improved safety of responders, crash victims and other motorists. The other benefits are qualitative. For example, the cooperation of response agencies is improved. The public gets to know, understand, and participate in the systems. Drivers feel more comfortable knowing the operation of such systems. These qualitative benefits are also very important.

One important thing related to this research needs to be mentioned here. Most incident management systems emphasize the response and clearance activities, which are proven to be effective. Except these activities, some consideration must be given to traffic, including not only how traffic affects the incident, but also how the incident affects traffic. The knowledge of how incident affects traffic is very important for good traffic management within incident management systems, which can help fulfill the purpose of releasing congestions. For example, this research computes the accident capacity reduction and models it as a random variable. The results can be used in queuing analysis and computer simulation models to estimate the number of vehicles queued. Then management strategies, such as route diversion, can be adopted to reduce the number of vehicles queued, and therefore, release congestions to some extents.

2.2 Previous Work on This Topic

Goolsby conducted a study on the influence of incidents on freeway quality of service in 1970. The Gulf Freeway in Houston was selected for the study because of the extensive surveillance system existing there. The 6.5-mile study section has three lanes in each direction. According to the author, an accurate log of freeway incidents including accidents and disabled vehicles was maintained on weekdays from 6:00am to 6:00pm for two years (1968 -1969) on the study section. This study collected the volume in 1-minute interval in the bottleneck created by an incident.

A total of 517 1-minute volume counts in the bottleneck were available for 27 incidents. 312 1-minute volumes under normal conditions were collected downstream of the study site to provide a frame-of-reference traffic volume. Based on these data, the author concluded that an accident or disabled vehicle blocking one lane out of three lanes reduces flow by 50 percent. An accident blocking two lanes out of three lanes reduces flow by 79 percent. An accident or disabled vehicle blocking shoulder lane(s) out of three lanes reduces flow by 33 percent.

This study initiated the research on incident capacity reduction and revealed the necessity of comprehensive research on this topic. A critical review of the paper reveals the following limitations of this study:

1. This study was conducted in 1970 and traffic conditions have changed significantly in the following 31 years. Current estimation of incident capacity reduction might be different from Goolsby's results.

2. This study only counted 312 1-minute volumes under normal conditions downstream of the study site, not the capacity under prevailing conditions, to provide a frame-of-reference. The incident capacity reduction might be overestimated.

3. This study only used the 517 1-minute volume counts through the bottleneck created by an incident, and the measurement of incident capacity has not been well described. The incident capacity might be overestimated or underestimated because of the unstable characteristics of traffic flow rates using short measurement intervals (1-minute).

4. This study modeled the incident capacity reduction as a deterministic value, not a random variable, and the small sample size (27 incidents) made it impossible to model the incident capacity reduction as a random variable.

2.3 Related Contents in the Highway Capacity Manual (2000)

According to the Highway Capacity Manual (2000), the behavior of traffic streams during and immediately after the occurrence of an incident is not well understood. The relationships among speed, density, and flow may be discontinuous at the point of capacity and the maximum queue departing flow rate may be less than capacity under stable flow. Various observations of freeway queue departing flow rate range from 1,800 pcphpl to 2,400 pcphpl.

Estimation of percentage of freeway capacity available under incident conditions is addressed in the Highway Capacity Manual (2000). Table 2.1 illustrates the results. Unfortunately, the research work supporting this information has not been found through the literature review, including the references provided in the Highway Capacity Manual (2000). The estimated values of incident capacity reduction with one lane and two lanes out of three lanes blocked from this table are very consistent with Goolsby's results. It is possible that Goolsby's work in 1970 is one of the researches supporting this information.

Table 2.1: Percentage of Freeway Capacity Available under Incident Conditions

Number of Freeway Lanes in Each Direction	Shoulder Disablement	Shoulder Accident	Lanes Blocked		
			1	2	3
2	0.95	0.81	0.35	0.00	N/A
3	0.99	0.83	0.49	0.17	0.00
4	0.99	0.85	0.58	0.25	0.13
5	0.99	0.87	0.65	0.40	0.20
6	0.99	0.89	0.71	0.50	0.25
7	0.99	0.91	0.75	0.67	0.36
8	0.99	0.93	0.78	0.63	0.41

Source: Highway Capacity Manual (2000)

2.4 Summary

This chapter gives a literature review about incident management systems, previous work on this topic, and related contents in the Highway Capacity Manual (2000). This literature review helps understand the background, motivation, and objective of this research furthermore.

CHAPTER 3: METHODOLOGY

3.1 Definition of Capacity

According to the Highway Capacity Manual (2000), the capacity of a facility is defined as the maximum hourly rate at which persons or vehicles can reasonably be expected to traverse a point or uniform section of a lane or roadway during a given time period under prevailing roadway, traffic, and control conditions. Also, the Highway Capacity Manual (2000) categorizes traffic flow within a basic freeway segment into three flow types: undersaturated flow, queue discharge flow, and oversaturated flow. Each flow represents different conditions on the freeway.

Undersaturated Flow represents traffic flow that is unaffected by upstream or downstream conditions. This flow is generally defined within a speed range of 55 to 75 mph at low to moderate flow rates and a range of 45 to 65 mph at high flow rates.

Queue Discharge flow represents traffic flow that has just passed through a bottleneck and is accelerating back to the free-flow speed of the freeway. This flow type is generally defined within a narrow range of flows, 2000 to 2300 pcphpl, with speeds ranging from 35 mph up to the free-flow speed of the freeway section.

Oversaturated Flow represents traffic flow that is influenced by the effects of a downstream bottleneck. Traffic flow in the congested regime can vary over a broad range of flows and speeds depending on the severity of the bottleneck.

According to these definitions and categorizations, the accident capacity can be defined as the ***minimum 15-minute oversaturated flow*** at the upstream of a bottleneck created by an accident. Because oversaturated flow upstream of a bottleneck means that the capacity level has been reached in the bottleneck, it is possible to make a reliable capacity estimate. Also, given the variation in observed capacities, analysts may wish to use appropriate measurement interval to get the minimum 15-minute oversaturated flow as accident capacity to reduce the risk of capacity overestimates or underestimates.

According to the Highway Capacity Manual (2000), the time period used in most capacity analyses is 15-minute, which is considered to be the interval during which stable flow exists. In order to provide a quantitative understanding of the impacts of short (less than 15-minute) measurement intervals on traffic flow rate, Smith (2001) conducted a study and found that stable flow rates may be calculated using measurement intervals as short as 10-minute, and that statistically significant improvements in stability can be achieved by adding 2-minute to any measurement interval. According to the Highway Capacity Manual (2000) and Smith's results (2001), the 10-minute interval is used in this work to estimate accident capacity reduction. 10-minute intervals are also used in this work to estimate capacity under prevailing conditions to provide a frame-of-reference.

3.2 Capacity Estimation Methods

3.2.1 Estimation of Capacity under Prevailing Conditions

Capacity under prevailing conditions can be estimated by calibrating a speed-flow and /or density-flow curve for a given segment of highway. The peak of this curve defines capacity. This kind of methods is based on the fundamental models describing speed-flow, flow-density, and speed-density relationships. Theoretical speed-density, speed-flow, and flow –density diagrams are shown in Figure 3.1, Figure 3.2 and Figure 3.3. A linear speed-density relationship is assumed to simplify these models. Flow is defined as the number of vehicles passing a specific point or short section in a given period of time in a single lane. It is expressed in vehicles per hour per lane. Speed is defined as the average rate of motion and is expressed in miles per hour. Density is defined as the number of vehicles occupying a linear section of roadway in a single lane. It is expressed in vehicles per mile per lane. q_m is capacity under prevailing conditions that could be estimated empirically or calculated theoretically. U_0 is optimum speed corresponding to q_m. k_0 is optimum density corresponding to q_m.

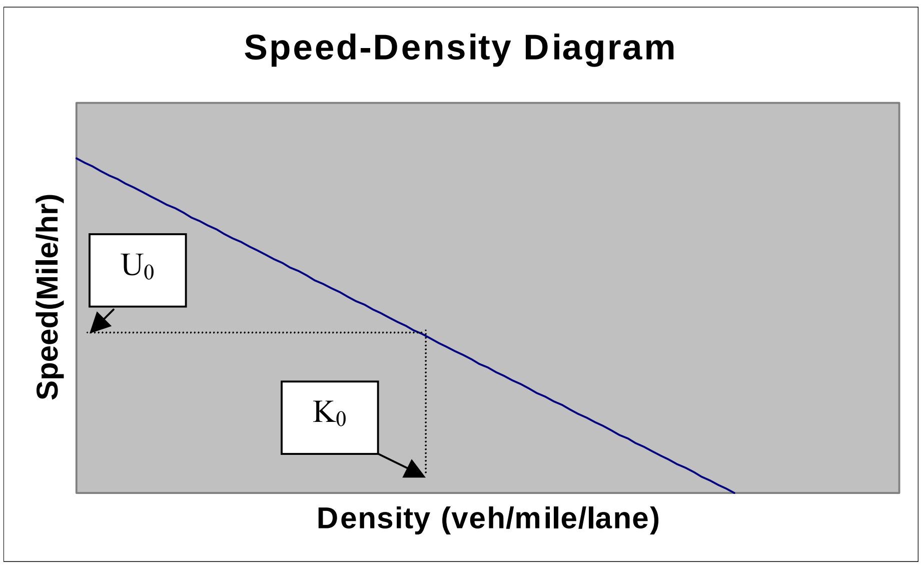


Figure 3.1: Speed-Density Diagram

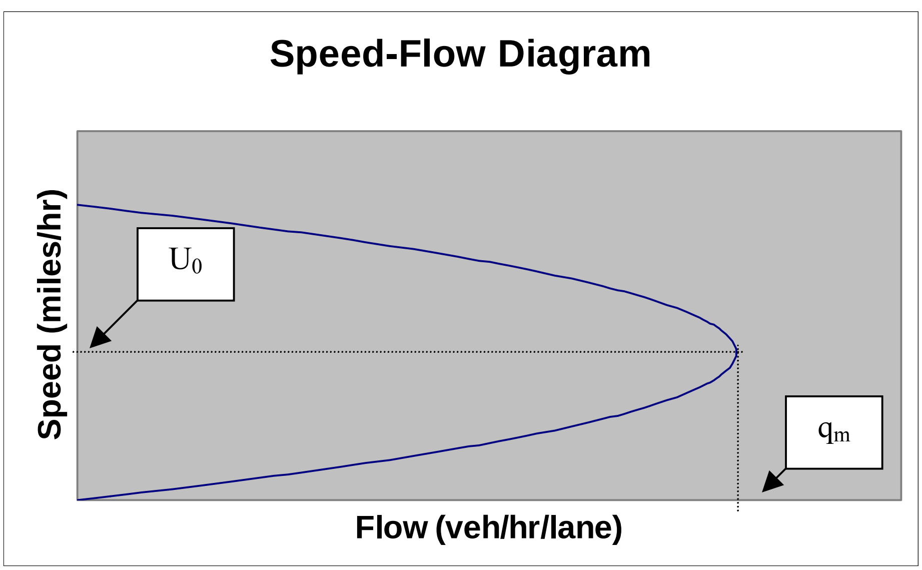


Figure 3.2: Speed-Flow Diagram

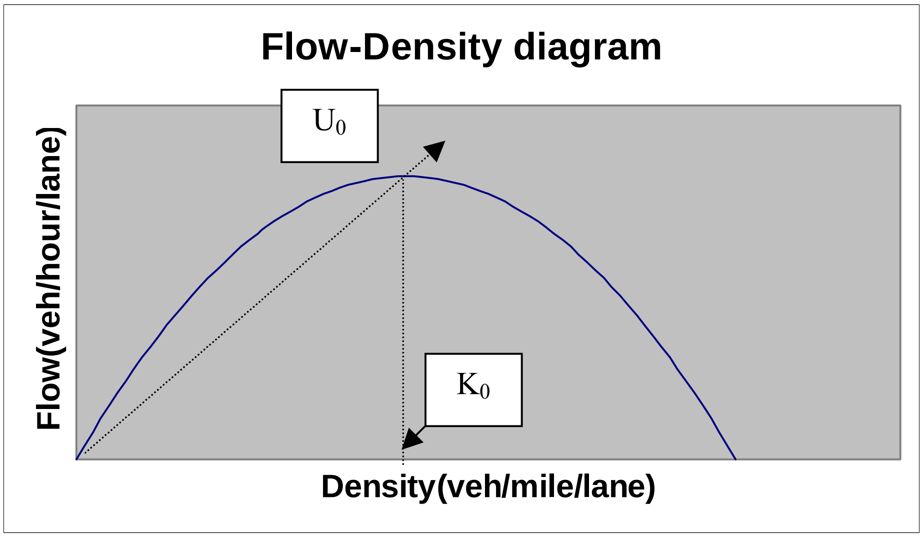


Figure 3.3: Flow-Density Diagram

Speed-density, speed-flow, and flow–density diagrams shown in Figure 3.1, Figure 3.2 and Figure 3.3 can be expressed as theoretical models in mathematical forms. Efforts have been devoted to calculate the capacity value from the theoretical models. But the stochastic nature of the observations near capacity makes it very difficult. Instead of this kind of analytical approach, the empirical approach can be used to estimate the capacity value.

Venkatanarayayana (2001) developed the speed-flow plots and estimated the capacities under prevailing conditions for several segments of Hampton Roads through an empirical approach in the Smart Travel Laboratory during the summer of 2000. According to Venkatanarayayana (2001), on plotting speed- flow diagram, a near parabola bounded by a top line can be observed for most of the segments of Hampton Roads considered. Figure 3.4 shows the speed-flow plot with 142,000 10-minute observations from June 15th, 1998 to July 29th, 1999 on the eastbound I-64. The top line exists there because of the maximum speed limits on the roads (65 mph). Also, a number of points can be seen inside the parabola because different roadway, traffic, and control conditions exist even on the uniform segments of the Hampton Roads. The process that Venkatanarayayana (2001) used to estimate the capacity for several segments of Hampton Roads during a given time period is discussed in Chapter Four in detail.

The traffic flow rate can be taken to the nearest integer, in multiples of 50, because it is impossible and unnecessary to measure traffic flow rate exactly and errors exist inherently. In Figure 3.4, a lot of points can be seen on the “peak” of the curve and form a “peak area”. The traffic flow rates within this “peak area” vary from 2450 vphpl to 2550 vphpl. To reduce the risk of underestimates or overestimates, the integer, in multiple of 50, within the “peak area”, 2500 vphpl is regarded as the capacity under prevailing conditions from June 15th, 1998 to July 29th, 1999 on the eastbound of I-64.

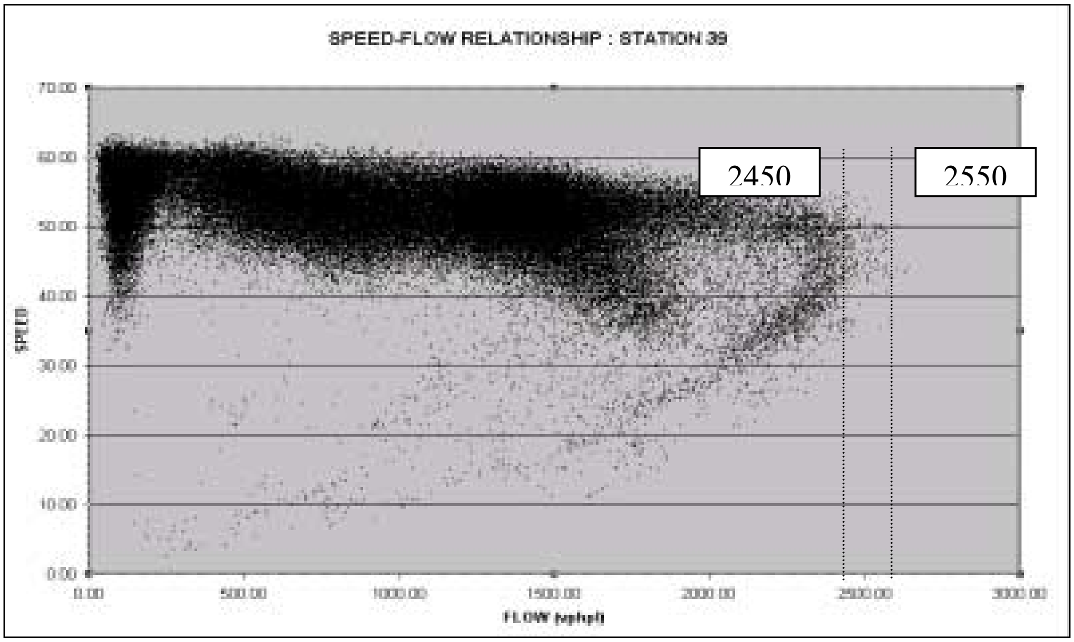


Figure 3.4: An Example of Speed-flow Plot

3.2.2 Accident Capacity Estimation

When an accident occurs and a bottleneck is formed, the capacity of the roadway is reached. There is no space for more traffic flow and traffic demand exceeds the capacity at that time. Thus accident capacity can be measured directly as bottleneck traffic flow according to the definition of capacity as the maximum hourly rate at which persons or vehicles can reasonably be expected to traverse a point or uniform section of a lane or roadway during a given time period under prevailing roadway, traffic, and control conditions (Highway Capacity Manual, 2000).

Figure 3.5 provides an example of accident flow. This accident occurred on I-564 and blocked the first lane. The duration period was recorded in the incident database from 6:29am to 6:44am. Traffic volume was collected every two minutes and transformed to an hourly rate. Figure 3.5 plots traffic flow from 30-minute before the accident to 30-minute after the accident. It shows that traffic flow fell at 6:18am, and was restored at 6:48am. When this kind of pattern appears, the judgment can be made that a bottleneck is formed and the capacity of the roadway is reached. For this accident situation, traffic flow began to fall before the beginning time recorded. It is reasonable because some accidents might not be detected and recorded immediately after it occurred.

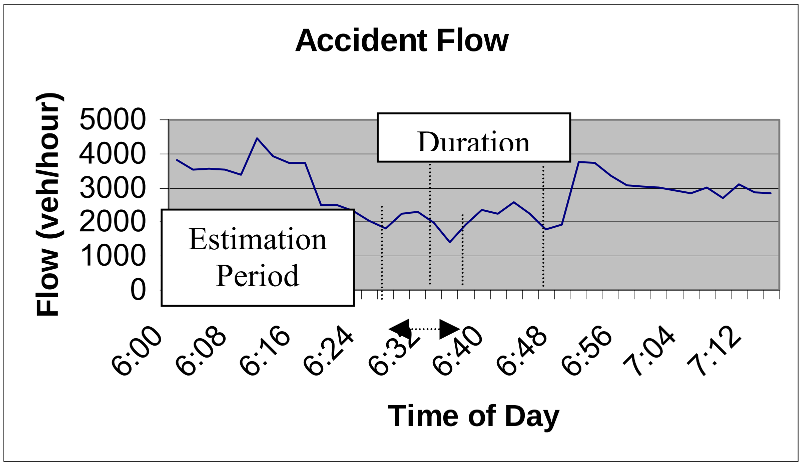


Figure 3.5: An Example of Accident Flow

The variation of traffic flow can be seen clearly in this figure because the time interval in this practice is 2-minute. There exists the risk of overestimates or underestimates of accident capacity because of the variation of traffic flow. To reduce the effect of the variation of traffic flow on accident capacity estimation, the moving average of five successive flows is calculated and then the minimum value is selected as an accident capacity. As discussed before, 10-minute interval is used in this work to estimate accident capacity reduction. This is why the moving average of five successive flows is used to estimate the accident capacity. For example, the moving average of five successive flows can be calculated as:

$M_t = (X_{t-2} + X_{t-1} + X_t + X_{t+1} + X_{t+2}) / 5$

Where M_t is the moving average of five successive flows

X_t is the traffic flow at time t

X_{t+1} is traffic flow at about two minutes after time t

X_{t-1} is traffic flow at about two minutes before time t

The moving average of five successive accident flows of the previous example is shown in Figure 3.6. The minimum value (1953 veh/hour) can be regarded as the accident capacity for this example. To simplify this task, analysts could base on his/her own judgment to select the five successive flows and calculate the average as the accident capacity. The criteria is that the average of these five successive flows is the minimum of all the average of these five successive flows during the period from 30-minute before the accident to 30-minute after the accident. For the illustrated example, accident capacity could be calculated as the average of traffic flow from 6:26am to 6:36am, which is 1953 veh/hour.

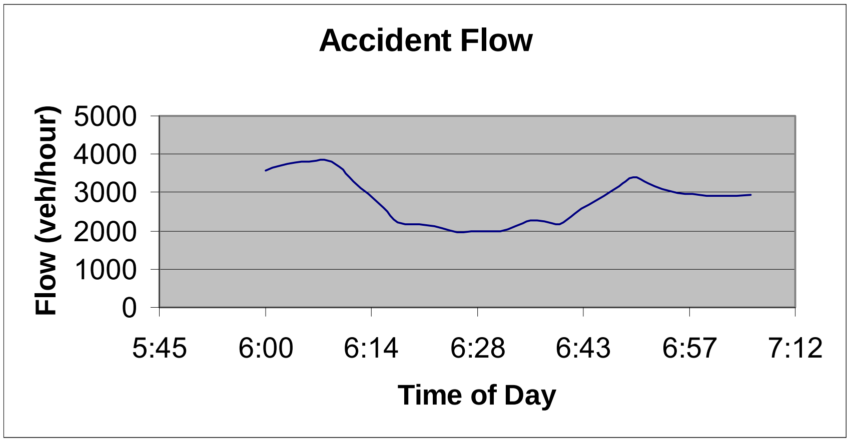


Figure 3.6: Moving Average of Five Successive Accident Flows

3.3 Modeling Accident Capacity Reduction as a Random Variable

3.3.1. Overview

The absolute value of accident capacity reduction can be calculated as the difference of the estimation of the capacity under prevailing conditions and accident capacity. Then the percentage value of accident capacity reduction can be calculated as the accident capacity reduction over the capacity under prevailing conditions. The following work is to model accident capacity reduction (refer to the percentage value) as a random variable, not a deterministic value. Chapter One has explained the importance of modeling accident capacity reduction as a random variable. This section will describe how to choose the distribution that best represent the observed data set. Because accident capacity reduction is continuous, this section will only address selecting the continuous distribution that best represent the observed data set.

The activities involve in choosing the "correct" distribution include 1. Families of distributions that might be representative of the observed data set are hypothesized on the basis of the summary statistics, histogram of the observed data set, the shapes of the hypothesized distributions, and the other information, 2. The parameter values are specified for these candidate distributions, and 3. The hypothesized distributions are evaluated on how representative they are for the observed data set and the best- fitted distribution is selected.

3.3.2. Activity : Hypothesizing Families of Distributions

3.3.2.1 Summary Statistics

Summary statistics, including minimum observation, maximum observation, mean, median, variance, coefficient of variation, and skewness, can be used to suggest families of distributions that might fit the observed data set. The coefficient of variation, calculated as the standard deviation divided by the mean, can be used to measure the variability or dispersion of a distribution as an alternative to variance. The skewness is a measure of the symmetry of the distribution. The skewness of a symmetric distribution is zero. The skewness of a distribution that has a longer "right tail" than "left tail" is positive. The skewness of a distribution that has a longer "left tail" than "right tail" is negative.

By comparing the summary statistics of the observed data set and characteristics of the theoretical distributions, families of distributions may be hypothesized. For example, the coefficient of variation of the exponential distribution is equal to one. The skewness of the normal distribution is equal to zero. The comparison between the summary statistics of the observed data set and characteristics of the theoretical distributions can at least exclude some theoretical distributions from the hypothesized family of distributions. For example, the normal distribution cannot represent the observed data set with the skewness different from zero apparently. Also, the exponential distribution cannot represent the observed data set with the coefficient of variation different from one apparently.

3.3.2.2 Histogram

A histogram provides a graphical estimation of the plot of the density function corresponding to the fitted distribution of the observed continuous data set. To make a histogram, the range of the values in the data set is broken into k adjacent intervals $[b_0, b_1)$, $[b_1, b_2)$, … , $[b_{k-1}, b_k]$. These intervals have the same interval width $\Delta b = b_j - b_{j-1}$. The definition of the histogram function h(x) is as follows:

$$h(x) = \begin{cases} 0 & \text{if} \quad x < b_0 \\ h_j & \text{if} \quad b_{j-1} \leq x < b_j \quad \text{for } j = 1,2, \ldots k \\ 0 & \text{if} \quad x \leq b_0 \end{cases}$$

where h_j is the proportion of the X_i's that are in the jth interval $[b_{j-1}, b_j]$.

The sample size and the interval width affect whether the histogram is representative of the observed data set. If the sample size is too small, the histogram will often be "ragged" regardless of how the interval width is chosen. If the interval width is too small, the histogram will also be "ragged". If the interval width is too big, it is possible that too much information in the observed data set is left out and the histogram cannot be representative. There is no definitive guide for choosing the interval width. Neiswanger (1943) proposed that the number of intervals should be between 10 and 25. Sturges (1926) proposed that the number of intervals should be estimated as follows:

$$I = \frac{\text{Range}}{1 + (3.322) \log N}$$

where I = number of intervals

Range = largest observed value minus smallest observed value

N = number of observations

Law and Kelton (2000) regarded such rules as not very useful and recommended trying several different values of interval width and choosing the smallest one that gives a "smooth" histogram. These rules and recommendations will be considered comprehensively in this research.

3.3.3. Activity : Estimating Parameters

In activity , families of distributions have been hypothesized to represent the observed data set. The following work is to estimate the parameter values to obtain the completely specified distributions from the observed data set. Maximum-likelihood estimator (MLEs) is a widely used technique for estimating parameter values for a given distribution. In the ***discrete*** case, given the observed data set X_1, X_2, …, X_n, suppose a discrete distribution has been hypothesized for this data set with one unknown parameter θ. Let $p_\theta \hat{(x)}$ denote the probability mass function for this distribution. The likelihood function is defined as

$$L(\theta) = p_\theta \hat{(x_1)}\ p_\theta \hat{(x_2)} \ldots p_\theta \hat{(x_n)}$$

Which is the joint probability mass function when the data are independent. The parameter θ is then estimated as the value θ that maximizes L(θ) over all other permissible values of θ.

In the ***continuous*** case, density function for the continuous distribution, instead of probability mass function for the discrete distribution, is used here because the probability for a continuous random variable equal to any fixed number is zero. Given the observed data set X_1, X_2, …, X_n, suppose a continuous distribution has been hypothesized for this data set with one unknown parameter θ. Let $f_\theta \hat{(x)}$ denote the density function for this distribution. The likelihood function is defined as

$$L(\theta) = f_\theta \hat{(x_1)}\ f_\theta \hat{(x_2)} \ldots f_\theta \hat{(x_n)}$$

The parameter θ is then estimated as the value θ that maximizes L(θ) over all other permissible values of θ. If the hypothesized distribution has several unknown parameters, these parameters can be estimated as the values that jointly maximizes L(θ) over all other permissible values of these parameters.

3.3.4 Activity : Determining How Representative the Fitted Distributions Are

In activity , one or more completely specified distributions have been determined with the estimated parameter values. The following work is to examine how well these distributions represent the true underlying distribution of the observed data set. Furthermore, the distribution that provides the best-fit needs to be determined if several distributions are evaluated as "representative". Heuristic procedures and goodness-of-fit hypothesis tests can be used to determine how representative the fitted distributions are.

3.3.4.1 Heuristic Procedures

The Density/Histogram overplot and the Distribution-Function-Differences Plot are two widely used heuristic procedures for comparing fitted distributions with the true underlying distribution. For continuous observed data set, the Density/Histogram overplot can be made by plotting the density function of the fitted distribution over the histogram. If the fitted distribution is a good representation for the observed data set and the sample size is sufficiently large, the density function of the fitted distribution and the histogram should look very similar.

The Density/Histogram overplot compares the individual probabilities of the fitted distribution and the true underlying distribution, while the Distribution-Function-Differences plot compares the cumulative probability of the fitted distribution and the true underlying distribution. The empirical cumulative distribution for the observed data set is defined as:

$$F_n(x) = \frac{\text{Number of } X_i\text{'s} \leq X}{N}$$

The Distribution-Function-Differences plot is a plot of the differences between the fitted cumulative distribution $\hat{F}(x)$ and the empirical cumulative distribution $F_n(x)$ for the observed data set. If the fitted distribution is a good representation for the observed data set and the sample size is sufficiently large, the Distribution-Function-Differences plot should be close to a horizontal line at height zero.

3.3.4.2 Goodness-of-fit Test

While heuristic procedures can provide graphic comparison between the fitted distribution and the true underlying distribution, goodness-of-fit test can assess formally whether the observed data set is an independent sample from a particular fitted distribution (Law and Kelton, 2000). In other words, given the observed data set $X_1, X_2, \ldots, X_n$, and the density function of the fitted distribution $\hat{f}(x)$, this statistical hypothesis test can be used to test the following null hypothesis:

H_0: The observed data set $X_1, X_2, \ldots, X_n$ is an independent sample from the distribution with density function $\hat{f}(x)$

According to Law and Kelton (2000), the t-statistics is computed as the measure of the "distance" between the fitted distribution and the observed data set. Different goodness-of-fit tests, such as the Chi-Square test, the Kolmogorov-Smirnov test, and the Anderson-Darling test, use different methods to calculate the T value. Decision is made whether to reject the null hypothesis based on the comparison of T and a critical value t (α). The probability that T is greater than t (α) is equal to α when the null hypothesis is true. Typically, the level α is set to be 0.05 to 0.1. The critical value t (α) depends on α, the sample size n, the test itself, and sometimes, the fitted distribution. For a test of level α, if T is greater than t(α), reject the null hypothesis. Otherwise, do not reject the null hypothesis.

Failure to reject the null hypothesis should not be interpreted as "accepting the null hypothesis as being true" (Law and Kelton, 2000). That is to say, goodness-of-fit tests can only assist determining whether to reject the null hypothesis. Whether to accept the null hypothesis cannot be determined through these tests. If the sample size is small, it is difficult for goodness-of-fit tests to examine the disagreements between the true underlying distribution of the observed data set and the fitted distribution based on the limited information provided by the short data set.

This research uses the chi-square test to assess whether the observed data set is an independent sample from a particular fitted distribution. To compute the Chi-Square test statistic in the continuous case, the entire range of the fitted distribution is first broken into k adjacent intervals $[b_0, b_1)$, $[b_1, b_2)$, … , $[b_{k-1}, b_k]$. Then given the density function $\hat{f}(x)$ of the fitted distribution, the proportion p_j of the X_i's that would fall in the jth interval is computed as:

$$p_j = \int_{a_{j-1}}^{a_j} \hat{f}(X)\,dx$$

Finally, the chi-square test statistic is computed as:

$$\chi^2 = \sum_{j=1}^{k} (N_j - nP_j)^2 / nP_j$$

The χ^2 test statistic for large n is approximately a χ^2 distribution. H_0 is rejected if $\chi^2 > \chi^2_{k-1,a}$. The number of degrees of freedom of the χ^2 distribution is calculated as:

$$N=(I - 1) - P$$

where N = number of degrees of freedom
I = number of intervals being compared
P = number of parameters estimated

3.4 Summary

This chapter describes the methodology used in this research. First, the existing definition of capacity and capacity estimation methods is presented. After that, the definition of accident capacity and methodology of estimating capacity under prevailing conditions and estimating accident capacity used in this research are discussed. Finally, the methodology of modeling the accident capacity reduction as a random variable is described.

CHAPTER 4: DATA ANALYSIS AND RESULTS

4.1 Study Site

The Hampton Roads region of Virginia is selected for this research because the Smart Travel Laboratory of the University of Virginia has incident data dating from March 28th, 1992 and traffic flow data dating from June 28th, 1998 for this region. The Smart Travel Laboratory is connected to the Hampton Roads Smart Traffic Center that is the main freeway data resource for this laboratory. For the purpose of traffic management, the Hampton Roads are divided into several segments, which are named as "locations" in the incident database. The locations with incident data include: 564-01, E64-01, E64-02, E-64-03, W64-01, W64-02, W64-03, W64-04, W64-05, W64-06, W64-07, and w64-08. The length of each segment is about one to three miles. Accident data was recorded by locations in the incident database. The location designations can be seen in Figure 4.1.

Traffic flow data was recorded by inductive loop detectors installed at 203 places on the interstate facilities of the region, referred to as "stations". In general, there are several stations within each location in each direction, and each station consists of a single loop detector installed in each of the travel lanes. Traffic flow data was recorded by station ID (the identification number of the station) in the traffic flow database. The relationship between location and station ID is the key to relate traffic flow data to incident data. The station designations can be seen in Figure 4.2, and the relationship between location and station ID can be seen in Table 4.1.

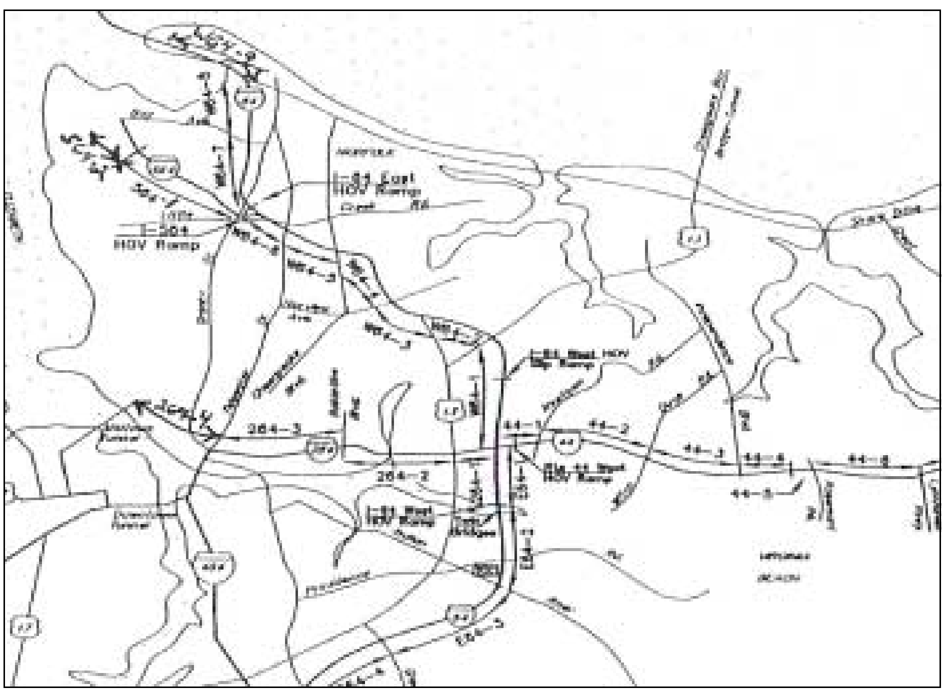


Figure 4.1: Hampton Roads Location Designations

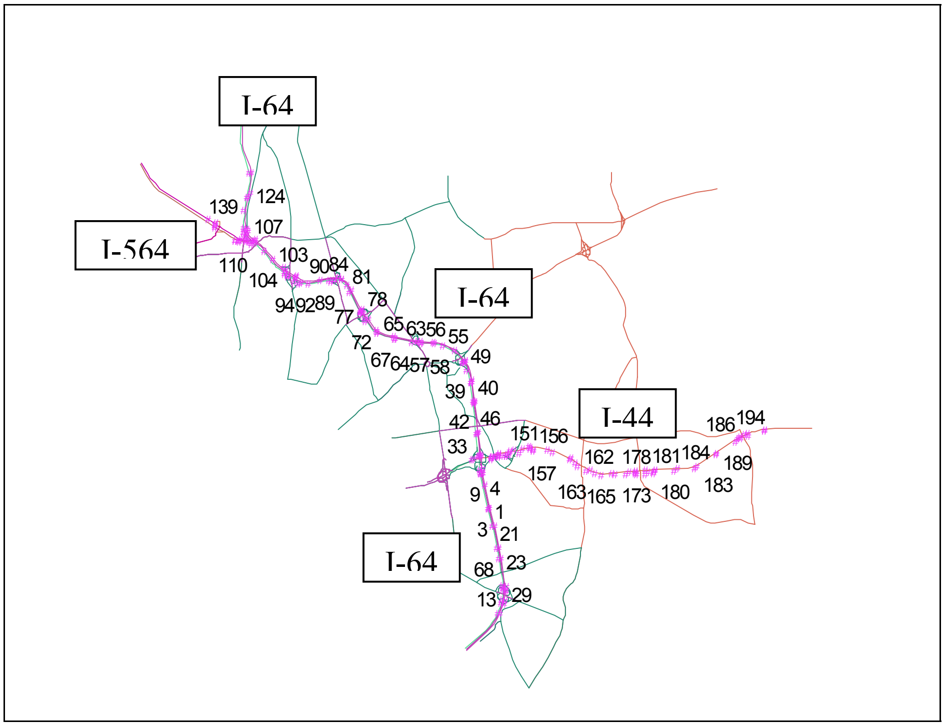


Figure 4.2: Hampton Roads Station Designations

Table 4.1: Relationship between Location and Station ID

Location	Station ID
564-01	E 132,135,136 W 131,138,139
E64-01	E 3,8 W 4,6
E64-02	E 22,24,26,68 W 21,23,30,44
E64-03	E 31 W 15
W64-01	E 19,39,43,47,51 W 17,36,40,46,54
W64-02	E 58,60 W 56,62
W64-03	E 67, 71 W 65, 69
W64-04	E 76, 83 W 80,81,85
W64-05	E 87,92 W 91,96
W64-06	E 98,105,111 W 104,108,117
W64-07	E 120,123 W 122

W64-08	E 126 W 125

This table only lists the stations on mainlines and does not include the stations on ramps. This research only uses the traffic flow data corresponding to the stations on mainlines. Traffic flow on ramps is often very low. When an accident occurred on ramps, the bottleneck often cannot be established and the methodology of accident capacity reduction discussed in Chapter Three cannot be used.

Station ID is corresponding to location and direction. For example, station 132 is on the eastbound of the location 564-01, while station 131 is on the westbound of the location 564-01. There is no information of the exact place where the accident occurred within the location. There are several stations within one location. It is possible that the traffic flow recorded by one station was affected by the accident more significantly than the traffic flow recorded by the other stations. It is difficult to decide which station best provides the information of traffic flow affected by accident to estimate accident capacity. This difficult situation needs to be considered during the process of accident capacity estimation and will be discussed later on.

4.2 Data Collection

4.2.1 Incident Data

The Hampton Roads' incident data in the Smart Travel Laboratory describes the type, location, lanes blocked, beginning time, duration and the other information of each reported incident that occurred at the locations described in section 4.1 dating from March 28th, 1992. The type of incidents, number of each type of incidents, and percentages of each type of incident dating from March 28th, 1992 until February 18th, 2001 (the end date for data analysis in this research) are summarized in Table 4.2. It can be seen that disabled vehicles account for 72.9 percent of reported incidents and accidents account for 8.2 percent of reported incidents. The other types, such as Abandoned, Bridge, Debris, TEOC, Tunnel, and VMS Change, are special cases reported for the Hampton Roads Smart Traffic Center. They are not within the scope of this research.

Table 4.2: Summary of Hampton Roads' Incident Data in the Smart Travel Laboratory

Type of incident	Total number	Percentage
Disabled	68410	72.9%
Accident	7698	8.2%
Abandoned	6958	7.4%
Bridge	2945	3.1%
Debris	2895	3.1%
TEOC	1843	2.0%
Tunnel	1734	1.8%
Condition Chg	752	0.8%
VMS Change	254	0.3%
Other	404	0.4%
Total	93893	100%

The Number of Lanes blocked by disabled vehicles and accidents, number of incidents of each category, and corresponding percentage are summarized in Table 4.3 and Table 4.4. The total number of lanes varies from two to four. There are more than one hundred descriptions of which lane or lanes were blocked by the incidents in the incident database. Those that cannot be categorized into one, two, or shoulder lanes blocked are categorized into "other".

Table 4.3: Number of Lanes Blocked by Disabled Vehicles

Number of lanes blocked	Total Number	Percentage
One	1513	0.22%
Two	54	0.10%
Shoulder	64518	94%
Other	2323	3.4%
Total	68408	100%

Table 4.4: Number of Lanes Blocked by Accidents

Number of lanes blocked	Total Number	Percentage
One	2063	26.8%
Two	1593	20.7%
Shoulder	2827	36.7%
Other	1275	16.6%
Total	7698	100%

The durations of incidents, number of incidents within each category of duration, and corresponding percentages of incidents dating from March 28th, 1992 until February 18th, 2001 are summarized in Table 4.5. There are three categories for the durations of incidents in this table: short, 0-15 minutes; medium, 15-30 minutes; and long, 30+ minutes. This categorization is widely used in practice. Also, only disabled vehicles and accidents are considered because the other types of incidents are not within the scope of this research, as mentioned before.

Table4.5: Duration of Disabled Vehicles and Accidents

	0-15 minutes		15-30 minutes		30+ minutes		Total
Duration	Number	Percentage	Number	Percentage	Number	Percentage	Number
Disabled	48210	70.5%	12556	18.4%	7644	11.2%	68410
Accident	1811	23.5%	1549	20.1%	4338	56.4%	7698

It can be seen that most disabled vehicles occurred on shoulder lanes with short durations, while most of the accidents blocked one lane, two lanes and shoulder lanes with long durations. This may be the reason that few cases with significant capacity reduction for disabled vehicles can be found, and most cases with significant capacity reduction are one lane, two lanes and shoulder lanes out of three lanes blocked by accidents, as discussed in Chapter One. The scope of this research is thus limited to estimating accident capacity reduction for one lane, two lanes or shoulder lanes out of three lanes blocked and modeling it as a random variable.

4.2.2 Traffic Flow Data

The Hampton Roads' traffic flow data in the Smart Travel Laboratory records date, station ID, traffic volume, traffic occupancy, time mean speed, collect length and the other information corresponding to the station ID from June 28th, 1998 and is updated every two minutes for the Hampton Roads region. The traffic volume is the number of vehicles on all the lanes of the freeway counted during the collection length. The collection lengths are between 100 and 255 seconds with the average of slightly more than 120 seconds. Traffic flow rate in vphpl is calculated by the formula below.

Traffic flow rate (vphpl) =
(volume /collect length in sec /number of lanes) * 3600 sec/hour

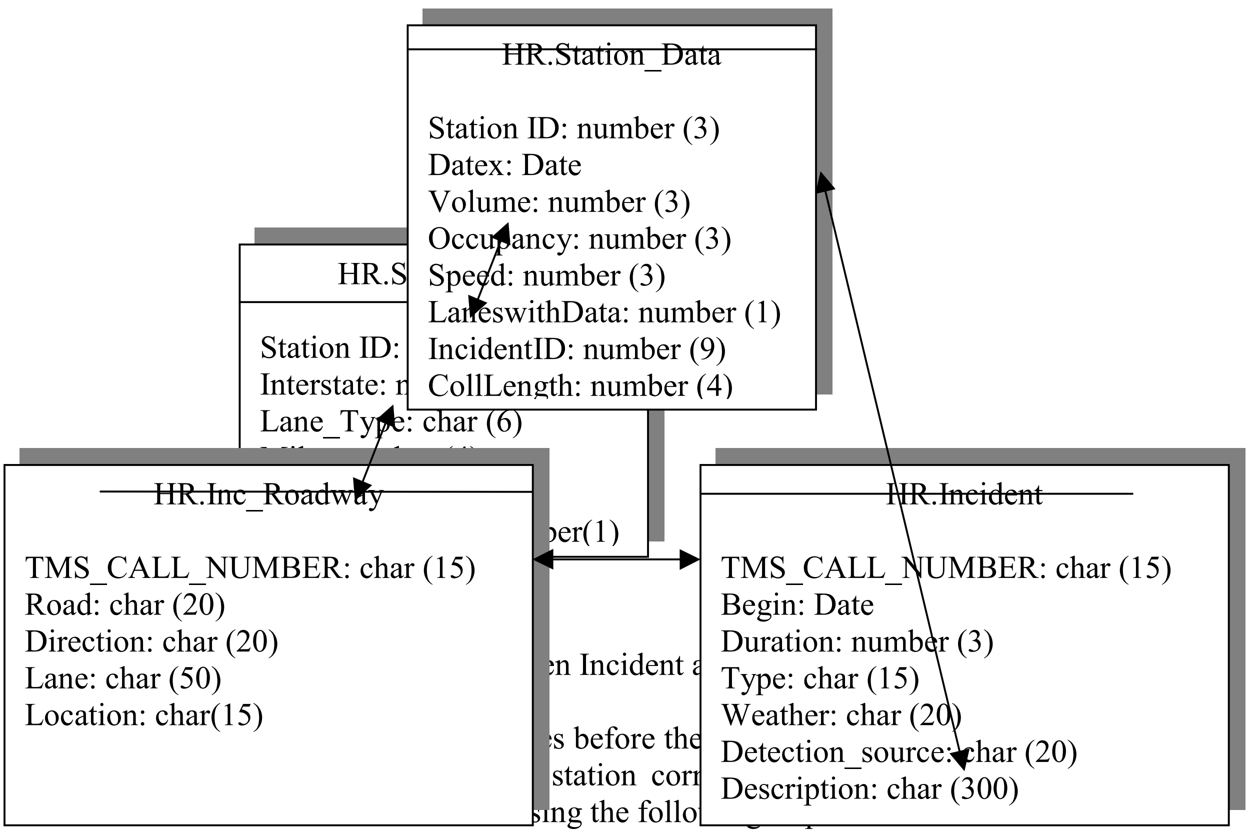
Thus, through this calculation the traffic volume in vehicle per second is transformed to traffic flow rate in vehicle per hour per lane. The stable traffic flow is calculated as 10-minute average traffic flow, as discussed in Chapter Three.

One important thing needs to be mentioned here. There is no information about the types of vehicles in the Hampton Roads' traffic flow data. As we know, the heavy vehicles other than passenger cars, such as trucks, buses, and recreational vehicles, affects traffic flow, and thus capacity of the roadway. The Highway Capacity Manual (2000) presents tables to determine the numerical value of the heavy vehicle factor that is used to consider the reduction in capacity due to the presence of heavy vehicles. Subramanyan (2000) presented the results of the estimation of the truck percentage at four study sites on I-64 and I-44 based on the field data in his thesis. The truck percentage on the westbound of I-64 was estimated as 10 percent, while the truck percentage on the eastbound of I-64 was estimated as 8 percent. The other two study sites are not related to this research. This research does not consider the heavy vehicle factor because the estimation of capacity under prevailing conditions and accident capacity reduction will all decrease due to the heavy vehicle factor. The percentage value of accident capacity reduction will not change so much when considering the heavy vehicle factor.

Time mean speed is defined as the arithmetic mean of the speeds of vehicles passing a point on a highway during an interval of time. Individual speeds are recorded passing a point, and are arithmetically averaged. Another speed measure, space mean speed, is defined as the length of the segment divided by the average running time of vehicles to traverse the segment. This research uses time mean speed as the speed measure. Occupancy is defined as the measure of the percentage of time for which a vehicle is detected over a detector on a highway during an interval of time. This research is not concerned about the occupancy.

4.2.3 Relationship between the Incident and the Traffic Flow Database

Four databases stored in the Smart Travel Laboratory are used in this research, including (1) HR.Inc_Roadway, which describes the location where an incident occurred; (2) HR.Incident, which stores information about each incident, uniquely identified by the identification number of incidents TMS_CALL_NUMBER; (3) HR.Station_Data, which records that traffic flow data corresponding to the station ID; This table stores information about each station; and (4) HR.Station_Info, which describes the relationship between location and station ID. One thing needs to be mentioned here to eliminate confusions. In some cases one keyword has different field names in the different databases. For example, the field "Location" in (1) HR.Inc_Roadway and the field "Interstate" in (4) HR.Station_Info all refer to the segments of Hampton Roads, while the field "Direction" in (1) HR.Inc_Roadway and the field "Lane_Type" in (4) HR.Station_Info all refer to roadway direction. This needs to be taken care of when connecting databases by keywords. Please refer to database documentation in the Smart Travel Laboratory to get more detailed information about these databases. The relationships among these four databases are shown in Figure 4.3.



Step1: Select incidents occurred on the specified location by the fields "Location" and "Direction" from (1) HR.Inc_Roadway. For example, all incidents occurred on the eastbound ("Direction") of 564-01("Location") can be selected from (1) HR.Inc_Roadway.

Step2: Select accidents from the incidents selected at Step One by the fields "Type" in (2) HR.Incident. This can be realized because (1) HR.Inc_Roadway and (2) HR.Incident are related through TMS_CALL_NUMBER. Then decide the beginning time and the ending time for each selected accidents by the field "Begin" and

"Duration" in (2) HR.Incident. The ending time is equal to the beginning time plus the duration in minute.

Step3: Find the stations corresponding to the specified location from (4) HR.Station_Info. For example, Station 132, 135, and 136 are on the eastbound of the location 564-01 (Please refer to table 4.1). Then the traffic flow from 30 minutes before the accident occurred to 30 minutes after the accident cleared at the special station corresponding to the location where the accident occurred can be selected from (3) HR.Station_Data by the joint information of the station ID, beginning time, and ending time decided in the previous steps.

4.3 Data Analysis and Results

4.3.1. Capacity under Prevailing Conditions

Using the method of estimating of capacity under prevailing conditions discussed in Chapter Three, capacities for several segments of Hampton Roads under prevailing conditions were estimated using the following steps:

Step1: Several segments of Hampton Roads were selected to estimate capacities under prevailing conditions. These segments were selected because each of them is believed to have uniform characteristics. These segments include I564 West Bound, I64 (south of I564 jct) East Bound, I64 (south of I564 jct) West Bound, and I64 (south of I264 jct) West Bound (Please refer to figure 4.1). Then station 139, 39, 69, and 4 were selected to estimate capacities for the corresponding segments under prevailing conditions.

Step2: Five successive traffic flow values were summarized to obtain volumes over 10-minute. The volumes over 10-minute were then converted to flow rates in vehicle per hour per lane. The time mean speeds were averaged within every 10-minute interval. Speed-flow diagram was plotted using about one year's traffic flow data for each station. On plotting speed-flow diagram, a near parabola bounded by a top line was observed for most of the basic sections considered. The speed-flow plots of station 69 and 123 are shown as expected in Figure 4.4 and Figure 4.5.

Step3: The capacities of station 139, 39, 69, and 4 were first estimated. The

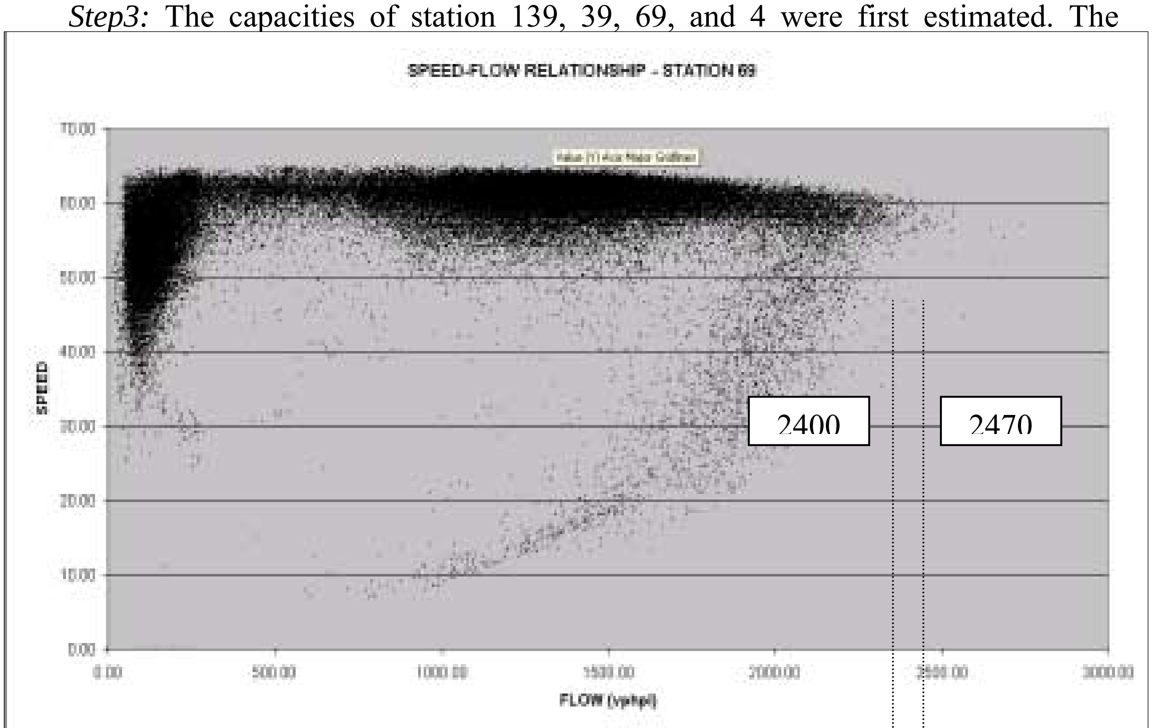


Figure 4.4: Speed-Flow Plot of Station 69

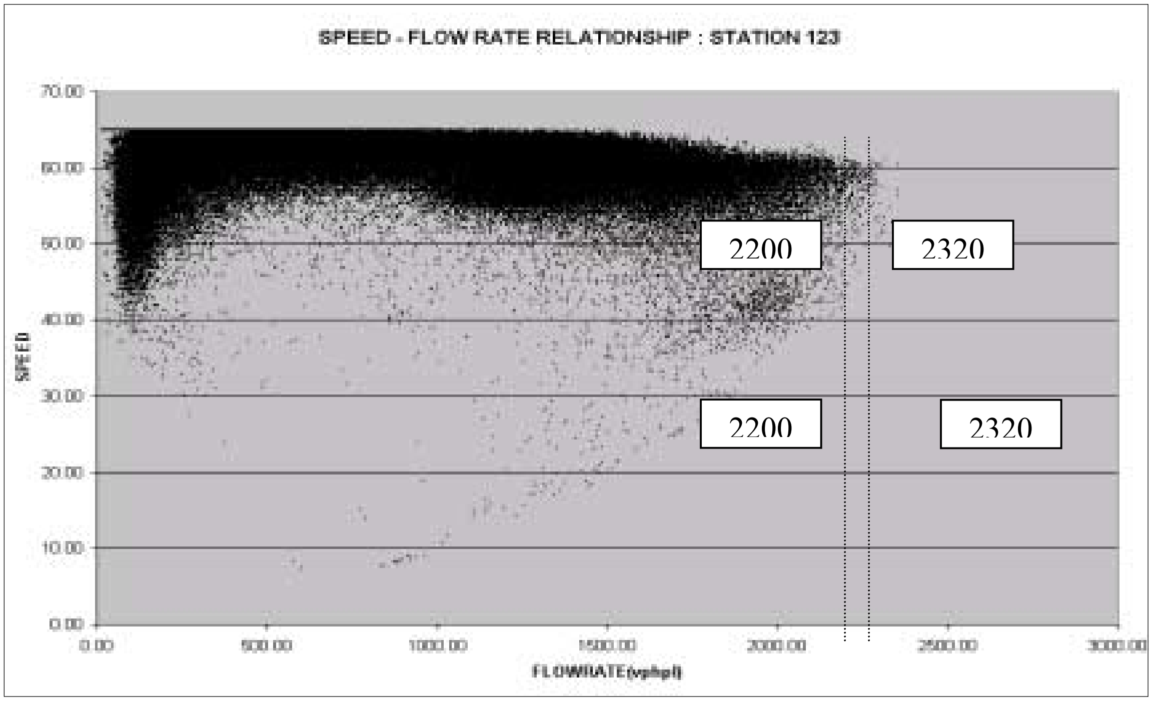


Figure 4.5: Speed-Flow Plot of Station 123

Table 4.6: Estimation of Capacity under Prevailing Conditions for Selected Stations

Station ID	Location Description	No. of lanes	Max flow (vphpl)	Data from (date)	Data to (date)	Total data points ('000)
139	I564 West Bound	3	1950	8/8/99	8/16/00	101
39	I64 (south of I564 jct) East Bound	3	2500	6/15/98	7/29/99	142
69	I64 (south of I564 jct) West Bound	3	2450	8/2/99	7/31/00	110
4	I64 (south of I264 jct) West Bound	3	2250	8/2/99	7/31/00	140

Source: Venkatanarayayana's Working Paper at the Smart Travel Laboratory

Step4: The estimation of capacity under prevailing conditions of station 139, 39, 69, and 4 can be used as the estimation of capacity for the corresponding locations under prevailing conditions, and then the estimation of capacity related to each station can be decided by the relationship between locations and stations. The results are shown in Table 4.7. The capacity under prevailing conditions is related to each station in Table 4.1 to provide a frame-of-comparison because estimation of accident capacity reduction is related to one of the stations, not limited to station 139, 39, 69, and 4.

Table 4.7: Estimation of Capacity under Prevailing Conditions for All Stations

Location	Station id	No. of lanes	Maximum flow (veh/hour/lane)
564-01	W 131,138,139	W 3	W 1950
E64-01	W 4,6	W 3	W 2250
E64-02	W 21,23,30,44	W 3	W 2250
E64-03	W 15	W 3	W 2250
W64-01	E 19,39,43,47,51 W 17,36,40,46,54	E 3 W 3	E 2500 W 2400
W64-02	E 58,60 W 56,62	E 3 W 3	E 2500 W 2400
W64-03	E 67, 71 W 65, 69	E 3 W 3	E 2500 W 2450
W64-04	E 76, 83 W 80,81,85	E 3 W 3	E 2500 W 2400
W64-05	E 87,92 W 91,96	E 3 W 3	E 2500 W 2400
W64-06	E 98,105,111 W 104,108,117	E 3 W 3	E 2500 W 2400

4.3.2 Accident Capacity Reduction

Using the method of accident capacity estimation discussed in Chapter Three, accident capacity reductions were calculated using the following steps:

Step1: Plot the traffic flow at the station corresponding to the location where accidents occurred from 30-min before the accident occurred to 30-min after the accident was cleared. Figure 4.6 gives an example. This accident (TMS_CALL_NUMBER: 1999-04712) occurred on the eastbound of the location W64-07 and blocked lane one, beginning at 13:44 and ending at 13:50. Traffic flow at station 120 (which is within W64-07) from 13:14 to 14:20 was plotted with time. Traffic flow from 13:36 to 13:52 is apparently lower than traffic flow before and after this period.

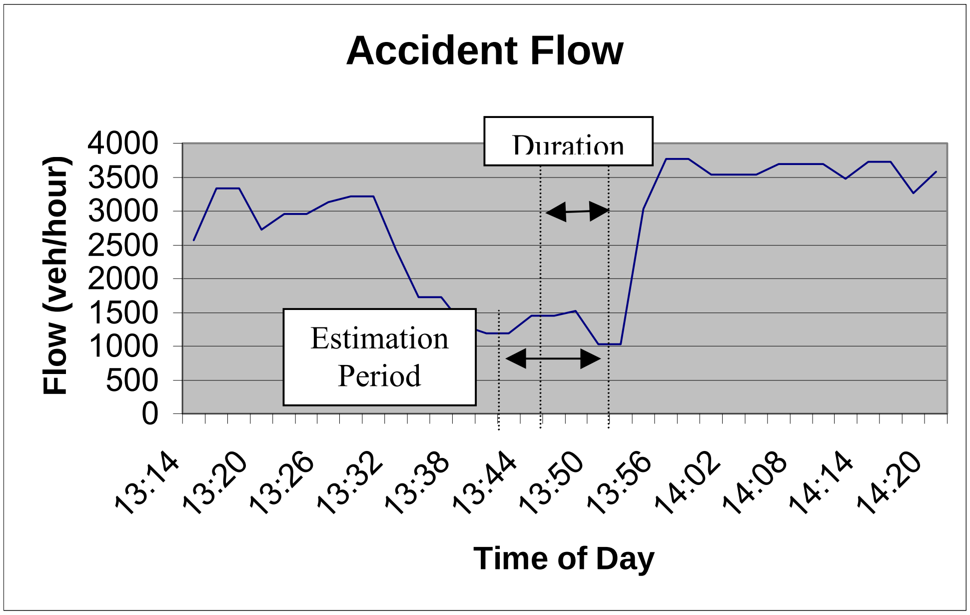


Figure 4.6: Accident Traffic Flow of 1999-04712

Step2: Select the samples to calculate the accident capacity according to the plot of traffic flow during an accident. Figure 4.6 shows that accident 1999-04712 could be selected as the sample to calculate the accident capacity. For accidents that occurred with low traffic demand, or with very short duration, or on shoulder lanes, this kind of pattern cannot often be found and then this accident was not selected as a sample to calculate the accident capacity. Figure 4.7 shows such an example. This accident (TMS_CALL_NUMBER: 2000-26305) occurred on the eastbound of the location W64-02 on the left shoulder, beginning at 16:16 and ending at 17:02. Traffic flow at station 58 (which is within W64-02) from 15:46 to 17:32 was plotted with time. Traffic flow did not decrease noticeably duration this period. There might be small accident capacity reduction that cannot be counted by the methodology used in this research. Slightly higher average accident capacity reduction value might be the result of this drawback of the methodology.

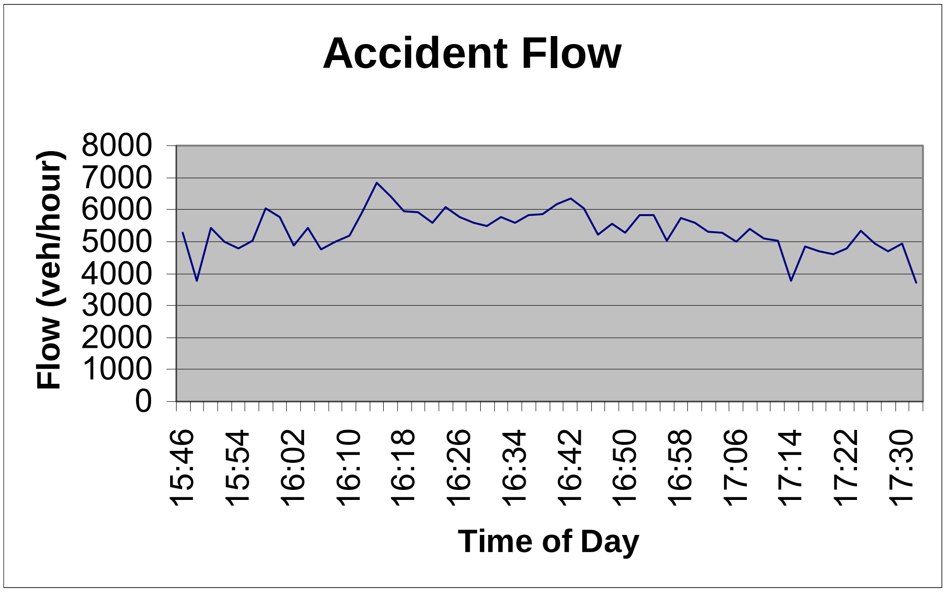


Figure4.7: Accident traffic flow of 2000-26305

Step3: Calculate the minimum moving average of five successive traffic flow during an accident as the accident capacity for the samples selected at step two. For accident 1999-04712, the average traffic flow from 13:40 to 13:50 was calculated as the incident capacity, which is 1360 veh/hour.

Step4: As discussed earlier, accident was recorded with location, and traffic flow was recorded with station ID. Because there are several stations within one location, it is possible that multiple stations evidenced the impact of one accident on capacity. If this happened, select the minimum value among these calculation results. Figure 4.8 gives an example. This accident (TMS_CALL_NUMBER: 1999-17390) occurred on the westbound of the location 564-01 and blocked lane one and lane two, beginning at 6:19am and ending at 6:57am. Traffic flow at station 131,138,139 (which is within 564-01) from 5:50am to 7:28 was plotted with time. It can be seen that traffic flow during this period of station 139 is slightly lower than traffic flow of station 131 and 138 so that traffic flow of 139 was selected to calculate accident capacity, which is 1480 veh/hour.

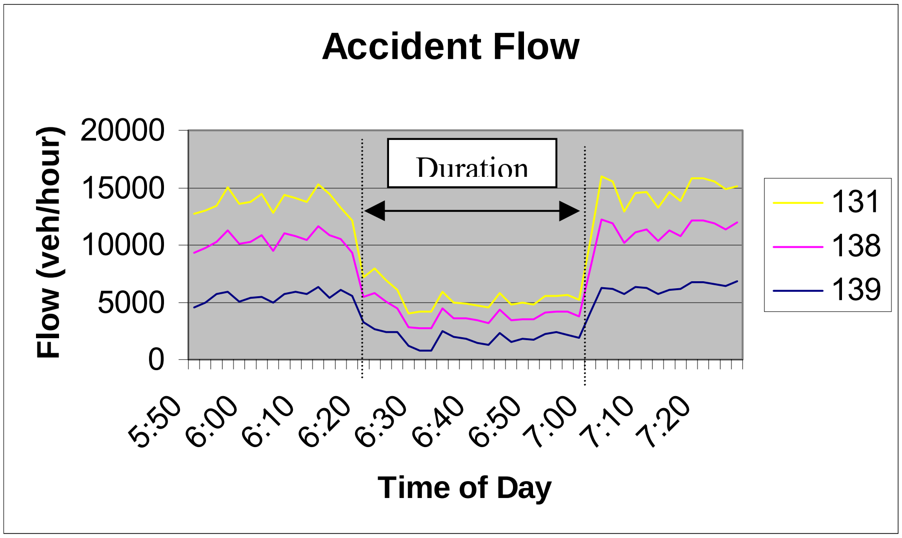


Figure 4.8: Accident Traffic Flow of 1999-17390 at Stations 131, 138, and 139

Step5: Calculate accident capacity reduction as the difference between capacity under prevailing conditions (Table 4.7) and accident capacity computed at Step Three and Step Four. Then the percentage value of accident capacity reduction was calculated as accident capacity reduction over capacity under prevailing conditions. For accident 1999-17390, the capacity under prevailing conditions was estimated as 1950 veh/hour/lane, and there are three lanes on the eastbound of the location 564-01 where the station 139 locates. The accident capacity was estimated as 1480 veh/hour, so the accident capacity reduction was calculated as (1950×3-1480), which is 4370 veh/hour. The percentage of accident capacity reduction was calculated as [4370/(1950×3)], which is 74.7 percent.

These five steps form the whole process of estimating of accident capacity reduction. Following these steps, 133 samples were selected to calculate accident capacity reduction for one lane out of three lanes blocked, 73 samples were selected to calculate accident capacity reduction for two lanes out of three lanes blocked. As for accidents occurred on the shoulder lane(s), 52 samples with significant capacity reduction were selected. But as discussed earlier, there might be small accident capacity reduction that cannot be counted by the methodology used in this research.

4.3.3 Modeling Accident Capacity Reduction as a Random Variable

ExpertFit (Averill M. Law & Associates, 1999) was used to assist modeling accident capacity reduction as a random variable. ExpertFit displays summary statistics, makes histograms, fits distributions to the data using the method of maximum likelihood, ranks the distributions in terms of the quality of fit, compares the best distribution(s) to the data to further determine the quality of fit, using Density/Histogram overplots, Distribution-Function-Differences plots, goodness-of-fit tests, etc.

4.3.3.1. One Lane out of Three Lanes Blocked by Accidents

a. Data Summary

The statistics of the data of accident capacity reduction for one lane out of three lanes blocked are summarized in Table 4.8. The mean accident capacity reduction with one lane out of three lanes blocked is 62.6 percent, which is fairly larger than Goolsby's result. The standard deviation is 14 percent. As discussed before, the variation of accident capacity reduction is due to the variations in roadway conditions, control conditions, traffic conditions, and incident characteristics. The distribution is a little skewed to the left. The information will be useful for hypothesizing families of distributions.

To test whether the result in this research (62.6 percent) is significantly different from Goolsby's result (50 percent) as the mean capacity reduction with one lane out of three lanes blocked by accident, the following hypotheses test is conducted:

$$H_0:\ \mu = 0.50 \quad \text{versus} \quad H_1:\ \mu \neq 0.50$$

The sample size n=133 being large, the test statistic is:

$$z = \frac{\overline{x} - \mu_0}{s/\sqrt{n}} = \frac{\overline{x} - 0.5}{s/\sqrt{133}} = \frac{0.626 - 0.50}{0.14/\sqrt{133}} = 10.4$$

Let $\alpha = 0.05$, then $\alpha/2 = .025$, and $z_{.025} = 1.96$. Thus, for $\alpha = 0.05$, the rejection region is $|Z| \geq 1.96$. Because $|Z| = 10.4$ is larger than 1.96, H_0: $\mu = 0.50$ is rejected at level $\alpha = 0.05$. That is to say, the result in this research (62.6 percent) is significantly different from Goolsby's result (50 percent) as the mean capacity reduction with one lane out of three lanes blocked by accident.

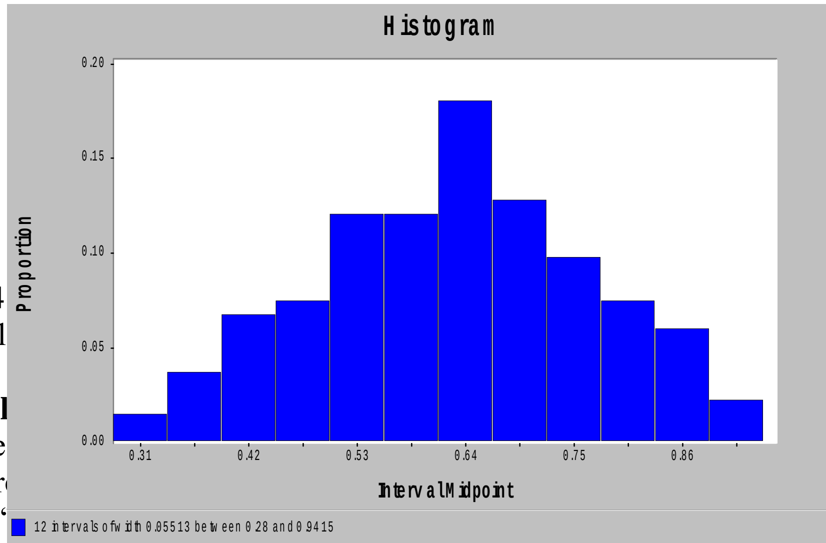
Table 4.8: Data Summary of Accident Capacity Reduction for One Lane out of Three Lanes Blocked

Number of observations	133
Minimum observation	28.76%
Maximum observation	90.69%
Mean	62.65%
Median	62.60%
Variance	1.97%
Coefficient of variation	0.22391
Skewness	-0.10718

b. Histogram

As discussed in Chapter Three, Law and Kelton (2000) recommended trying several different values of interval width and choosing the smallest one that gives a "smooth" histogram. Experfit provides the function buttons to decrease or increase the interval width by five percent, and these functions can be applied repeatedly. Thus, the interval width can be adjusted by applying these functions repeatedly until a "smooth" histogram is obtained. In this work, a "smooth" histogram with 12 intervals of width

0.05513 was finally obtained. The number of intervals is between 10 and 25, the range proposed by Neiswanger (1943). Also, the number of intervals is calculated as eight according to the equation proposed by Sturges (1926), which is not between 10 and 25 and is not used in this research. The histogram of accident capacity reduction for one lane out of three lanes blocked is shown in Figure 4.9.



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c. Model

The distributions best repr elative Score" and an " distribution. According to Law and Kelton (2000), there are 15 heuristics in the ExpertFit to be used to discriminate between a good fitting and bad fitting distribution. Tests need to be performed to determine which heuristics are the best for choosing the specified distribution. For this purpose, a random sample of size n is generated from the specified distribution, and each of the 15 heuristics is applied to see if it could choose the correct distribution. An estimated probability that each heuristic will pick the correct distribution for the specified sample size is given based on the repeated tests for 200 independent samples. Once the distribution changes, the repeated tests for 200 independent samples are performed once. Also, once the sample size changes, the repeated tests for 200 independent samples are performed once. There are 175 distribution/sample size pairs in the ExpertFit and each pair is given an estimated probability for each of the 15 heuristic to choose the specified distribution for the specified sample size. Several heuristics may be proved to be superior. The "Relative Score" and the "Absolute Evaluation" are then computed by these heuristics combined and the generated data sets in the previous process.

According to the documentation of ExpertFit, the "Relative Score" can only give the rank of several fitted distributions. Even if a distribution is ranked first, this does not necessarily mean that it is a good fit. The "Absolute Evaluation" can only give the information that whether there is apparent evidence for rejecting the fitted distributions. Even if the "Absolute Evaluation" for a fitted distribution is "good" in the ExpertFit, this also does not necessarily mean that it is a good fit. Graphical plots and goodness-of-fit tests are recommended to be used to obtain additional confirmation.

The selected distributions and estimated parameters of accident capacity reduction for one lane out of three lanes blocked are shown in Table 4.9. Beta distribution is ranked the first, and furthermore, the "absolute Evaluation" for Beta distribution is "good" in the ExpertFit. Accordingly, there is no current evidence for not using Beta distribution to represent Accident capacity reduction for one lane out of three lanes blocked. Graphical plots and goodness-of-fit tests will be used to obtain additional confirmation.

Table 4.9: Selected Distributions and Estimated Parameters of Accident Capacity Reduction for One Lane out of Three Lanes Blocked

Model	Relative Score	Parameters
1 - Beta	100	Lower endpoint Default0.00000 Upper endpoint Default1.00000 Shape #1 ML estimate 6.83057 Shape #2 ML estimate 4.05907
2 - Johnson SB	66.67	Lower endpoint Default0.00000 Upper endpoint Default1.00000 Shape #1 Quantile estimate -0.86612 Shape #2 Quantile estimate 1.50976
3 - Power Function	33.33	Lower endpoint Default0.00000 Upper endpoint Default1.00000 Shape ML estimate 2.02114

The density function and parameters of Beta distribution are given as follows.

Beta Distribution: Beta (α_1, α_2)

Density

$$f(X) = \begin{cases} \dfrac{x^{\alpha 1-1}\,(1-x)^{\alpha 2-1}}{B(\alpha_1, \alpha_2)} & \text{if } 0< x <1 \\ 0 & \text{otherwise} \end{cases}$$

where $B(\alpha_1, \alpha_2)$ is the beta function, defined by

$$B(z_1, z_2) = \int_0^1 t^{z_1 - 1}(1-t)^{z_2 - 1}\,dt$$

for any real numbers z1 >0 and z2 >0

Parameters: shape parameters $\alpha_1 > 0$ and $\alpha_2 > 0$

Range [0,1]

Mean $\dfrac{\alpha_1}{\alpha_1 + \alpha_2}$

Variance $\alpha_1\,\alpha_2$

$$\overline{(\alpha_1 + \alpha_2)^2(\alpha_1 + \alpha_2 + 1)}$$

d. Density/Histogram Overplot

Figure 4.10 gives a Density/Histogram overplot for the Beta, Jounson SB, and Power Function distributions over the histogram of the observed data set for accident capacity reduction with one lane out of three lanes blocked.

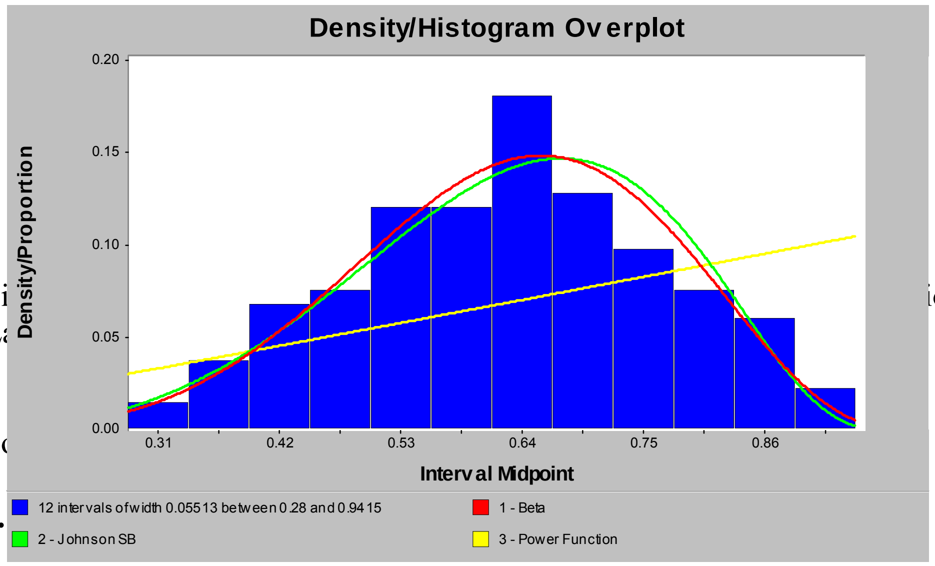

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Figure 4.11 gives a Distribution-Function-Differences plot for the three distributions. As discussed before, The Distribution-Function-Differences plot is a plot of the differences between the fitted cumulative distribution and empirical cumulative distribution from the observed data set. The smaller the differences are, the better the fitted distribution represented the observed data set. The ExpertFit draws the error bounds as the dotted horizontal lines in Figure 4.11. These error bounds depend on the sample size n and are determined from the generated data sets in the process of determining which heuristics are the best for choosing the specified distribution. If a differences plot crosses these lines, then this is a strong indication of a bad fit.

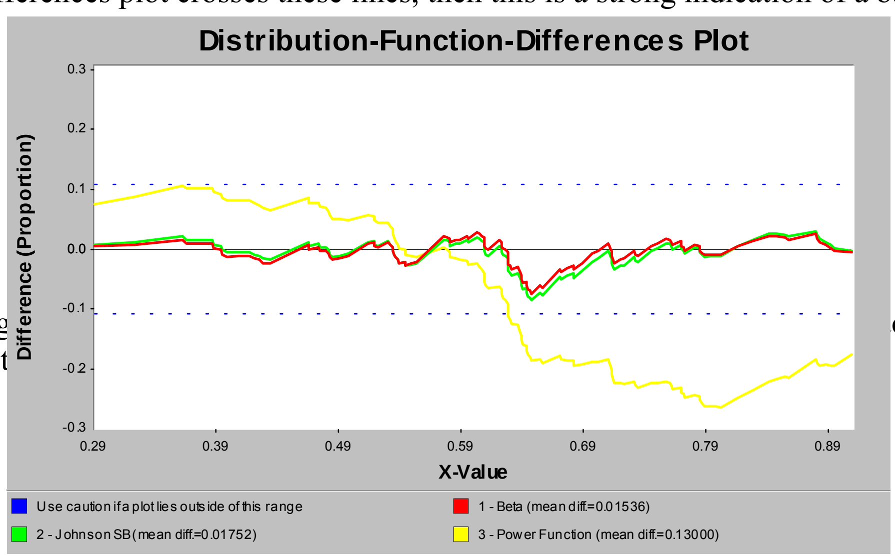

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Figure 4.11 shows the superiority of the beta distribution to the other fitted distributions and the differences plot for Beta distribution does not cross the error bounds. That is to say, there is no indication of a bad fit for the Beta distribution.

f. Goodness-of-Fit Test

Chi-Square test is used to obtain additional confirmation for Beta distribution to model accident capacity reduction for one lane out of three lanes blocked. The calculation of Chi-Square test is shown in Table 4.10. The first two and the last two intervals were combined separately to satisfy npj ≥ 5 (May, 1990).

Table 4.10: Chi-Square Test Calculations

Interval	Upper Limit	N_j	NP_j	$(N_j - NP_j)^2$	$(N_j - NP_j)^2/NP_j$
1	0.33513	2	3.21461		
2	0.39026	5	4.15891	0.14	0.018921
3	0.44539	9	7.15673	3.397644	0.474748
4	0.50052	10	10.83551	0.698077	0.064425
5	0.55565	16	14.66325	1.786901	0.121863
6	0.61078	16	17.85924	3.456773	0.193557
7	0.66591	24	19.56829	19.64005	1.003667
8	0.72104	17	19.11343	4.466586	0.233688
9	0.77617	13	16.28319	10.77934	0.661992
10	0.8313	10	11.58563	2.514222	0.217012
11	0.88643	8	6.28292		
12	1	3	2.27829	5.95	0.694726
				Chi-Square Statistic	3.684599

The degree of freedom is calculated as follows, as discussed in Chapter Three.

$$N = 10 - 1 - 2 = 7$$

The critical values of Chi-Square Test with the degree of freedom equal to seven are shown in Table 4.11.

Table4.11: The Critical Values of Chi-Square Test (DF=7)

α	0.1	0.05	0.025	0.01	0.005
Critical Value	12.0	14.1	16.0	18.5	20.3

The Chi-Square test statistic value is smaller than the critical values for α equal to 0.1, 0.05, 0.025, 0.01, and 0.005. That is to say, there is no evidence to reject Beta distribution to model accident capacity reduction for one lane out of three lanes blocked through the Chi-Square test at these levels of significance. Thus, based on the Absolute Evaluation, the graphic plots, and the goodness-of-fit tests, there is no reason to think that Beta distribution is not a good representation of accident capacity reduction with one lane out of three lanes blocked.

4.3.3.2 Two lanes out of Three Lanes Blocked by Accidents

a. Data Summary

The statistics of the observed data set of accident capacity reduction for two lanes out of three lanes blocked are summarized in Table 4.12. The mean accident capacity reduction with two lanes out of three lanes blocked is 77 percent, which is a little lower than Goolsby's result (79 percent). The standard deviation is 12 percent. The distribution is skewed to the left.

To test whether the result in this research (77 percent) is significantly different from Goolsby's result (79 percent) as the mean capacity reduction with one lane out of three lanes blocked by accident, the following hypotheses test is conducted:

$$H_0:\ \mu = 0.79 \quad \text{versus} \quad H_1:\ \mu \neq 0.79$$

The sample size n=73 being large, the test statistic is:

$$z = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} = \frac{\bar{x} - 0.79}{s/\sqrt{73}} = \frac{0.77 - 0.79}{0.12/\sqrt{73}} = 1.42$$

Let $\alpha = 0.05$, then $\alpha/2 = .025$, and $z_{.025} = 1.96$. Thus, for $\alpha = 0.05$, the rejection region is $|Z| \geq 1.96$. Because $|Z| = 1.42$ is smaller than 1.96, H_0: $\mu = 0.50$ cannot rejected at level $\alpha = 0.05$. That is to say, the result in this research (77 percent) is not significantly different from Goolsby's result (79 percent) as the mean capacity reduction with two lanes out of three lanes blocked by accident.

Table 4.12: Data Summary of Accident Capacity Reduction for Two Lanes out of Three Lanes Blocked

Number of observations	73
Minimum observation	46.45%
Maximum observation	99.27%
Mean	76.89%
Median	78.83%
Variance	1.43%
Coefficient of variation	0.15544
Skewness	-0.52264

b. Histogram

The histogram of accident capacity reduction for two lanes out of three lanes blocked is shown in Figure 4.12. In this work, a "smooth" histogram with 11 intervals of width 0.049 was finally selected. . The number of intervals is between 10 and 25, the range proposed by Neiswanger (1943). Also, the number of intervals is calculated as seven according to the equation proposed by Sturges (1926), which is not between 10 and 25 and is not used in this research.

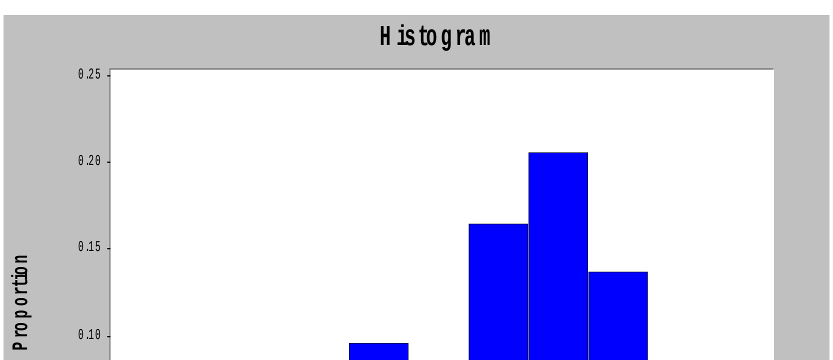


Figure 4.12: Histogram of Accident Capacity Reduction for Two Lanes Out of Three Lanes Blocked

c. Model Parameters

The selected distributions and estimated parameters of accident capacity reduction for two lanes out of three lanes blocked are shown in Table 4.13. Beta distribution is ranked the first, and furthermore, the “absolute Evaluation” for Beta distribution is “good” in the ExpertFit. Accordingly, there is no current evidence for not using Beta distribution to represent Accident capacity reduction for two lanes out of three lanes blocked. Graphical plots and goodness-of-fit tests will be used to obtain additional confirmation.

Table 4.13: The selected Distributions and Estimated Parameters of Accident Capacity Reduction for Two Lanes out of Three Lanes Blocked

Model	Relative Score	Parameters
1 - Beta	100	Lower endpoint Default0.00000 Upper endpoint Default1.00000 Shape #1 ML estimate 5.47708 Shape #2 ML estimate 1.82044
2 - Johnson SB	66.67	Lower endpoint Default0.00000 Upper endpoint Default1.00000 Shape #1 Quantile estimate -1.32816 Shape #2 Quantile estimate 1.01653
3 - Power Function	33.33	Lower endpoint Default0.00000 Upper endpoint Default1.00000 Shape ML estimate 3.21603

d. Density/Histogram Overplot

Figure 4.13 gives a Density/Histogram overplot for the Beta, Jounson SB, and Power Function distributions. It can be seen that Beta distribution matches the histogram well and that the Power Function distribution is clearly inferior.

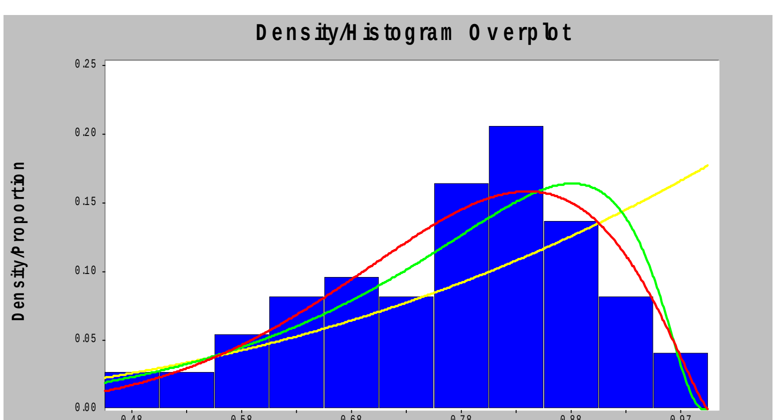
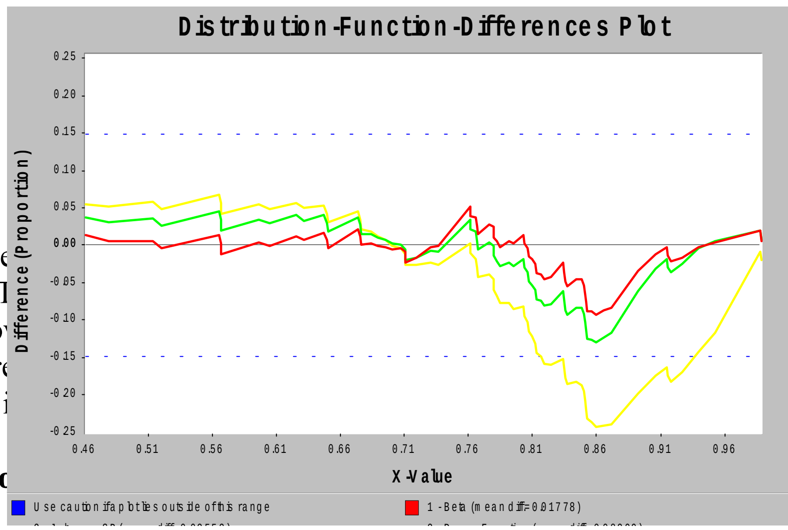


Figure 4.13: Density/histogram Overplot for Accident Capacity Reduction With Two Lanes out of Three Lanes Blocked

e. Distribution-Function-Differences Plot

Figure 4.14 gives a Distribution-Function-Differences plot for the three distributions.



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Chi-Square test is used to obtain additional confirmation for Beta distribution to model accident capacity reduction for two lanes out of three lanes blocked. The calculation of Chi-Square test is shown in Table 4.14. The first three and the last two intervals were combined separately to satisfy npj ≥ 5 (May, 1990).

Table 4.14: Chi-Square Test Calculations

Interval	Upper Limit	N_j	NP_j	$(N_j - NP_j)^2$	$(N_j - NP_j)^2/NP_j$
1	0.509	2	2.66231		
2	0.558	2	2.20825		
3	0.607	4	3.44414	0.10	0.011911
4	0.656	6	5.03262	0.935824	0.185952
5	0.705	7	6.8985	0.010302	0.001493
6	0.754	6	8.85344	8.14212	0.919656
7	0.803	12	10.55288	2.094156	0.198444
8	0.852	15	11.46757	12.47806	1.088117
9	0.901	10	10.89817	0.806709	0.074022
10	0.95	6	8.10008		
11	1	3	2.88204	3.93	0.357745
			Chi-Square Statistic		2.837341

The degree of freedom is calculated as follows, as discussed in Chapter Three.

$$N = 8 - 1 - 2 = 5$$

The critical values of Chi-Square Test with the degree of freedom equal to five are shown in Table 4.15.

Table 4.15: The Critical Values of Chi-Square Test (DF=5)

α	0.1	0.05	0.025	0.01	0.005
Critical Vaule	9.24	11.1	12.8	15.1	16.8

The Chi-Square test statistic value is smaller than the critical values for α equal to 0.1, 0.05, 0.025, 0.01, and 0.005. There is no evidence to reject Beta distribution to model accident capacity reduction for two lanes out of three lanes blocked through the Chi-Square test at these levels of significance. Thus, based on the Absolute Evaluation, the graphic plots, and the goodness-of-fit tests, there is no reason to think that Beta distribution is not a good representation of accident capacity reduction for two lane out of three lanes blocked.

4.3.3.3. Shoulder Lane Blocked out of Three Lanes by Accidents

a. Data Summary

The statistics of the data of accident capacity reduction for shoulder lane out of three lanes blocked are summarized in Table 4.16.

Table 4.16: Data Summary of Accident Capacity Reduction for Shoulder lane(s) out of Three Lanes Blocked

Number of observations	52
Minimum observation	22.21%
Maximum observation	92.00%
Mean	54.38%
Median	52.78%
Variance	2.39%
Coefficient of variation	0.28427
Skewness	0.37288

Just as talked before, there are 52 samples selected to calculate accident capacity reduction for shoulder lane out of three lanes blocked, while there were still 79 samples with probably small capacity reduction when shoulder lane(s) out of three lanes were blocked by accidents. Although the mean accident capacity reduction of the 52 samples is 54.4 percent, the mean accident capacity reduction of the 131 samples (including the 79 samples with probably small capacity reduction) is 21 percent, which are lower than Goolby’s result (33 percent). The work of modeling capacity reduction for shoulder lane(s) out of three lanes blocked by accidents, as a random variable cannot be done based the samples obtained.

4.4 Summary

This chapter describes the study site, data collection, data analysis and results of this research. The important issues about the incident data and traffic flow data of Hampton Roads from the Smart Travel Laboratory are discussed. The relationship between the incident data and traffic flow data are presented. The processes of estimating capacity under prevailing conditions for several segments of Hampton Roads, estimating accident capacity reduction, and modeling accident capacity reduction as a random variable are discussed in detail. Finally, the mean values and the fitted distributions (Beta distribution) are given for accident capacity reduction with one lane and two lanes out of three lanes blocked. Also, the mean value is given for accident capacity reduction with shoulder lane(s) out of three lanes blocked and the problem in modeling accident capacity reduction with shoulder lanes out of three lanes blocked as a random variable is talked. These results are compared with Goolby's results briefly and believed to be more reliable than Goolby's results.

CHAPTER 5: CONCLUSIONS

5.1 Conclusions

In this research, accident capacity reduction was estimated and modeled as a random variable based on the extensive accident data and traffic flow data from the Smart Travel Laboratory. From this research, conclusions can be drawn as follows:

1. The comparison of the mean values of accident capacity reduction determined in this research with Goolsby's results is shown in Table 5.1. For one lane out of three lanes blocked, the mean of accident capacity reduction (63 percent) calculated in this research is fairly higher than and statistically significantly different from Goolby's result (50 percent). For two lanes out of three lanes blocked, the mean of accident capacity reduction (77 percent) calculated in this research is a little lower than and is not statistically significantly different from Goolby's result (79 percent).

Table 5.1: Comparison of Mean Values of This Research with Goolsby's Results

Accident Capacity Reduction	This research	Goolsby
One lane out of three lanes blocked	63%	50%
Two lanes out of three lanes blocked	77%	79%

2. Accident capacity reduction should be modeled as a random variable, not a deterministic value, from the theoretical and practical point of view. The Beta distribution provides a good representation of accident capacity reduction for one or two lane out of three lanes blocked.

3. The results of this research are more reliable comparing with Goolsby's results because of advantages of the methodology used in this research over the methodology used in Goolsby's study, as shown in Table 5.2.

Table 5.2: Comparison of the Methodology Used in This Research with the Methodology used in Goolsby's Study

Comparison	This Research	Goolsby's Study
Sample Size	Accidents blocking one lane out of three lanes: 133 Accidents blocking two lanes out of three lanes: 73	Incidents: 27
Measurement Interval	10-minute	1-minute
Accident Capacity	Stable Minimum Congested Flow	1-minute bottleneck flow
Frame-of-comparison	Estimation of capacity under prevailing conditions by calibrating a speed-flow curve	1-minute normal flow downstream of the study site
Result	Random variable	Deterministic value

4. The related content of the Highway Capacity Manual (2000) should be updated according to the results of this research. These results are obtained from a

comprehensive study on accident capacity reduction and are modeled as random variables instead of deterministic values based on the extensive traffic flow and accident data for the Hampton Roads region of Virginia in the Smart Travel Laboratory of the University of Virginia. There are significant improvements of this research over Goolby's study.

5.2 Contributions of This Work

This research conducted a comprehensive study on accident capacity reduction and made significant improvements over previous research. The main contributions of this work include:

1. Developing the comprehensive methodology and process to estimate accident capacity reduction.
2. Updating the mean values of accident capacity reduction with one lane and two lanes out of three lanes blocked based on the comprehensive methodology and process and sufficient observed data set. These values are more reliable than the results of previous research.
3. Modeling accident capacity reduction as a random variable, not a deterministic value. This form of a model will more effectively support the incident management systems, advanced traveler information systems, queuing analysis, computer simulation models and so on.
4. Providing useful information to update the related contents in the Highway Capacity Manual (2000). This research has been proved to be a significant improvement over previous research and the results will be useful for further research on incidents and practice in incident management.
5. Providing a good example for ITS research. Extensive data are now available through previous effort in ITS area. Researches need to be conducted to extract useful information from these data to help improve transportation management.

5.3 Suggested Future Research

5.3.1 Improving the Quality of the Data from the Smart Travel Laboratory

One problem about the quality of the data from the Smart Travel Laboratory encountered in this research is the various data entries for the lane(s) blocked by the incidents. Sometimes there exists obvious mistake. For example, some records indicate that lane four or five was blocked by the incident. But actually, there are only a total of three lanes of the segments of Hampton Roads where the incident occurred. Some records indicate that mainlines were blocked by the incident. It is hard to decide how many lanes were blocked. Some records indicate that three lanes out of three lanes were all blocked by the incident, but the traffic flow during the incident was still relatively high. This problem affects the accuracy of the estimation of accident capacity reduction because these estimations were based on the categorization of one lane or two lanes out of three lanes blocked by the accident.

5.3.2 Future Research Efforts

5.3.2.1 Improving the Methodology Used in This Research

The main drawback of the methodology used in this research is that it cannot detect small accident capacity reduction, For example, there are 52 cases with significant capacity reduction with shoulder lane(s) out of three lanes blocked by the accidents in the incident database of the Smart Travel Laboratory. But there are still 79 cases which might have small capacity reduction that cannot be detected by the methodology of this research. When the traffic demand right before the accident occurred are very high, it is very possible that the capacity was reached when the accident occurred. The methodology used in this research should be improved to detect small accident capacity reduction in order for a more complete study on accident.

5.3.2.2 Improving Traffic Condition Forecasting

Efforts have been devoted into the forecasting of traffic flow in the Smart Travel Laboratory. These efforts are very meaningful because effective strategies can be employed to improve the performance of the transportation system if the traffic conditions can be forecasted accurately. These efforts have not incorporated the significant impact of incidents on traffic flow. Further research can be conducted on forecasting traffic flow incorporating the impact of incident on traffic flow.

5.5.2.3 Further Research on the Impact of Incidents on Traffic Flow

As discussed in Chapter Two, evaluation of the impact of incident on traffic flow is very important for good traffic management within incident management systems. This research focuses on computing and modeling accident capacity reduction as a random variable. There are still some important things unknown on the impact of incident on traffic flow in the transportation systems. For example, it will be useful for us to detect the occurrence of incident from incident traffic flow data. Furthermore, the incident will not only affect the traffic flow near the sites of occurrence, but also the traffic flow of the whole transportation system. Also, the management strategies used to release the congestion caused by the incident will also have impact on the traffic flow of the whole transportation system. The impact of incident on traffic flow should be evaluated in temporal, spatial, and interactive transportation system.

5.4 Summary

This chapter draws the conclusions of this research. Based on the comparison of the methodology and results of this research and those of previous work on this topic, it is recommended that the related contents of the Highway Capacity Manual (2000) should be updated according to the results of this research. Then, the contributions of this work are presented. Finally, future researches are suggested.

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