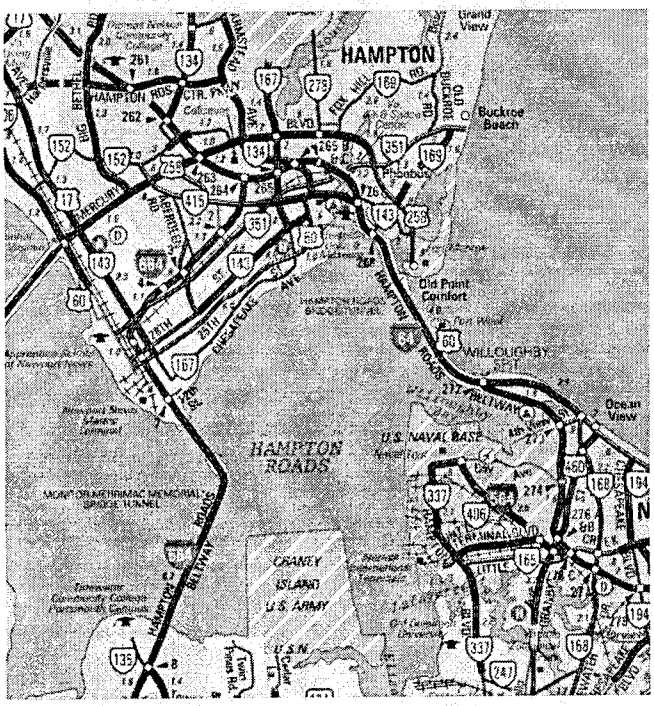
PB2002-107975

FINAL REPORT

FEASIBILITY OF INCORPORATING CRASH RISK IN DEVELOPING CONGESTION MITIGATION MEASURES FOR INTERSTATE HIGHWAYS: A CASE STUDY OF THE HAMPTON ROADS AREA



NICHOLAS J. GARBER, Ph.D.
Faculty Research Scientist
and Professor of Civil Engineering

SANKAR SUBRAMANYAN
Graduate Research Assistant

V · I · R · G · I · N · I · A
VTRC
TRANSPORTATION RESEARCH COUNCIL

VIRGINIA TRANSPORTATION RESEARCH COUNCIL

Reproduced from
best available copy.

PROTECTED UNDER INTERNATIONAL COPYRIGHT
ALL RIGHTS RESERVED
NATIONAL TECHNICAL INFORMATION SERVICE
U.S. DEPARTMENT OF COMMERCE

REPRODUCED BY:
U.S. Department of Commerce
National Technical Information Service
Springfield, Virginia 22161

Standard Title Page - Report on Federally Funded Project

1. Report No. FHWA/VTRC 02-R17	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Feasibility of Incorporating Crash Risk in Developing Congestion Mitigation Measures for Interstate Highways: A Case Study of the Hampton Roads Area		5. Report Date June 2002 6. Performing Organization Code
7. Author(s) Nicholas J. Garber and Sankar Subramanyan		8. Performing Organization Report No. VTRC 02-R17
9. Performing Organization and Address Virginia Transportation Research Council 530 Edgemont Road Charlottesville, VA 22903		10. Work Unit No. (TRAIS) 11. Contract or Grant No. UPC 0005463-6940
12. Sponsoring Agencies' Name and Address Virginia Department of Transportation 1401 E. Broad Street Richmond, VA 23219 FHWA P.O. Box 10249 Richmond, VA 23240		13. Type of Report and Period Covered Final Report 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

A relationship between traffic flow variables and crash characteristics can greatly help the traffic engineer in the field to arrive at appropriate congestion mitigation measures that not only alleviate congestion and save time but also reduce the probability of crashes. Currently, no such decision support tool is readily available to traffic engineers who now mainly make vital decisions using their experience and intuition.

This project investigated the feasibility of developing a methodology in which real-time data can be used to decide on diversion strategies that also consider crash risk. Models showing the interaction between flow and density (occupancy) and the relationship of these traffic flow parameters to crash characteristics were developed for specific sites in the Hampton Roads area of Virginia. These models were then used as the basis for developing a methodology that incorporates crash risk in identifying congestion strategies that consider crash risk.

The results show that it is feasible to incorporate crash risk in developing congestion mitigation strategies. To use the methodology developed in this study, it is necessary to develop the appropriate models for each site that relate flow and occupancy and crashes and occupancy.

17 Key Words Congestion mitigation, crash risk, real-time data	18. Distribution Statement No restrictions. This document is available to the public through NTIS, Springfield, VA 22161.		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 30	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

FINAL REPORT

FEASIBILITY OF INCORPORATING CRASH RISK IN DEVELOPING CONGESTION MITIGATION MEASURES FOR INTERSTATE HIGHWAYS: A CASE STUDY OF THE HAMPTON ROADS AREA

Nicholas J. Garber, Ph.D.
Faculty Research Scientist
and
Professor of Civil Engineering

Sankar Subramanyan
Graduate Research Assistant

Virginia Transportation Research Council
(A Cooperative Organization Sponsored Jointly by the
Virginia Department of Transportation and
the University of Virginia)

In Cooperation with the U.S. Department of Transportation
Federal Highway Administration

Charlottesville, Virginia

June 2002
VTRC 02-R17

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Virginia Department of Transportation, the Commonwealth Transportation Board, or the Federal Highway Administration. This report does not constitute a standard, specification, or regulation.

NTIS is authorized to reproduce and sell this report. Permission for further reproduction must be obtained from the copyright owner.

Copyright 2002 by the Commonwealth of Virginia.

ABSTRACT

A relationship between traffic flow variables and crash characteristics can greatly help the traffic engineer in the field to arrive at appropriate congestion mitigation measures that not only alleviate congestion and save time but also reduce the probability of crashes. Currently, no such decision support tool is readily available to traffic engineers who now mainly make vital decisions using their experience and intuition.

This project investigated the feasibility of developing a methodology in which real-time data can be used to decide on diversion strategies that also consider crash risk. Models showing the interaction between flow and density (occupancy) and the relationship of these traffic flow parameters to crash characteristics were developed for specific sites in the Hampton Roads area of Virginia. These models were then used as the basis for developing a methodology that incorporates crash risk in identifying congestion strategies that consider crash risk.

The results show that it is feasible to incorporate crash risk in developing congestion mitigation strategies. To use the methodology developed in this study, it is necessary to develop the appropriate models for each site that relate flow and occupancy and crashes and occupancy.

FINAL REPORT

FEASIBILITY OF INCORPORATING CRASH RISK IN DEVELOPING CONGESTION MITIGATION MEASURES FOR INTERSTATE HIGHWAYS: A CASE STUDY OF THE HAMPTON ROADS AREA

Nicholas J. Garber, Ph.D.
Faculty Research Scientist
and
Professor of Civil Engineering

Sankar Subramanyan
Graduate Research Assistant

INTRODUCTION

The use of real-time data for congestion forecasting and management is expected to increase significantly in the next few years. It is, however, essential that crash risk be incorporated in congestion management. Most of the research in crash modeling has focused on developing analytical models to predict crashes and relate them to speed variance and other geometric characteristics. However, not much research has been done to relate the real-time traffic data obtained from the Virginia Department of Transportation's (VDOT) Smart Traffic Centers to crashes. This type of relationship can be used to study the impact of congestion mitigation strategies, for example, traffic diversion, on crashes. The hypothesis is that diverting traffic from one highway to another may have a significant impact on the probability of crashes on one or both highways.

Many research projects conducted in traffic flow modeling relate the three basic flow variables (speed, density, and flow). However, not much research has been done to ascertain the relationship of these traffic flow variables to crash characteristics. It is important to develop models that describe the relationship between crash characteristics and the three basic traffic flow variables for which real-time data can be obtained at the Smart Traffic Centers. Such models would greatly enhance the selection of appropriate congestion mitigation measures that would not only alleviate congestion and save time but also reduce the probability of crashes. Currently, no such decision-support tool is readily available. Engineers make the vital decisions regarding traffic diversion and congestion mitigation based on their experience and intuition.

PURPOSE AND SCOPE

The objective of this project was to investigate the feasibility of developing a methodology in which real-time data could be used to decide on mitigation strategies that also consider crash risk. This study investigated the feasibility of developing such a decision-support tool using the Hampton Roads area of Virginia as a case study.

The Hampton Roads area was used in this project because real-time traffic data from the Hampton Roads Smart Traffic Center were available in the Smart Travel Laboratory of the University of Virginia and the Virginia Transportation Research Council (VTRC).

The objectives of this study were as follows:

- Determine the relationship between time mean speed and space mean speed as a precursor for the modeling effort.
- Develop relationship between time mean speed and occupancy.
- Develop traffic flow models relating occupancy and flow.
- Establish relationships between the occupancy and the number of crashes.
- Evaluate the feasibility of incorporating crash risk in selecting strategies for congestion mitigation.

METHODOLOGY AND RESULTS

To achieve the objectives of the study, a methodology was used that consisted of six tasks:

1. A literature review was conducted to identify research in traffic flow and crash modeling.
2. Sites in the Hampton Roads area were identified for which adequate crash data (to carry out crash modeling) and consistent traffic flow data were available.
3. Spot speed data were collected at these sites.
4. The relationship between time mean speed and space mean speed for each site was developed.
5. The relationship between flow and occupancy for each study site was developed.
6. The relationship among flow, occupancy, and number of crashes for each site was established.
7. A procedure for identifying congestion mitigation measures was developed using the relationship among flow, occupancy, and number of crashes for the selected sites.

Task 1: Literature Review

A review of research in traffic flow modeling and crash modeling was carried out using the Transportation Research Information Service (TRIS) and sources at the VTRC Library and the University of Virginia Library. Several traffic flow models (both single regime and multi regime) that relate flow, speed, and density were identified. Research in crash modeling and relating crash characteristics to traffic flow variables was also identified.

Traffic Flow Modeling

Traffic stream models provide the fundamental relationships of macroscopic traffic stream characteristics, which include flow, speed, and density characteristics. Macroscopic traffic flow models describe the traffic flow in terms of these three flow variables and are generally adequate for most practical purposes and have been widely used in the planning, design, and operation of transportation facilities.[1] These relationships are for uncongested (low occupancies with demand traffic flow less than or approaching capacity) and congested (higher occupancies with demand traffic flow higher than capacity or approaching jam condition) flow conditions.

Macroscopic models can be broadly classified into two groups: single-regime and multi-regime models. Single-regime models,[1-21] for example the Greenshield model, represent the uncongested and congested flow regimes with a single model. The early macroscopic models were single-regime models. Multi-regime models represent the uncongested flow and congested flow regimes with separate models.

The microscopic modeling of traffic characteristics is concerned with the individual time headways between vehicles, speeds of individual vehicles passing a point or short segment during a specified period, and the individual distance headways between vehicles. The car-following models, which describe how one vehicle follows another vehicle, are microscopic models. The car-following models developed by the researchers at General Motors[1] take the form:

$$\text{Response} = f(\text{sensitivity, stimulus}).$$

The response is represented by the acceleration (or deceleration) of the following vehicle and the stimulus represented by the relative velocity of the lead and following vehicle. These models are of particular importance as they facilitated the discovery of the mathematical bridge between microscopic and macroscopic theories of traffic flow.

Crash Rates and Traffic Characteristics

Crash Rate Vs. Traffic Volume

Several studies were identified that relate crash rates and traffic volumes.[22-29] It has been generally assumed that crash rates increase with increasing traffic volume, the reasoning being

that the higher interaction among vehicles at higher volumes increases the probability of crashes. However, several research efforts have shown the opposite to be true. Intuitively this seems to be true as the crash rate of reported crashes should start decreasing once the demand flow reaches a certain level (congested condition) and the traffic enters a stop and go phase.

Studies by Pfundt[22] and Gwynn[23] showed a U-shaped relationship between crash rate and traffic volumes. The U-shaped curve indicates that the crash rates are higher when the traffic volume is either very high or very low. Several other studies by Hall and Pendelton[24] and Brodsky and Hakkert[25] provided possible explanations for this phenomenon. As identified in these studies, under very high traffic volumes, all vehicles travel at about the same lower speed, which in turn decreases the speed variance, resulting in lower crash rates.

Several models have related expected crash frequency (number of crashes per unit time) to traffic flow (number of vehicles per unit time). A few of these were identified in the research work carried out by Abraham and Hauer.[26] These include the exponential model and the quadratic model. The exponential function is the most commonly used. With this model, the crash frequency always increases with traffic volume. Hence, this model cannot be used to predict single vehicle crash rates as these rates do not indefinitely increase in volume. The quadratic function is less commonly used. Its main advantage is that it can represent the situation when the expected number of crashes decreases after a particular traffic flow is reached.

Lundy[27] found that the crash rates for four-, six-, and eight-lane freeways normally increase with an increasing average daily traffic (ADT). In addition, the rate of increase in crashes per 10,000 vehicles was higher for four-lane highways than for six-lane and eight-lane highways.

The Poisson regression model developed by Jovanis and Chang[28] reveals that automobile and truck crashes are directly related to automobile and truck travel. It also reveals a decrease in the auto-auto collisions and an increase in the auto-truck collisions as the truck vehicle miles traveled (VMT) increases.

Hall and Pendelton[24] determined the relationship between the hourly crash rates and the ratio of traffic volume to capacity (v/c). Though the v/c rarely exceeded 0.5, an interesting result was obtained from this study. Crash rates decrease with increasing volumes and v/c up to 0.5. The highest crash rates occurred between 2 A.M. and 5 A.M. when the traffic volume was the least. However, these were single-vehicle crashes and were attributed to the dark driving conditions.

Brodsky and Hakkert[25] obtained contradictory results in their study in which they determined the relationship between crash rates and traffic volumes. Their analysis of primary and secondary highways showed that the injury crash rates increased with increasing traffic volumes. However, the relationship is the opposite for interstate highways. This is attributed to the minimal chances of head-on multi-vehicle and pedestrian crashes on divided interstate highways compared to primary and secondary highways.

Persaud et al.[29] used an exponent for the traffic volume to estimate the expected number of crashes in their study to evaluate safety in Ontario, Canada.

Crash Rate Vs Speed of Traffic

The average speed, posted speed limit, and speed standard deviation are the important speed characteristics that studies have identified as affecting the crash rates at a given location. A study on speed and crashes by the Research Triangle Institute[30] identified the extent to which the speed deviation from the mean speed plays an important role in crash rates. The study revealed that the probability of crashes increases with increasing deviation from the average speed. This was also cited as the reason for the increased crash rates at lower volumes in several studies that developed models describing the relationship between crash rates and traffic volumes.[30-32]

Garber and Gadiraju[31] found that the speed variance decreases as average speed increases. In addition, their research revealed that the crash rate increases with increasing speed variance for all road types and that the crash rate does not necessarily increase with an increase in the average speed on the highways.

In a study by Garber and Ehrhart,[32] models relating the crash rates to the speed, flow, and geometric characteristics were developed for different types of highways. The research considered data from freeways (104.7 and 88.6 km/h [65 and 55 mph]) and four-lane and two-lane non-freeways in Virginia. The research revealed that linear and robust regression models did not adequately relate speed and crash characteristics. However, the multivariate ratio of polynomial form was successful in describing the relationships among crash rate and speed standard deviation, mean speed, and flow per lane. For the four types of highways considered, specific models relating the crash rates to speed, speed standard deviation, and flow per lane were developed. The results established that the crash rate is not linearly related to speed characteristics but is related in a complicated fashion. In addition, the developed models of the multivariate ratio of polynomial form showed distinct trends between the speed, flow, and geometric characteristics and the crash rate, which can be used to control the occurrence of crashes. Garber and Joshua[33] investigated the major factors associated with large truck crashes, including the effect of highway facility type and geometry and percentage of trucks in the traffic stream, and developed mathematical models relating these factors to the probability of crash occurrence

Summary

The nature of the traffic models differs from one site to another on the same highway depending on the geometric and traffic characteristics of the site and the time for which data were collected. Hence, it is important to specify when and where on the roadway the data were collected to allow a clear understanding of the relationship between the traffic flow variables.

The literature on crash and traffic characteristics was inconsistent in relating traffic volume to crash rates. Although some studies indicated an increase in crash rate with increasing

volume, others indicated otherwise. The literature review also identified the standard deviation of speed to be an important speed characteristic that affects crash rate. Although research has related crash rates to traffic volumes and highway geometric characteristics, very little research has been done to relate number of crashes to the flow or occupancy. Garber and Ehrhart[32] identified several models that relate crash rates to speed and flow characteristics. However, this effort resulted in very complicated models that cannot be easily used by the engineer in the field.

Task 2: Identifying the Study Sites

The first step was to identify several sites in the Hampton Roads area for which consistent traffic flow data were available through the Smart Travel Laboratory. These sites were chosen from I-64 and I-264. Since the main objective of the study was to relate the flow variables to crash rates for the highways, the selection of the sites also depended on the availability of complete crash records for the 4 years (1995, 1996, 1997, and 1998) used in the study. The crash data were obtained from VDOT's Highway Traffic Records Information System (HTRIS) database. The following were the four criteria considered in identifying the study sites:

1. availability of consistent traffic data from the Smart Travel Laboratory
2. availability of crash data for at least 40 crashes (to allow meaningful crash models) from the HTRIS database
3. sufficient distance from ramps and interchanges (at least 0.2 mi) to be considered a basic freeway segment
4. availability of a safe location to collect the spot speed data in the field.

Based on these criteria, the nine sites listed in Table 1 were chosen. Table 1 also gives the interstate on which each site is located and the major roads on either end of the location. The station ID gives the ID of the detector station located on the site. The length of the site is the distance between the ramps (major roads) on either side. Of the nine sites, only four could be used for the study (see Table 2) because the sensors at the other sites were not functioning properly.

Table 1. Initial Sites Considered

Site No.	Location	Length (m) (ft)	Station ID
1	64W: Bay Ave. & Granby St.	1402 (4600)	125
2	64W: I-264 & Indian River Rd.	3353 (11000)	4
3	64W: I-264 & Rt. 13	2467 (8100)	40
4	64E: 1-94 & Norview Ave.	1158 (3800)	83
5	64E: I-264 & Indian River Rd.	3353 (11000)	22
6	264W: Independence & Rosemont	3200 (10500)	183
7	264W: Rosemont & Lynnhaven	2286 (7500)	194
8	264E: Independence & Rosemont	3200 (10500)	182
9	264E: Rosemont & Lynnhaven	2286 (7500)	195

Table 2. Final Study Sites

Site	Location	Station
1	64W: I-264 & Indian River Rd.	4
2	64E: I-264 & Indian River Rd.	22
3	264W: Independence & Rosemont	183
4	264E: Independence & Rosemont	182

Task 3: Data Collection

This step involved the following three subtasks:

1. collection of spot speed data for the chosen sites in the field to compute space mean and time mean speeds

2. compilation of the traffic flow data (time mean speed, flow, and occupancy) for the selected sites from the Smart Travel Laboratory

3. compilation of the crash data for the selected sites from the HTRIS database.

Spot Speed Data

The models are based on time mean speed and occupancy rather than the more commonly used variables of space mean speed and density in theoretical models. Occupancy and time mean speed were used in developing the models as they could be obtained directly from the Smart Travel Laboratory and are readily available to traffic engineers for decision making.

To collect the spot speed data in the field, a computer program was written that assigned a time stamp to each spot speed entered into the computer. This was of particular importance as it allowed for the computing time mean speed and space mean speed for a specific time interval and modeling the relationship between the two speeds.

A laser gun with an accuracy of ∀1.6 km/h (1 mph) was used to collect the spot speed data in the field. At each of the nine initial sites, a safe spot was identified to collect the field data during a preliminary tour. The person who operated the laser gun called out the spot speed-reading, which was entered into the computer immediately. The program that was running in the computer automatically assigned the time when the speed was recorded (the lag between the time when the vehicle was spotted and the time it was entered in the computer was negligible). Spot speeds were collected for time periods ranging from 75 to 90 min at the nine sites.

The spot speeds were collected only for the vehicles on the outer lane. This is because the angle at which the laser beam hits the vehicle influences the spot speed recording greatly (known as the cosine effect). The greater the angle, the greater is the error in the laser gun reading. As it is not possible to keep this angle to acceptable levels for the inner lanes because of the short length of the highway under consideration, it was decided that the spot speeds of the

outer lane vehicles only would be collected. Also, since the objective of this study was only to develop models relating the time mean and space mean speeds computed from the spot speeds, the lane from which the data were collected did not affect the analysis.

Traffic Data from the Smart Travel Laboratory

The Smart Travel Laboratory is connected to the Hampton Roads Smart Traffic Center and the Northern Virginia Smart Traffic Center. The laboratory receives time mean speed, traffic volume, and occupancy data from the 203 detector stations on 31 km (19 mi) of freeway and associated interchanges in the I-264/I-64 corridor (this corresponds to more than 1,200 loop detectors) in the Hampton Roads system. The laboratory receives the traffic flow data every 2 min from the detector stations, and these data are archived in an Oracle database.

By identifying the station numbers at the chosen sites, the traffic flow data were thus obtained directly from the Smart Travel Laboratory in a spreadsheet format. This allowed for the selection of specific time periods that had reasonable traffic data for modeling purposes.

Data Mining and Data Screening

Data screening tests developed by Turochy and Smith[34] were used to eliminate erroneous data from the traffic database. The following five criteria were used to eliminate potentially erroneous data:

1. occupancy maximum threshold (90%)
2. collection length minimum threshold (90 seconds)
3. average vehicle length (AVL) minimum and maximum thresholds (9 and 60 ft)
4. maximum volume threshold for records with zero occupancy (set at corresponding volume for an average vehicle length of 10 ft and 2% occupancy)
5. overall maximum volume threshold (3,100 vehicles per hour per lane).

The threshold values used for the criteria were obtained from research in data screening for traffic management systems[34] and the range of data obtained from the Smart Travel Laboratory (i.e., the minimum and the maximum values for each parameter from the Smart Travel Laboratory database). In addition, prescreening consisted of identifying records with negative values in speed, volume, or occupancy. Thus, records with negative speed, flow, or occupancy were eliminated. The occupancy stuck (i.e., occupancy remains at the same level for an unreasonably long period of time) phenomenon was also included in the final screening test module. This test eliminates records in which the occupancy appears to be stuck at a particular value.

The Excel database generated by the AnalyX tool, a software application developed in the laboratory to access and process data in the Oracle database, has the same fields as the original file, which include the following:

1. data and time of the traffic data
2. station ID
3. sensor number (each station has more than one sensor corresponding to the number of lanes at the location)
4. collection length, which indicates the time period for which the traffic data were collected
5. number of vehicles spotted during the collection length
6. time mean speed (in mph) of the vehicles spotted during the collection length
7. occupancy of the vehicles (in %) spotted during the collection length
8. incident ID.

Table 3 shows part of the Excel file for the site on I-264E represented by station 182, and Table 4 gives the description of the fields. The incident ID field was the only field that was not used in this project. The incident ID field data are incorrect and do not represent the incidents at the detector stations. Crash data for the different sites were obtained from the HTRIS database.

Table 3. Traffic Flow Data from Smart Travel Laboratory

DATEX	SENS ORID	SPEED	VOLUME	OCC	COLLLENGHT	LANESWIDTH	INCIENTID
11/2/99 8:00	182	43	111	4	123	4	0
11/2/99 8:02	182	54	95	3	118	4	0
11/2/99 8:04	182	53	104	3	130	4	0
11/2/99 8:06	182	52	97	3	122	4	0
11/2/99 8:08	182	48	86	4	117	4	0
11/2/99 8:10	182	51	95	3	122	4	0
11/2/99 8:12	182	44	115	4	117	4	0

Table 4. Fields in Smart Travel Laboratory Traffic Database

Field	Remarks
DATEX	Date and time
SENSORID	Station number
SPEED	Time mean speed (in mph)
VOLUME	Number of vehicles detected
OCC	Occupancy (in %)
COLLLENGTH	Collection length (in sec)
LANESWIDTH	Number of lanes reporting data
INCIDENTID	Incident ID

Data Reduction

The traffic data for the four chosen study sites were obtained from the database using the AnalyX software. The next step was to reduce the data to develop the traffic flow models. Only the weekday traffic flow data were included for the final study. Time mean speed and occupancy were used in the modeling step. Hence, these two fields required no conversion and were used directly. The volume was converted to equivalent hourly flow by use of the following formula

Equivalent hourly flow = (Number of vehicles)*3,600/(Collection length in sec)

Table 5 shows the number of records included in modeling the traffic flow for the selected sites. Each record corresponds to a flow, occupancy, and speed value for a 2-min interval obtained from the Smart Travel Laboratory database. Figures 1 through 3 show the final scatter plots for flow versus occupancy, speed versus flow, and speed versus occupancy respectively for site 1. These scatter plots are similar to those identified in several research efforts involving freeway segments.[1,8,10-12]

Table 5. Number of Traffic Flow Records for Study Sites

Site No.	Station No.	No. Records
1	4	6,443
2	22	8,367
3	183	5,996
4	182	10,513

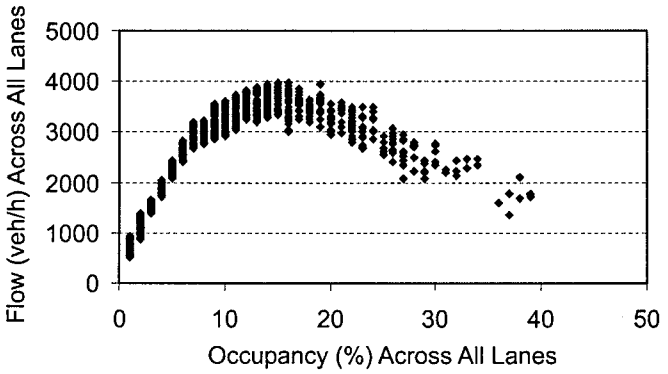


Figure 1. Flow vs. Occupancy Scatter Plot for Site 1

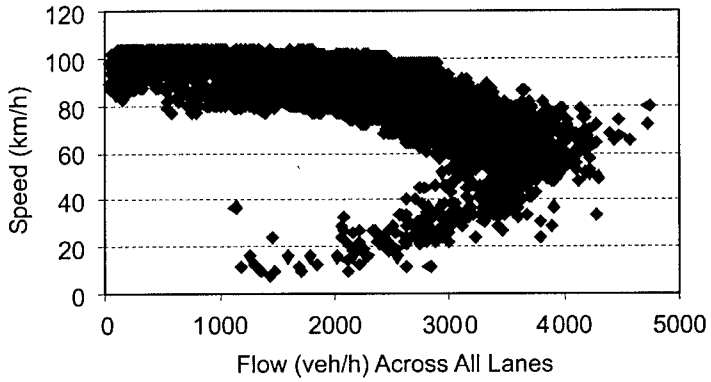


Figure 2. Speed vs. Flow Scatter Plot for Site 1

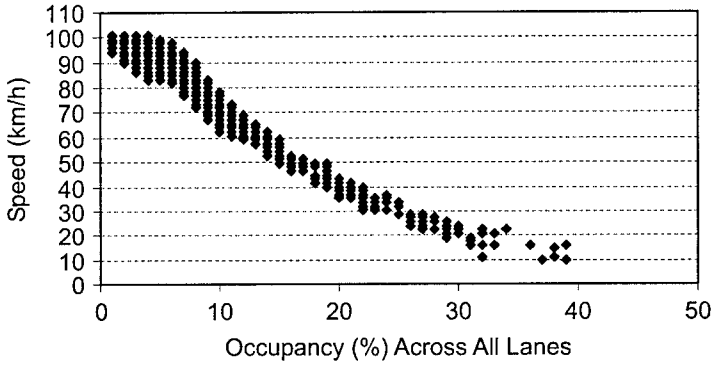


Figure 3. Speed vs. Occupancy Scatter Plot for Site 1

Crash Data from HTRIS Database

The crash data for the four sites were obtained from the HTRIS database and the police reports. The police reports were used to obtain the crash ID for each crash at each site. The crash ID was then used to obtain other details about the crash such as time and date of occurrence, distance from the interchange, type of accident, and number of vehicles involved in the crash from the HTRIS database. A crash database was then developed that had all the acceptable crashes for the different sites (acceptable crashes are those that occurred at a distance of at least 0.32 km (0.2 mi) from the interchange in the basic freeway segment). In addition, only the crashes that occurred during weekdays were included in the study. The estimated time of occurrence of each crash was obtained from the police reports. A sample spreadsheet showing the crash ID and the fields of interest for some of the crashes at the site on I-264E (site 4) is shown in Table 6. Figures 4 through 7 show the hourly distributions of crashes for each site.

Table 6. Crash Data for Site 4 on 44E

Crash ID	Date	Time
950620820	2/13/95	6:39
951372116	5/12/95	18:30
951390823	2/13/95	6:39
951792563	6/19/95	2:20
952350577	8/1/95	8:55
953562071	12/20/95	18:00
953562072	12/20/95	22:00
953562073	12/20/95	17:15

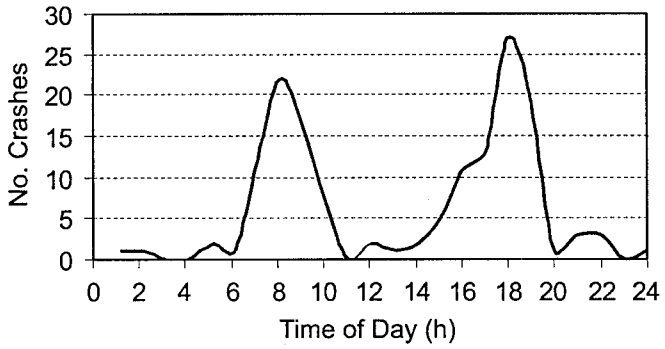


Figure 4. Crash Distribution for Site 1

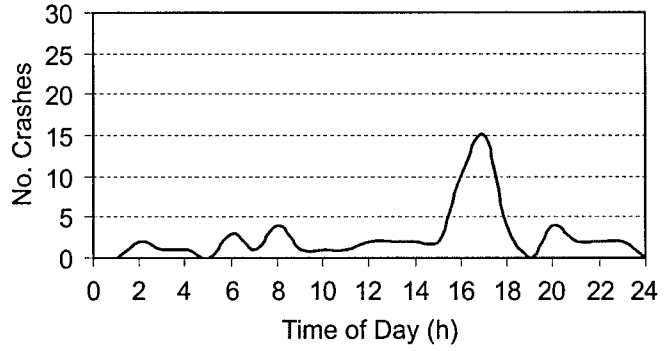


Figure 5. Crash Distribution for Site 2

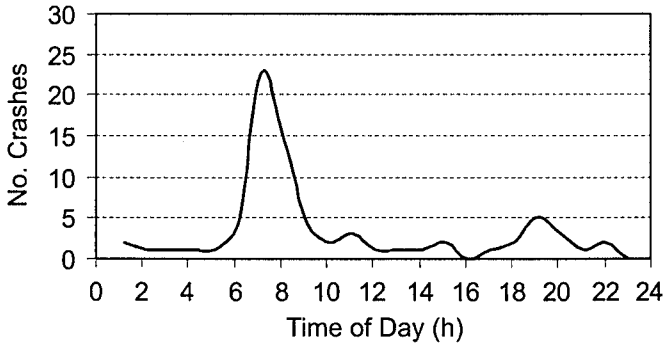


Figure 6. Crash Distribution for Site 3

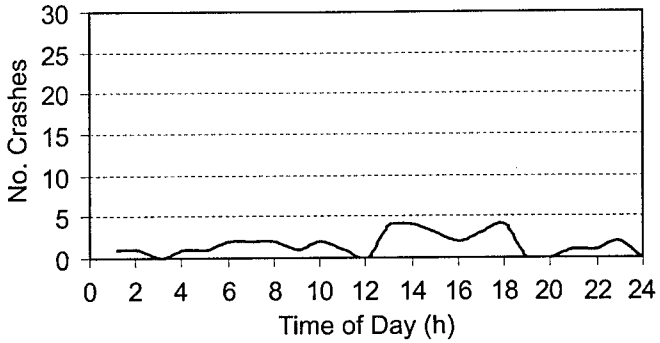


Figure 7. Crash Distribution for Site 4

Task 4: Modeling Time Mean Speed and Space Mean

Models relating the time mean speeds and space mean speeds were obtained for the study sites using regression analysis. Time mean speed, also known as arithmetic mean speed, is defined as the arithmetic mean of the speeds of vehicles passing a point on a highway during an interval of time.[15] Space mean speed, also known as harmonic speed, is defined as the harmonic mean of the speeds of vehicles passing a point on a highway during an interval of time.[15]

The time mean and space mean speeds were computed using the spot speed data collected in the field. As mentioned previously, spot speed data were collected in the field for each site for of 75 to 90 min. The data set was divided into 30-second time bins to compute the time mean and space mean speeds. The arithmetic average of the spot speeds of all vehicles observed during the intervals was used to obtain the time mean speed. Similarly, the harmonic average of the spot speeds of all vehicles observed in the intervals was used to obtain the space mean speed.

The assumption made here was that the speed of the vehicles remained the same over the short distance represented by the 30-sec interval. Since all sites were basic freeway segments and the time interval was small, this assumption was reasonable.

In the next step, curve fitting techniques were used to obtain the model that best represented the computed time mean and space mean speed data. At least 150 data points were used for each site. Linear regression was used to obtain the models for the observed data. Linear regression was used because the observed scatter plots indicated a linear relationship between the two speeds for all the four sites. The R-squared value was used as the criterion for choosing the best model. The analysis was done in two ways. In the first approach, the fitted curved was forced through the origin. This is the general model that relates the time mean speed and the space mean speed obtained from the field spot speed data.

The result of this analysis for site 1 is presented in Figure 8. Similar results were obtained for the other three sites. Table 7 shows the models obtained and the associated R^2 values for each site. The results show that the time mean speed and space mean speed are related by a linear relationship with very little difference between the two for all the basic freeway segments considered in this study. A similar study by Drake et al.[3] also showed a linear relationship between the two speeds for freeway segments with little difference between the two.

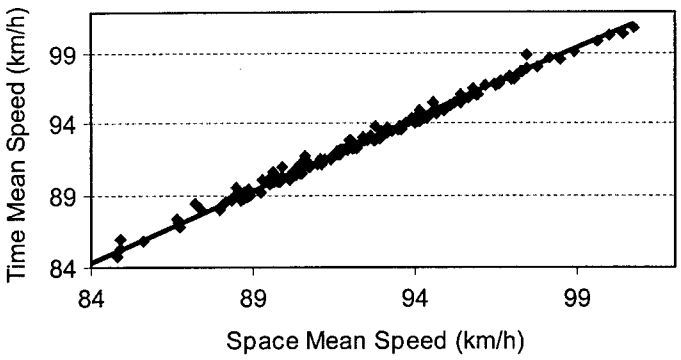


Figure 8. Space Mean Speed vs. Time Mean Speed for Site 1

Table 7. Space Mean Speed vs. Time Mean Speed Relationship (model forced through origin)

Site	Station	Location	Equation	R-Squared
1	4	64W: I-264 & Indian River Rd.	FTM = 1.003*FSM	0.993
2	22	64E: I-264 & Indian River Rd.	FTM = 1.004*FSM	0.992
3	183	264W: Independence & Rosemont	FTM = 1.006*FSM	0.971
4	182	264E: Independence & Rosemont	FTM = 1.004*FSM	0.989

FTM = field time mean speed; FSM = field space mean speed.

These results support the rationale for using time mean speed instead of space mean speed in developing the traffic flow models. As there is an equipment error of approximately ∀1.6 km/h (∀1 mph) in recording the spot speeds in the field, the use of time mean speed instead of space mean speed in traffic flow modeling for basic freeway segments does not introduce a significant statistical error in the analysis. The models developed using time mean speed are more useful to the traffic engineer as he or she has access only to the time mean speed data from the traffic management centers.

In the second approach, the fitted curve was not forced through the origin. These models have an intercept that represents the maximum difference between the time mean and space mean speeds, which occurs at low speeds. In addition, the difference between the two speeds becomes smaller with increasing speed, as can be seen from the equations in Table 8.

Table 8. Space Mean Speed vs. Time Mean Speed Relationship (model not forced through origin)

Site	Station	Location	Equation	R-Squared
1	4	64W: I-264 & Indian River Rd.	FTM = 0.980*FSM + 2.1835	0.993
2	22	64E: I-264 & Indian River Rd.	FTM = 0.966*FSM + 3.5413	0.994
3	183	264W: Independence & Rosemont	FTM = 0.971*FSM + 3.2102	0.976
4	182	264E: Independence & Rosemont	FTM = 0.968*FSM + 3.3222	0.996

FTM = field time mean speed; FSM = field space mean speed.

Task 5: Traffic Flow Modeling

This step involved modeling the relationship between flow and occupancy for the chosen sites. The scatter plots for flow versus occupancy rates were used in developing the flow-occupancy models.

Flow vs. Occupancy Modeling

Visual inspection of the scatter plots for the four sites was used to identify the occupancy at capacity (the occupancy after which the flow starts decreasing from the maximum). In addition, the number of regimes in the flow occupancy model was identified by visual inspection of the scatter plots. The scatter plots indicated a clear two-regime distribution with a marked transition around the observed break point for all four study sites. The breakpoint obtained from visual inspection of each site was used to split the entire range of data points into two regimes: the uncongested and the congested.

The data for the two regimes were analyzed separately. Regression analysis techniques were used to develop the models for the observed data, using the NCSS statistical software package. Non-linear regression was used to obtain the models for the free flow regime as the free-flow regime showed a non-linear pattern for all the sites. Robust regression (a regression technique that identifies outliers and minimizes their impact on the coefficient estimates) was used to obtain the models for the congested regime as the congested regime for all the sites indicated a linear pattern. Models with high R^2 values were obtained for all the sites indicating good fit with the observed data. Three sites (sites 2, 3, and 4) had a second-order parabolic model for the free flow regime and a linear model for the congested flow regime. Site 1 on I-64 West had a third order model for the free flow regime and a linear model for the congested flow regime. The third order model was chosen for site 1 since this model had a highest R^2 value and fitted the observed data the best among all the models considered.

Figures 9 through 12 show the results of the flow versus occupancy modeling for the four sites. Tables 9 and 10 show the model equations and the corresponding R^2 values for the free flow regimes and congested flow regimes for the four sites.

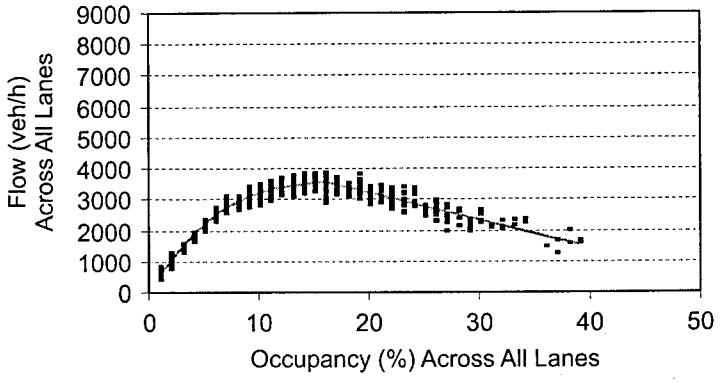


Figure 9. Flow vs. Occupancy Model for Site 1

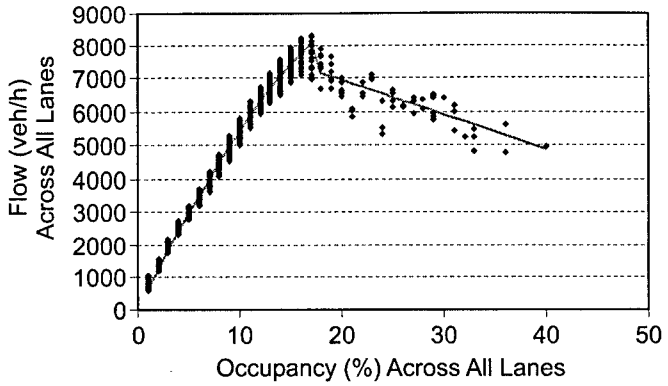


Figure 10. Flow vs. Occupancy Model for Site 2

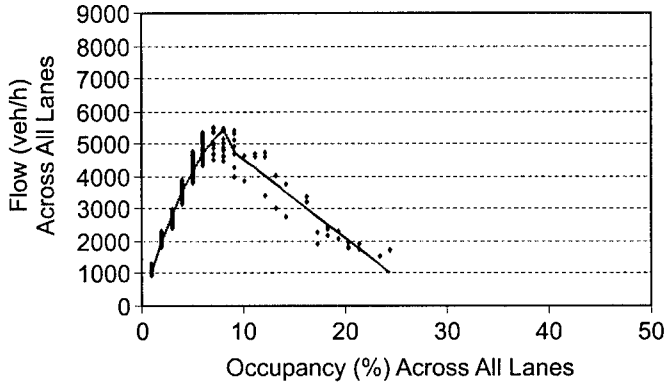


Figure 11. Flow vs. Occupancy Model for Site 3

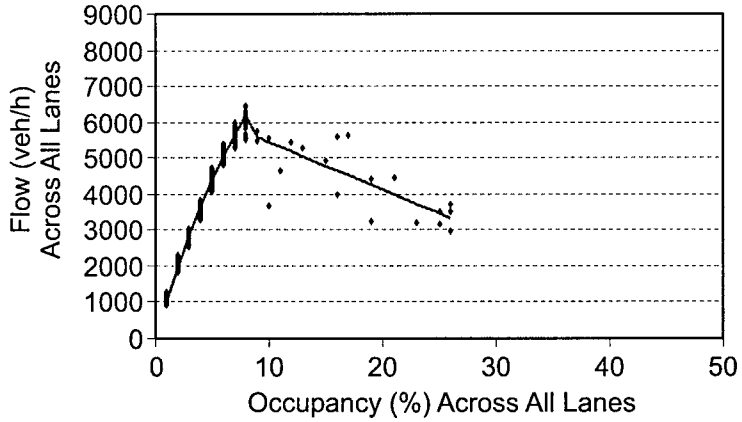


Figure 12. Flow vs. Occupancy Model for Site 4

Table 9. Flow vs. Occupancy Modeling Results: Free Flow Regime

Site	Equation	R-Squared
1	$F = 620.2866*O - 36.4690*O^2 + 0.7487*O^3$	0.97
2	$F = 641.8901*O - 9.8075*O^2$	0.99
3	$F = 1101.652*O - 51.0303*O^2$	0.95
4	$F = 1049.362*O - 34.7705*O^2$	0.98

F = flow, O = occupancy.

Table 10. Flow vs. Occupancy Modeling Results: Congested Flow Regime

Site	Equation	R-Squared
1	F = 5091.255 - 88.5036*O	0.88
2	F = 9003.047 - 103.239*O	0.76
3	F = 7158.766 - 256.035*O	0.93
4	F = 6773.952 - 132.269*O	0.83

F = flow, O = occupancy.

Table 11. Optimum Occupancy and Capacity for Study Sites

Site	Station	No. Lanes	Optimum Occupancy (%)	Capacity (veh/h)
1	4	2	16	3655
2	22	4	17	8078
3	183	4	8	5548
4	182	4	8	6170

Table 11 gives the number of lanes, optimum occupancy (occupancy at maximum flow) and the capacity as predicted by the fitted models (for all the lanes) for the four study sites.

The peak flow values for the two sites on I-64 were between 1,800 and 2,000 vehicles per hour per lane. Using the truck percentages to convert these values to passenger cars per hour per lane yields a peak flows varying between 2,000 and 2,250 passenger cars per hour per lane. These values are similar to those specified in the *Highway Capacity Manual* [8] (HCM) for freeways (the HCM specifies an ideal capacity of 2,300 passenger cars per hour per lane). However, the maximum flows at sites 3 and 4 (both on I-264) were considerably lower than the HCM-specified capacity for freeways. Several factors are identified by the HCM that affect the capacity of a highway. [8] These include the geometric characteristics (lane width, shoulder width, grade), truck percentage, percentage of commuters, spacing of interchanges, free flow speed, and number of lanes. The two sites on I-264 have lanes 3.66 mm (12 ft) wide and shoulders wider than 1.83 mm (6 ft). In addition, the terrain is level with no steep grades, and only weekday traffic data were used for this analysis. Hence, it is reasonable to assume that most of the drivers are commuters. The site has four lanes for each direction (plus one shoulder lane in each direction), and the interchange density is within the limit specified in the HCM (one interchange per 1.609 km [2 mi]) of the highway).[8] The geometric characteristics of the road sections at which sites 3 and 4 were located were therefore not the cause of the relatively low values for the maximum flow at these sites.

To determine whether the truck percentages at sites 3 and 4 affected the maximum flows, field data were collected to obtain the truck percentages at all sites. The results indicated lower truck percentages at sites 3 and 4 than at sites 1 and 2, indicating that the relatively lower values of the peak flows at sites 3 and 4 were not due to the impact of higher truck percentages in the traffic streams.

The HCM also indicates a strong correlation between the capacity of the freeway and the free flow speed.[8] Sites 3 and 4 on I-264 have a lower free flow speed (96.6 km/h [60 mph]) than sites 1 and 2 on I-64, which had a free flow speed of about 104.7 km/h (65 mph). This may be part of the reason for the lower capacity values for these two sites.

Task 6: Relationship Between Occupancy and Crashes

Occupancy vs. Crashes

The crashes and their time of occurrence were obtained from the HTRIS database and the police reports. The HTRIS database gives the time of occurrence of the crash to the nearest hour. Since the estimated time of occurrence of the crash was needed to get the corresponding occupancy value from the traffic database, the police reports were used to get the estimated time of occurrence. Table 12 shows the years and the number of crashes that were used in the final analysis for the four sites.

Table 12. Crash Data for Study Sites

Site No.	Station No.	Years (for Crashes)	No. Crashes
1	4	1996-1998	150
2	22	1996-1998	60
3	183	1995-1998	74
4	182	1995-1998	41

The occupancy values corresponding to the crash times were obtained by averaging the occupancy values for the same times for the different days from the traffic data used in the flow vs. occupancy modeling. The occupancy values thus obtained were broken into bins, and the number of crashes in each of these bins was identified. This result was used to develop the occupancy vs. crash plots. These plots for the four sites are shown in Figures 13 through 16.

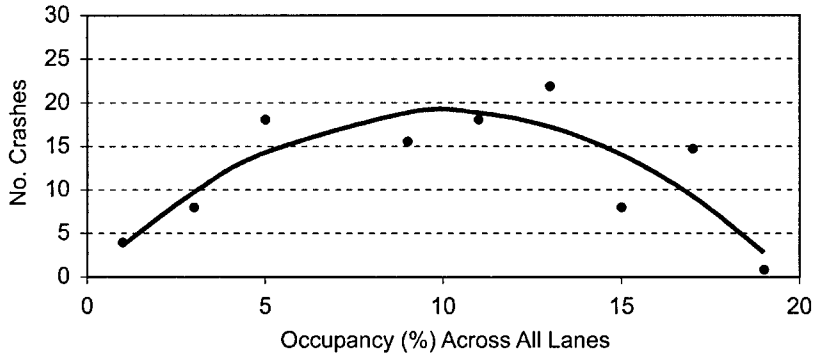


Figure 13. Occupancy vs. Number of Crashes for Site 1

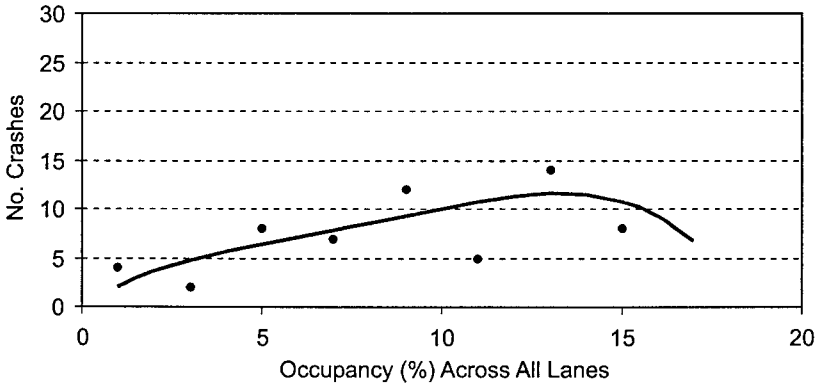


Figure 14. Occupancy vs. Number of Crashes for Site 2

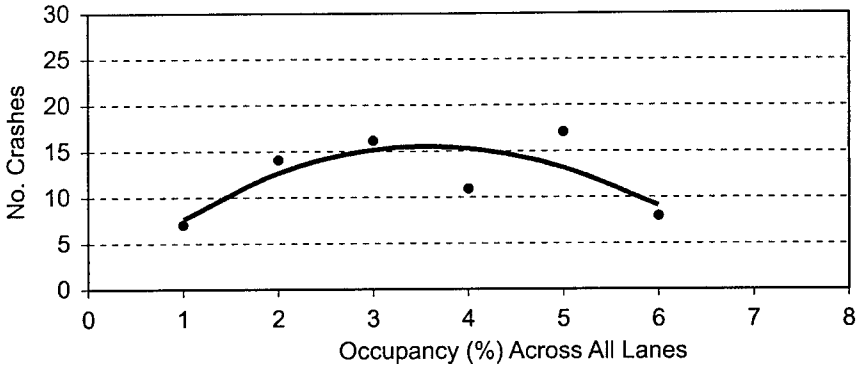


Figure 15. Occupancy vs. Number of Crashes for Site 3

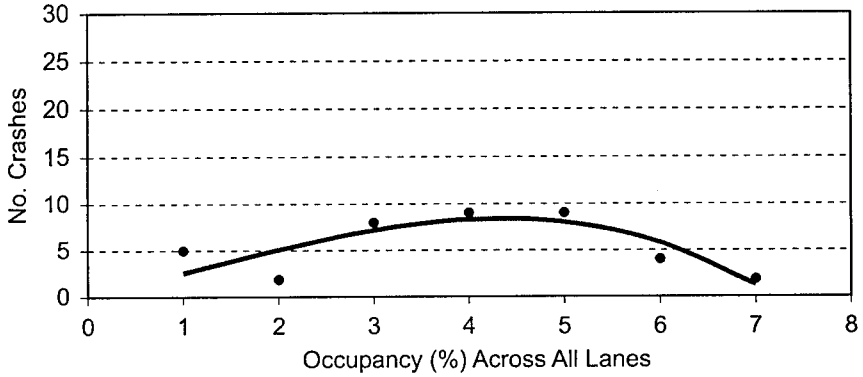


Figure 16. Occupancy vs. Number of Crashes for Site 4

Table 13 shows the non-linear models and the corresponding R^2 values for the crash vs. occupancy models for the four sites. As can be seen, the R^2 values for the crash models are not very high. However, the plot of the number of crashes vs. the occupancy does show a common pattern for the sites. The number of crashes tends to increase with increasing occupancy and reaches a maximum well before the optimum occupancy (at which the flow reaches its maximum value). In addition, almost all the crashes occurred in the uncongested regime.

Table 13. Crash Modeling Results for Study Sites

Site	Station	Equation	R-Squared
1	4	$C = 3.7996*O - 0.1858*O^2 - 0.000336*O^3$	0.70
2	22	$C = 2.3953*O - 0.3729*O^2 + 0.0354*O^3 - 0.0012*O^4$	0.43
3	183	$C = 9.0651*O - 1.4206*O^2 + 0.0271*O^3$	0.57
4	182	$C = 2.3875*O + 0.2399*O^2 - 0.07936*O^3$	0.62

C = number of crashes; O = occupancy.

Speed Variance vs. Crashes

As part of the crash modeling effort, the effect of speed variance on the crashes was also studied. Several research efforts[30-32] revealed a strong correlation between the number of crashes and the speed variance. Hence, it was decided to verify this trend for the four study sites.

The speed data obtained from the Smart Travel Laboratory were the average time mean speed of all vehicles the sensor detects over a 2-min period. Thus, the data do not include the individual speeds of the vehicles. So, the speed variance was calculated using these 2-min average time mean speed data. Though this is not the exact speed variance estimate, it gives a good indication of how the speed variance changes over time of day and with occupancy. The speed vs. occupancy plot described previously was used in this step. For each occupancy value, the variance of all the speed data points (i.e., the 2-min values) was computed and a speed variance vs. occupancy plot was obtained for each site. These plots are presented in Figures 17 through 20. Table 14 shows the speed variance vs. occupancy models and the corresponding R^2 values for the four sites.

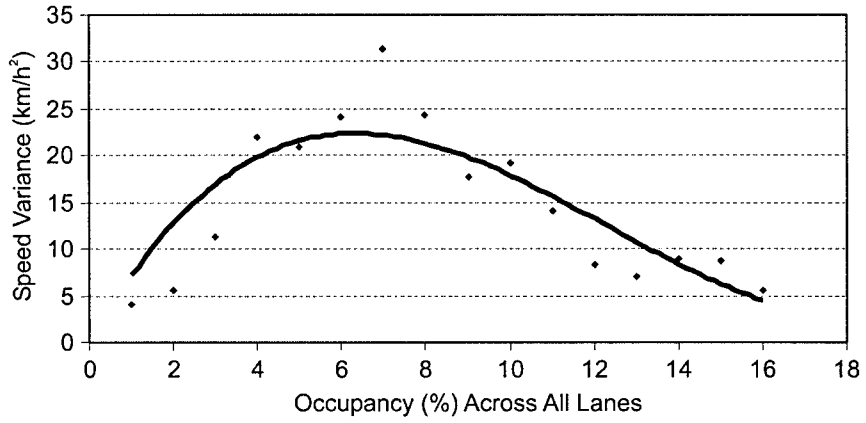


Figure 17. Speed Variance vs. Occupancy for Site 1

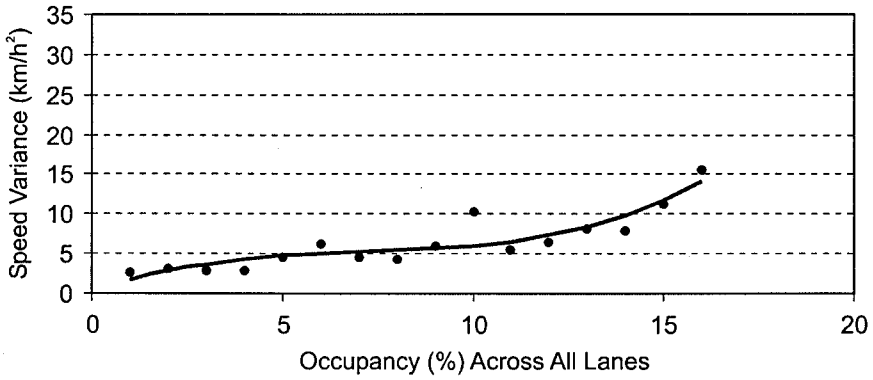


Figure 18. Speed Variance vs. Occupancy for Site 2

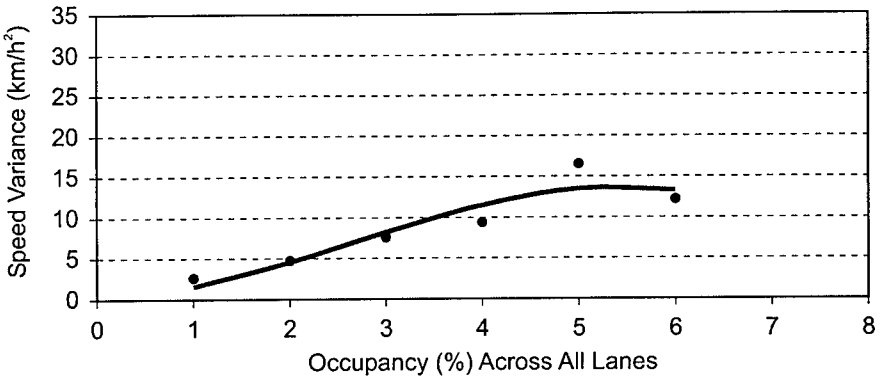


Figure 19. Speed Variance vs. Occupancy for Site 3

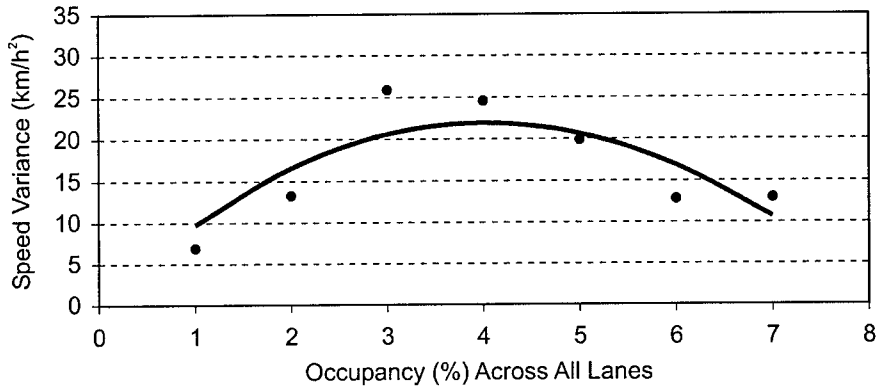


Figure 20. Speed Variance vs. Occupancy for Site 4

Table 14. Speed Variance vs. Occupancy

Site	Station	Equation	R-Squared
1	4	$SV = 7.9933*O - 0.8502*O^2 + 0.023*O^3$	0.76
2	22	$SV = 1.8057*O - 0.2241*O^2 + 0.0104*O^3$	0.82
3	183	$SV = 0.4661*O + 1.2206*O^2 - 0.1548*O^3$	0.86
4	182	$SV = 11.2190*O - 1.4999*O^2 + 0.0165*O^3$	0.74

SV = speed variance; O = occupancy.

The models presented in the Figures 17 through 20 indicate that the speed variance increases with occupancy for all the sites up to a particular value and then starts decreasing. This trend is similar to the relationship between number of crashes and the occupancy for all sites, indicating a strong correlation between speed variance and number of crashes. The speed variance for higher occupancies could not be calculated because of the very few data points at high occupancies in the congested regime. Hence, the models include only the occupancy values in the uncongested regime. However, as seen from the crash models presented previously, most of the crashes occurred in the uncongested regime for all the study sites. Thus, these models show the trend between the speed variance of the traffic stream and its influence on the number of crashes. The trend is in line with results from research[30-32] that show a strong correlation between speed variance and number of crashes.

Task 7: Crash Risk and Congestion Mitigation Strategies

The models developed for number of crashes and occupancy and flow and occupancy for the study sites were used to evaluate the feasibility of incorporating crash risk in identifying congestion mitigation strategies. For all sites, the number of crashes increased with occupancy and reached a maximum before starting to decrease and becoming negligible at high occupancies. This appears to be intuitively correct as congestion sets in at high occupancies and the speeds are considerably lower than the free mean speed. This results in a fewer of crashes at higher occupancies. In addition, most of the crashes occurred in the uncongested regime, where speeds were high and flows were below capacity. In addition, the number of crashes reached a maximum at an occupancy level that was lower than the optimum occupancy. The impact of these results is discussed here for each study site.

Figures 21 through 24 show the flow and number of crashes over occupancy for the four sites. These figures were used to show how a congestion mitigation strategy, in this case traffic diversion, can be implemented while the risk of crashes is also being considered. (The darker curve represents the crash vs. occupancy model, and the lighter curve represents the flow vs. occupancy model.)

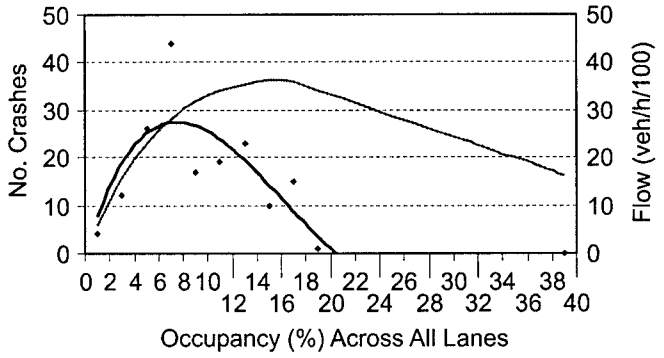


Figure 21. Flow, Number of Crashes vs. Occupancy for Site 1

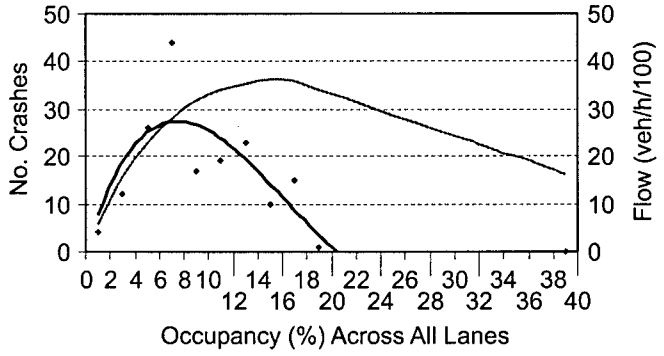


Figure 22. Flow, Number of Crashes vs. Occupancy for Site 2

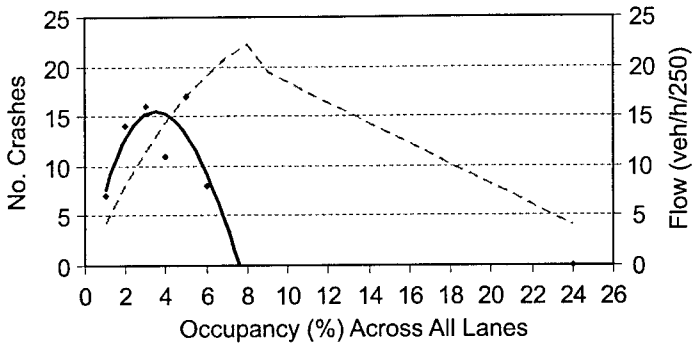


Figure 23. Flow, Number of Crashes vs. Occupancy for Site 3

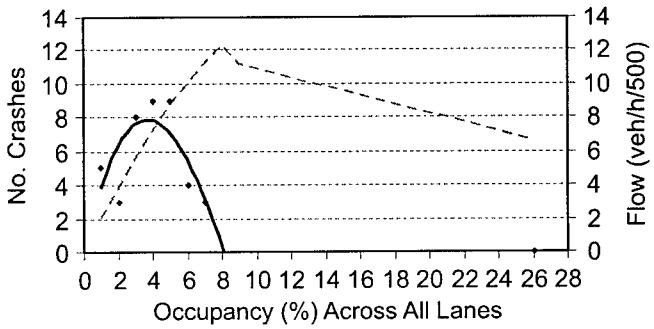


Figure 24. Flow, Number of Crashes vs. Occupancy for Site 4

Number of Crashes, Flow, Occupancy, and Congestion Mitigation Strategies

Site 1: I-64W (Station 4)

Figure 21 shows that the optimal occupancy (at capacity) was about 16 percent whereas the occupancy at which the number of crashes reached a maximum was 7 percent. Only 16 of the 171 crashes occurred at occupancies greater than 16 percent, and none occurred at occupancies greater than 19 percent. For occupancy values between 0 and 7 percent, a reduction in flow decreased the number of crashes. However, at such a low occupancy range, the need for a congestion mitigation strategy is minimal. For occupancy values between 7 and 16 percent (optimum occupancy at capacity), a reduction in flow increased the number of crashes. Beyond 16 percent occupancy, the flow and number of crashes decreased with increasing occupancy.

The area of greatest interest is the occupancy range between 7 and 16 percent. In this region, the number of crashes increased with flow and occupancy. As flows approach capacity, the engineer may want to implement a congestion mitigation strategy (e.g., diversion of traffic) to improve the level of service (LOS) and prevent the onset of congestion and queue buildup. If, for example, the engineer diverts traffic to the extent that the occupancy reduces to 12 percent, the expected number of crashes will increase. Thus, for any occupancy in this range, when traffic is being diverted, the engineer should divert traffic such that the occupancy falls below 7 percent to avoid an increase in the number of crashes.

Site 2: I-64E (Station 22)

Figure 22 shows that the optimal occupancy (at capacity) was 17 percent whereas the occupancy at which the number of crashes reached a maximum was about 12 percent. In addition, all crashes occurred in the uncongested flow regime (occupancy less than 17 percent) and none occurred at occupancies greater than the optimum occupancy. For occupancy values between 0 and 12 percent, a reduction in flow caused a decrease in the number of crashes. However, at such a low occupancy range, the need for reducing traffic volume is minimal. For occupancy values between 12 and 17 percent (optimum occupancy at capacity), a reduction in flow increased the number of crashes. In addition, this is the occupancy range at which the engineer may try to reduce demand by traffic diversion to prevent the onset of congestion. Thus, for any occupancy in this range, the engineer should divert traffic such that the occupancy falls below 12 percent so that there is no significant increase in the number of crashes.

Sites 3 and 4: I-264E and I-264W (Stations 183 and 182)

Figures 23 and 24 show that the optimal occupancy (at capacity) is 8 percent and the occupancy at which the number of crashes peak is about 4 percent. In addition, all crashes occurred in the uncongested flow regime (occupancy less than 8 percent) and none occurred at occupancies greater than the optimum occupancy. For occupancies between 0 and 4 percent, a reduction in flow caused a decrease in the number of crashes. However, at such a low occupancy range, the need for a congestion mitigation strategy is minimal. For occupancies between 4 and 8 percent (optimum occupancy at capacity), a reduction in flow increases the number of crashes.

The area of greatest interest is the occupancy range between 4 and 8 percent. In this region, because of the increasing flow (tending to capacity) and high speeds, the number of crashes increased with increasing flow and occupancy. In addition, this is the occupancy range at which the engineer may want to reduce demand by implementing a congestion mitigation strategy such as traffic diversion to prevent congestion. Thus, for any occupancy in this range, the engineer should divert traffic such that the occupancy falls below 4 percent so that there is no significant increase in the number of crashes.

SUMMARY OF RESULTS

Space Mean Speed vs. Time Mean Speed

The analysis of the space mean speed and time mean speed for the four study sites indicated a linear relationship with little difference between the two. In addition, the difference between the two speeds was high at lower speeds, decreased with increasing speeds, and became negligible at higher speeds.

Flow vs. Occupancy

The flow occupancy models for the four sites indicated a two-regime model. The free flow regime models for sites 2, 3, and 4 were second order with very gentle slopes, indicating a small drop in the speed with flow in this regime. This is consistent with several recent research efforts,[8-10, 33] which also showed a very small drop in speeds until flow tended to capacity. The free flow model for site 1 was a third order model with a greater slope, indicating a greater drop in speed with flow. This site has a very gentle change of slope between the two regimes. A single-regime model was fitted for this site. However, the two-regime model seemed to fit the observed data better than the single-regime model and hence was selected.

The congested flow regime model for all the four sites is linear in nature. This again is consistent with research done in the past.

Number of Crashes Over Occupancy

The distribution of the number of crashes with respect to occupancy yielded similar and interesting results for all sites. The number of crashes tended to increase with increasing occupancy and started dropping after reaching a peak occupancy rates between 4 and 10 percent for all four sites. In addition, the occupancy at which the number of crashes reached its peak was well below the optimum occupancy at which the flow reached the capacity.

Relationship Between Speed Variance and Number of Crashes

The relationship between speed variance and occupancy is similar to that between crashes and occupancy for all the sites, indicating a strong correlation between speed variance and crash characteristics.

GUIDELINES FOR TRAFFIC ENGINEERS

The results of the crash analysis for the selected sites indicate that the number of crashes tends to increase with increasing occupancy until a particular point, which occurs at occupancy rates between 4 and 10 percent. After reaching a peak value, crashes start dropping with increasing occupancy. The occupancy at which crashes reach a maximum is well below the optimum occupancy at which flow reaches capacity. Although the specific values obtained from these models cannot be generalized to all sites, the results indicate a trend in the relationship between crashes and occupancy for freeway segments. In addition, the models indicate the expected changes in the number of crashes with changing flow and occupancy.

The traffic engineer in the field can use suitable traffic flow models to predict the occupancy resulting from diverting a selected volume of traffic. The crash models can then be used to determine whether the new flow and occupancy conditions can be expected to cause an

increased number of crashes. If the diversion does result in an increased number of crashes, carrying out such a diversion may not be very beneficial even though it may reduce travel time.

The increase in the number of crashes per year for a site attributable to the change in flow and occupancy may be small, as can be seen from the developed graphs shown in Figures 21 through 24. The crashes used in developing these models occurred over a period of 2 years for sites 1 and 2 and 3 years for sites 3 and 4. However, if diversions are made during the peak hour on several highways in a highway system, with no consideration to the results of this study, the total increase in the number of crashes attributable to diversions between the highways in the network can be significant. Thus, the benefits of reduced crashes can be significant when the methodology developed in this study is implemented on a systemwide basis. The following procedure can help incorporate crash risk in congestion mitigation strategies for a network of roads:

1. Survey the entire network (including freeways and secondary roads), and divide it into zones with similar traffic and geometric characteristics.

2. Randomly choose sample sites in each zone, and develop traffic flow and crash models.

3. Compare these models for the different sites in the same zone, and develop general flow and crash models for each zone.

4. Use the models developed for the different zones to identify how the total number of crashes can be expected to change with the different diversion strategies under consideration for the entire network (including the major highways and the secondary roads).

5. If speed flow models are developed for the different zones, compare the changes in the traffic speed and travel time corresponding to different diversion strategies. The decrease in average travel time can be compared with the change in the number of crashes to determine if the diversion strategy is feasible.

6. If the crash rate and the critical crash rate can be determined for each zone within the network, develop the crash models using the crash rates instead of the number of crashes. This will allow the engineer to determine if the proposed diversion will cause the crash rate to exceed the critical crash rate for the different zones in the network.

CONCLUSIONS

- Traffic engineers can use the time mean speed directly from the detector stations in developing congestion mitigation strategies rather than converting it to space mean speed.

- There is a consistent relationship between flow and occupancy.

- The models provide the engineer in the field with a decision-support tool to decide on diversion strategies that also consider the risk of crashes.
- There is a strong correlation between the number of crashes and the variance of speed.
- Although the specific models developed cannot be generalized for all freeway segments, it is feasible to develop congestion mitigation measures that incorporate crash risks.
- Because of the extensive data that will be required, only traffic engineers in the traffic management centers should be expected to carry out the method developed in this study
- Because of the detailed analysis required for applying this procedure, the appropriate models for interstate highways should be developed and made available first to traffic engineers at the traffic management centers.
- Congestion mitigation strategies should not be implemented without due consideration of the effect on crash occurrence.

RECOMMENDATIONS

1. Extend this study to include areawide models for different interstate highways in Virginia.
2. Develop a user-friendly computerized procedure for incorporating crash risk in developing congestion mitigation strategies that can be implemented in the traffic management centers.

ACKNOWLEDGMENTS

The authors acknowledge the support given by the Virginia Transportation Research Council and offer special thanks to Lewis Woodson who played a very important role during the field data collection phase of the project.

REFERENCES

1. May, A.D., Jr. 1990. *Traffic Flow Fundamentals*. Prentice Hall, Englewood Cliffs, N.J.
2. Del Castillo, J.M., and Benitez, F.G. 1995. On the Functional Form of Speed Density Relationship. I: General Theory. *Transportation Research,* Vol. 29B, pp. 373-389.
3. Drake, J.S., Schofer, J.L., and May, Jr., A.D. 1967. A Statistical Analysis of Speed Density Hypotheses. In *Highway Research Record 154,* pp. 53-87. Highway Research Board, Washington, D.C.

4. Pipes, L.A. 1967. Car Following Models and the Fundamental Diagram of Road Traffic. *Transportation Research,* Vol. 1, No. 1, pp. 21-29.

5. May, Jr., A.D., and Keller, H.E.M. 1967. Non-Integer Car Following Models. In *Highway Research Record 199,* pp. 19-32. Highway Research Board, Washington, D.C.

6. Easa, S.M., and May, Jr., A.D. 1980. Generalized Procedure for Estimating Single and Two-Regime Traffic Flow Models. In *Transportation Research Record 772,* pp. 24-37. Transportation Research Board, Washington, D.C.

7. Easa, S.M. 1982. Selecting Two-Regime Traffic Flow Models. In *Transportation Research Record 869,* pp. 25-36. Transportation Research Board, Washington, D.C.

8. Transportation Research Board. 2000. *Highway Capacity Manual.* Washington, D.C.

9. Hall, F.L., and Brilon, W. 1994. Comparison of Uncongested Speed-Flow Relationships in German Autobahn and North American Freeways. In *Transportation Research Record 1457,* pp. 35-42. Transportation Research Board, Washington, D.C.

10. Banks, J.H. 1989. Freeway Speed-Flow-Concentration Relationships: More Evidence and Interpretations. In *Transportation Research Record 1225,* pp. 53-60. Transportation Research Board, Washington, D.C.

11. Hall, F.L., Allen, B.L., and Gunter, M.A. 1986. Empirical Analysis of Freeway Flow-Density Relationships. *Transportation Research,* Vol. 20A, No. 3, pp. 197-210.

12. Hall, F.L., Pushkar, A., and Shi, Y. 1993. Some Observation on Speed-Flow and Flow-Occupancy Relationships Under Congested Conditions. In *Transportation Research Record 1398,* pp. 24-30. Transportation Research Board, Washington D.C.

13. Zhou, M., and Hall, F.L. 1999. Investigation of Speed Flow Relationship Under Congested Conditions on a Freeway. In *Transportation Research Record* 1678, pp. 64-72. Transportation Research Board, Washington D.C.

14. Transportation Research Board. 1975. *Traffic Flow Theory.* Special Report 165. Washington D.C.

15. Garber, N.J., and Hoel, L.A. 1999. *Traffic and Highway Engineering.* PWS Publishing, Pacific Grove, Calif.

16. Lum, K.M., Fan, H.S.L., Lam, S.H., and Olszewski, P. 1998. Speed Flow Modeling of Arterial Roads in Singapore. *Journal of Transportation Engineering,* May/June, pp. 213-222.

17. Hall, F.L., Hurdle, V.F., and Banks, J.H. 1992. Synthesis of Recent Work on Nature of Speed Flow and Flow Occupancy Relationships on Freeways. In *Transportation Research Record* 1365, pp. 12-18. Transportation Research Board, Washington, D.C.

18. Ceder, A., and May, A.D. Further Evaluation of Single Regime and Two Regime Traffic Flow Models. In *Transportation Research Record 567,* pp. 1-15. Transportation Research Board, Washington, D.C.

19. Drew, D.R. 1968. *Traffic Flow Theory and Control.* McGraw-Hill Book Company, New York.

20. Hurdle, V.F., and Dutta, P.K. 1983. Speeds and Flows on Urban Freeway: Some Measurements and a Hypothesis. In *Transportation Research Record 905,* pp. 127-137. Transportation Research Board, Washington, D.C.

21. Persaud, B. N., and Hurdle, V. F. 1998. Some New Data that Challenge Some Old Ideas About Speed Flow Relationships. In *Transportation Research Record 1194,* pp, 191-198. Transportation Research Board, Washington, D.C.

22. Pfundt, K. 1969. Three Difficulties in the Comparison of Accident Rates. *Accident Analysis and Prevention,* Vol. 1, No. 3, pp. 253-259.

23. Gwynn, D.W. 1967. Relationship of Accident Rates and Accident Involvements with Hourly Volumes. *Traffic Quarterly,* Vol. XXI, No. 3., pp. 407-418.

24. Hall, J.W., and Pendelton, O.J. 1990. Rural Accident Rate Variations with Traffic Volume. . In *Transportation Research Record 1281,* pp. 62-70. Transportation Research Board, Washington, D.C.

25. Brodsky, H., and Hakkert, A.S. 1983. Highway Accident Rates and Rural Travel Densities. *Accident Analysis and Prevention,* Vol. 15, No. 1, pp. 73-84.

26. Mensah, A., and Hauer, E. 1998. Two Problems of Averaging Arising in the Estimation of the Relationship Between Accidents and Traffic Flow. In *Transportation Research Record 1635,* pp. 37-43. Transportation Research Board, Washington, D.C.

27. Lundy, R.A. 1965. Effect of Traffic Volumes and Number of Lanes On Freeway Accident Rates. In *Highway Research Record 99,* pp. 139-156. Highway Research Board, Washington, D.C.

28. Jovanis, P.P., and Chang, H.-L. 1986. Modeling the Relationship of Accidents to Miles Traveled. In *Transportation Research Record 1068,* pp. 43-51. Transportation Research Board, Washington, D.C.

29. Persaud, B., Mucsi, K., and Ugge, A. 1996. Safety Evaluation of Freeway Traffic Management System in Toronto, Canada. In *Transportation Research Record 1553,* pp. 111-114. Transportation Research Board, Washington, D.C.

30. Research Triangle Institute. 1970. *Speed and Accidents,* Vol. 2. Durham, N.C.

31. Garber, N.J, and Gadiraju, R. 1988. *Factors Affecting Speed Variance and Its Influence on Accidents*. AAA Foundation for Traffic Safety, Falls Church, Va.

32. Garber, N.J., and Ehrhart, A. 2000. *The Effect of Speed, Flow, and Geometric Characteristics on Crash Frequency on Different Types of Highways*. VTRC Report No. 00-R15. Charlottesville, Virginia Transportation Research Council.

33. Garber, N.J., and Joshua, S.C. 1991. *Traffic and Geometric Characteristics Affecting the Involvement of Large Trucks in Accidents*. Charlottesville, Virginia Transportation Research Council.

34. Turochy, R., and Smith, B.L. 2000. New Procedure for Detector Data Screening in Traffic Management Systems. In *Transportation Research Record 172,* pp. 127-131. Transportation Research Board, Washington, D.C.