SAN ANTONIO INCIDENT DETECTION ALGORITHM STUDY

by

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16. Abstract

The Texas Department of Transportation; San Antonio District, is developing the San Antonio Traffic Management System (TransGuide). TransGuide is envisioned to be the next evolution in control systems in the management of traffic. The initial phase of the Advanced Traffic Management System program is now under construction.

This study has identified and implemented alternative algorithms, evaluated the operational effectiveness of the San Antonio ATMS algorithm, evaluated the potential of advanced techniques in improving San Antonio ATMS operations, and recommended operational improvements to the existing system operations. The study has found that the existing San Antonio Incident Detection Algorithm worked well as compared to other algorithms in San Antonio, Texas. However, other algorithms, evaluated in this study, may also have potential with more data available for calibration. This study has also recommended system enhancements.

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IMPLEMENTATION STATEMENT

Based on the results of this study, a number of recommendations are made regarding the uses of Automatic Incident Detection Algorithms for freeway traffic management. Among the most important is the operator capability of specifying different data smoothing periods and speed thresholds for different freeway sections when speed-based incident algorithms are used. In addition, the operator should monitor and flag the end of incident through video monitoring techniques to reduce the false alarms. Also, methods should be devised to check data collection systems for malfunctions. Other suggestions to improve the algorithm performance as an effective freeway traffic management tool are provided in Chapter 5.

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 Texas Department of Transportation (TxDOT) or the Federal Highway Administration (FHWA). This report does not constitute a standard, specification, or regulation, nor is it intended for construction, bidding, or permit purposes. The engineer in charge of the project was Dr. Tom Urbanik (Texas P.E. registration #42384).

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SUMMARY

The Texas Department of Transportation, San Antonio District, is developing the San Antonio Traffic Management System (TransGuide). TransGuide is envisioned to be the next evolution in control systems in the management of traffic. The initial phase of the Advanced Traffic Management System program is now under construction. This study evaluates alternative incident detection-algorithms for automatic incident management.

This study has identified and implemented alternative algorithms, evaluated the operational effectiveness of the San Antonio ATMS algorithm, evaluated the potential of advanced techniques in improving San Antonio ATMS operations, and recommended operational improvements to the existing system operations.

The study has found that the existing San Antonio Incident Detection Algorithm worked well as compared to other algorithms in San Antonio, Texas. However, other algorithms evaluated in this study may also have potential with more data available for calibration. This study has also recommended system enhancements to assist the San Antonio District in the refinement of their speed-based algorithm.

1.0 INTRODUCTION

1.1 STUDY BACKGROUND

With increasing traffic congestion in the United States, many states have constructed transportation management centers to improve service vehicle response to incidents and decrease delays. To reduce the time to respond to incidents, the traffic management system must quickly and correctly detect incidents. One method of detecting incidents is to apply volume, occupancy, or speed data to an incident detection algorithm. One or more algorithms attempt to determine whether an incident has occurred based on variations in traffic flow patterns. When an algorithm determines that an incident may have occurred, it produces an alarm. Next, the operators check the area using Closed Circuit Television (CCTV), activate necessary control devices, and dispatch appropriate service vehicles.

The Texas Department of Transportation, San Antonio District, is developing the San Antonio Traffic Management System (TransGuide). The initial phase of the TransGuide program is now operational. The San Antonio TransGuide system uses a speed-based algorithm created by the Texas Department of Transportation (TxDOT). This algorithm is simple in structure, sounding an incident alarm when the average speed drops below a specified threshold. This research tested this algorithm to determine its effectiveness for automatic incident detection purposes. Other algorithms were also selected for comparative testing against this algorithm.

Incident detection algorithms have been used since the 1960s. The most popular algorithm developed in that decade was the California algorithm. Several modifications were made to the algorithm to create the California #7 and #8 algorithms which are still employed at traffic management centers today (*1*). While a number of other algorithms have been developed over the years, there is still no single algorithm which can detect all incidents and distinguish between recurrent and non-recurrent congestion. When an algorithm produces too many false alarms, operators begin ignoring the incident alarms, and service vehicles may not be promptly dispatched. Therefore, it is desirable that the algorithm detects incidents as accurately as possible.

Incident congestion, bottleneck congestion, slow traffic due to steep grades, congestion from a single slow moving vehicle, and slow movement caused by geometric design deficiencies all affect speed, occupancy, and volume loop detector data. For an algorithm to appropriately detect incidents, it must distinguish between data for recurrent and non-recurrent congestion conditions. Algorithm performance also depends on calibration methods and the definition of conditions when thresholds should change. Accuracy of algorithms is dependent on all of these factors and is essential in having an effective traffic management system.

1.2 STUDY OBJECTIVES

The research was conducted by the Texas Transportation Institute (TTI) at Texas A&M University System for TxDOT. The primary objectives of the proposed research were to:

1. Identify and implement alternative algorithms by which to assess the effectiveness of the San Antonio ATMS algorithm.
2. Evaluate the effectiveness of the San Antonio ATMS algorithm in comparison to the alternative algorithms.
3. Evaluate the potential of advanced techniques in improving San Antonio ATMS operations.

1.3 STUDY SCOPE

This research assessed which algorithm can most quickly and correctly identify an incident by generating an alarm near the incident site. In particular, the Texas Transportation Institute performed the following tasks for the TxDOT San Antonio District:

Task 1. Operational Test Computer. TTI purchased a VAX station 4000 Model 90 computer system for use by TTI in the Incident Detection phase of the Operational Test Study.

Task 2. Determine Alternative Algorithms. This task has selected a group of the algorithms used to comparatively assess the effectiveness of the San Antonio ATMS incident detection algorithm. A list of candidate algorithms were developed from a current TTI research effort through which existing and proposed incident detection algorithms are being identified. Final selection of these algorithms were made prior to the ATMS becoming fully operational.

Task 3. Implement Alternative Algorithms. The algorithms chosen in Task 2 were implemented concurrently with the San Antonio algorithm. These alternative algorithms were operated off-line (in parallel). In this fashion, a direct comparison was made between the various algorithms using real-time data from the field without having an adverse impact on the ATMS operations. This task was initiated just prior to the ATMS becoming fully operational and includes the coding, testing, and calibration of the alternative algorithms.

1.4 CONTENTS

This report contains six chapters which present the research study methods and results. Chapter 1 includes the study background, objective, and scope. Chapter 2 presents previous research regarding incident detection algorithms. The structure and theory of each algorithm is defined, and the performance results of the algorithms from other studies are stated. The chapter also provides a discussion of why each algorithm was or was not selected for comparison with the TxDOT algorithm. Chapter 3 outlines the study design for this research, traffic patterns, and test cases. It also provides a description of the study site selection process and states which sites were selected with their corresponding camera and loop detector names/numbers. The process of calibrating the algorithms for each site is described, and the selected thresholds are presented. The traffic characteristic analysis was followed which includes normal weekday and weekend patterns, and incident patterns. The chapter also provides a description of test cases which include seven incidents. Chapter 4 provides evaluation results, presenting the performance of each algorithm and the statistic analysis. Chapter 5 presents operational sensitivity analysis and investigates further improvements of TxDOT's speed-based algorithm with different smoothing periods and speed thresholds. Chapter 6 includes the conclusions and recommendations of this research. Chapter 7 provides references. The appendix includes algorithm listings.

2.0 LITERATURE REVIEW

2.1 DIFFERENT ALGORITHMS

A literature review of existing incident detection algorithms was conducted to determine the appropriate algorithms for comparison with the TxDOT algorithm. This chapter provides a brief description of each algorithm as a background for selecting which algorithms to examine in this study. There are seven sections which group the algorithms by theoretical approach:

- Comparative Algorithms
- Statistical Algorithms
- Time-Series Algorithms
- Smoothing/Filtering Algorithms
- Modeling Algorithms
- Low Volume Algorithms
- Algorithms Using Advanced Techniques

Each algorithm is described within its respective section. The Algorithm Selection section discusses why each algorithm was or was not selected for comparison with the TxDOT algorithm.

2.1.1 Comparative Algorithms

Comparative algorithms are the simplest of all existing algorithms. These algorithms are based on the theory that loop detector volume and occupancy will increase while speed will decrease if an incident should occur. The algorithms compare actual occupancy, volume, and/or speed data with predefined thresholds. The TxDOT speed algorithm, variations of the California algorithm, and the All Purpose Incident Detection algorithms are categorized as comparative algorithms.

2.1.1.1 TxDOT Speed Algorithm

The TxDOT speed algorithm attempts to detect incidents with loop detector speeds using a two minute moving average (six 20 second polling cycles). If no vehicles pass over a detector during a polling period, the reported zero speed is not computed in the two minute average. The algorithm sounds an incident alarm when the two minute average speed is less than the predefined threshold. This algorithm has not been tested against other algorithms.

2.1.1.2 California Algorithms

The family of California algorithms compare loop detector data with defined thresholds to detect incidents. Based on the original California algorithm, ten variations were developed with various parameters and program structures. This report describes the most commonly applied variations of the California algorithm.

2.1.1.2.1 Basic Algorithm

The California algorithm is typically used for comparison purposes to evaluate the performance of a new algorithm. Occupancy data from system loop detectors are applied to the parameters which are defined in Table 1. Incidents are detected by applying the OCCDF, OCCRDF, and DOCCTD tests. For this study, the time interval, t, is 20 seconds, and I denotes the station number. When OCCDF, OCCRDF, and DOCCTD exceed their thresholds, the algorithm produces an alarm that an incident occurred between station I and the adjacent downstream station, I+1. The primary structure of the California algorithm is shown in Figure 1. The structure of the basic California algorithm can be expanded by increasing the number and type of parameters applied to its structure to account for the variations of wide data fluctuations and congestion.

The other California algorithms discussed in this report represent an attempt to improve the basic California algorithm. The algorithms were run with Los Angeles Freeway data to determine which algorithms had the best performance. According to the evaluation, the basic California algorithm had an 82% detection rate, a 1.73% off-line false alarm rate, and an average detection time of 0.85 minutes (*2*).

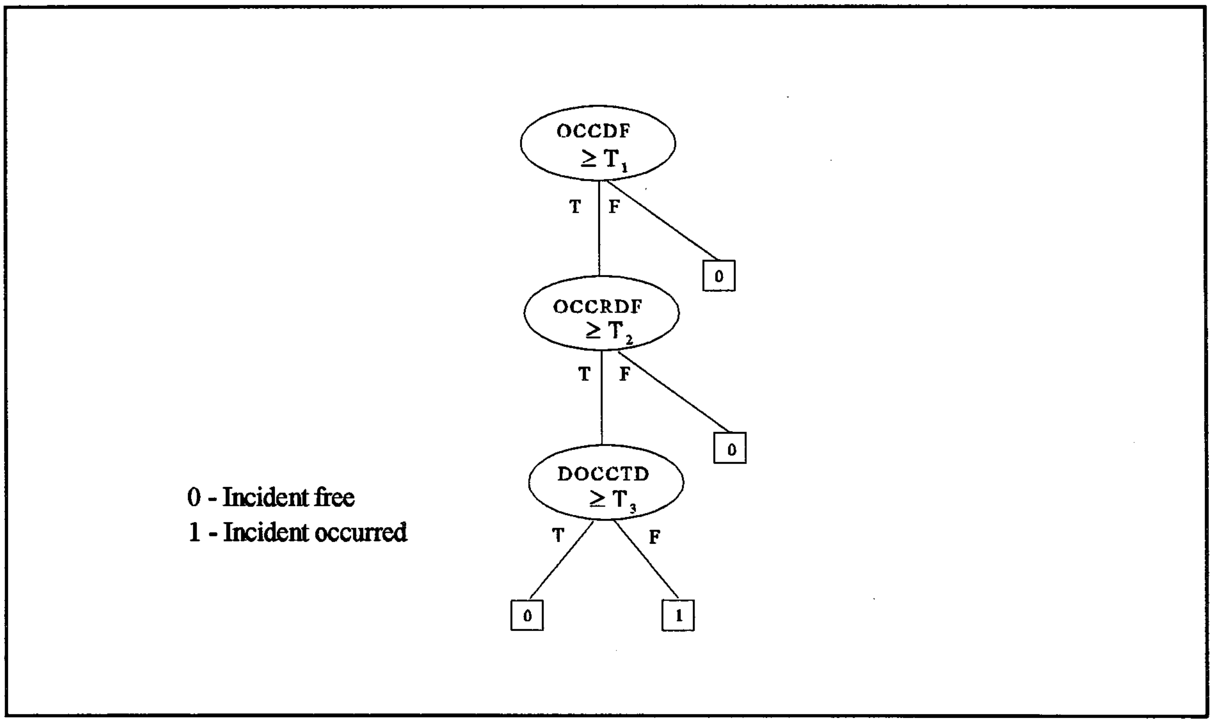


Figure 1. Basic Decision Tree for the California Algorithm (*2*)

Table 1. Parameters Applied to California Algorithms (*2*)

Parameter	Equation	Definition
OCC (i,t)	$OCC\ (I,\ t)$	Occupancy at station I for time interval t
DOCC (i,t)	$OCC\ (I+1,\ t)$	Downstream occupancy at station I for interval t
OCCDF (i,t)	$OCC\ (i,t) - OCC(I+1,t)$	Spatial difference in occupancies
OCCRDF (i,t)	$\dfrac{OCCDF(i,t)}{OCC(i,t)}$	Relative spatial difference in occupancies
DOCCTD (i,t)	$\dfrac{OCC(i+1,t-2)-OCC(i+1,t)}{OCC(i+1,t-2)}$	Relative temporal difference in downstream occupancy

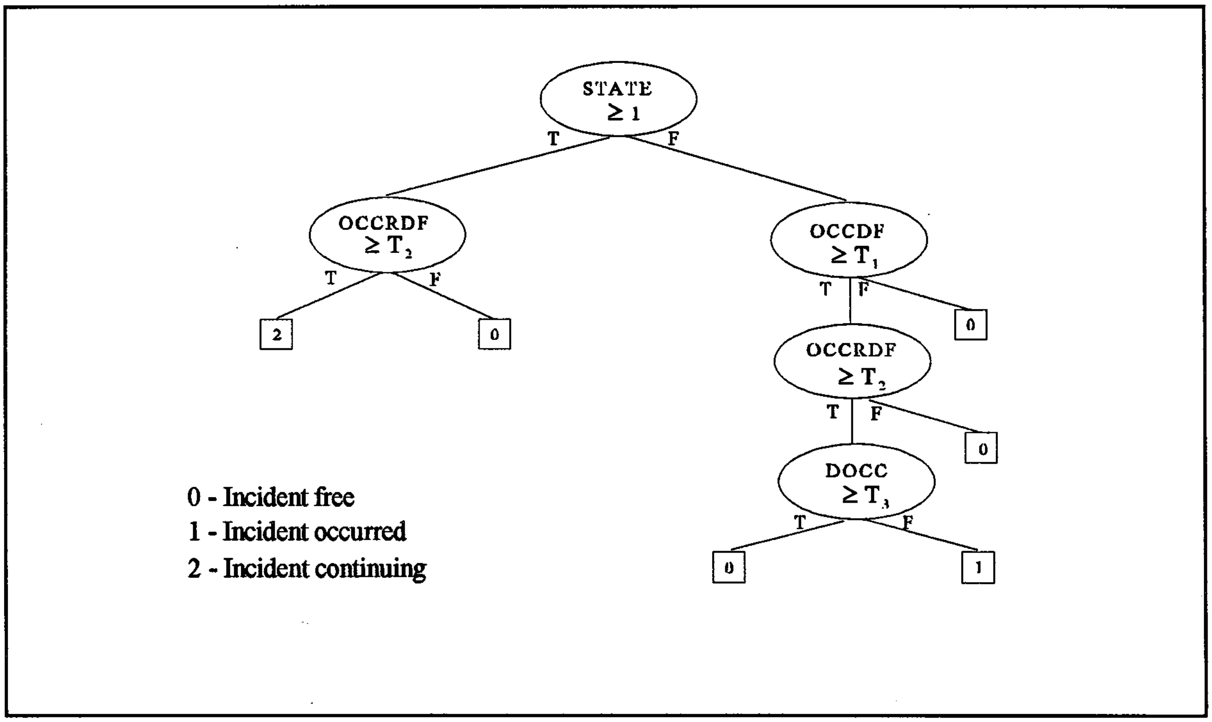


Figure 2. California Algorithm #4 Decision Tree (*2*)

2.1.1.2.2 California Algorithm #4

The basic California algorithm was modified in an attempt to detect compression waves. Compression waves occur in heavy stop-and-go traffic, forming at speeds of about 8 to 24 km/hr (5 to 15 mph) in the opposite direction of the flow of traffic. Compression waves increase occupancies at the downstream station to values greater than 20%. In an incident situation, on the other hand, downstream occupancies are typically much less than 20% (*3*). Based on this phenomenon, it is appropriate to replace the time differential in the occupancy (DOCCTD) parameter of the basic California algorithm with the downstream detector station occupancy (DOCC). The DOCC parameter improves the algorithm structure because it also looks at the downstream station to detect compression waves. Figure 2 shows the structure of California algorithm #4.

This algorithm was originally tested with Los Angeles Freeway data. The evaluation produced a detection rate of 82%, a 1.577% off-line false alarm rate, and an average of 0.64 minutes to detect an incident (*2*).

2.1.1.2.3 California Algorithm #7

Algorithm #7 is nearly the same as algorithm #4, but it includes a persistence check (see Figure 3). When the algorithm applies a persistence check, a tentative incident is declared for the first few time periods that the data exceed the threshold; if the conditions continue, the algorithm produces an incident alarm. A longer persistence check will decrease the number of false alarms but increase the detection time. A persistence check may last for as many periods as selected by the programmer or operator. Typically, a persistence check will delay declaring an alarm by four 20 second (1:20) or three 30 second (1:30) time periods.

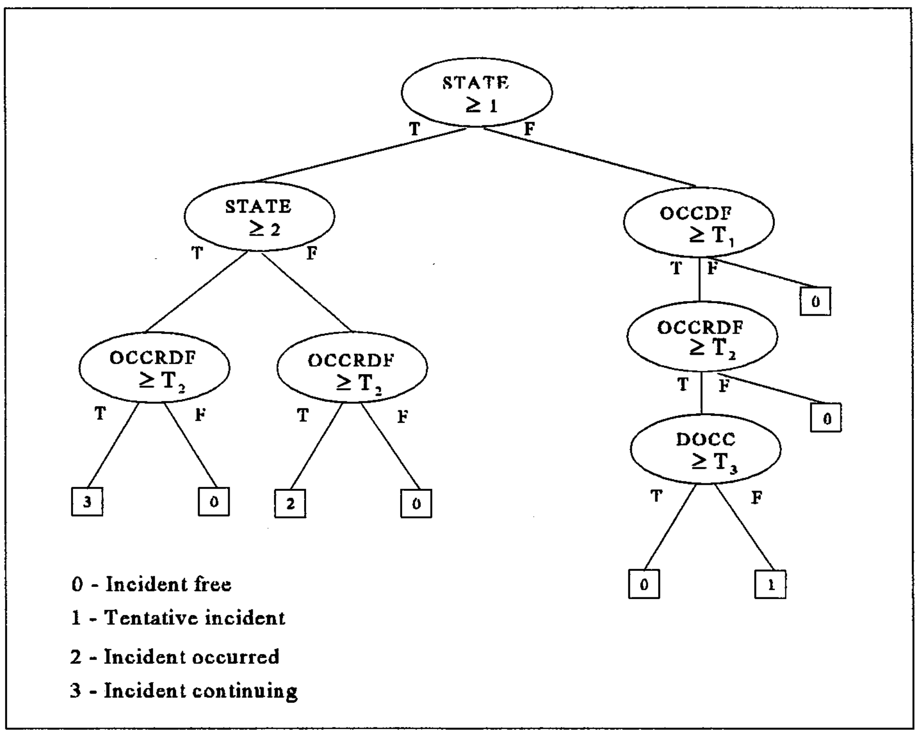


Figure 3. California Algorithm #7 Decision Tree (*2*)

California algorithm #7 compares the spatial difference in occupancy (OCCDF), relative spatial difference in occupancy (OCCRDF), and relative temporal difference in downstream occupancy (DOCC) values computed from the loop detector data with predefined thresholds. If the OCCDF and OCCRDF values exceed their given thresholds while DOCC does not, then the algorithm compares OCCRDF to its threshold value during the next iteration. If OCCRDF exceeds the threshold, the algorithm will continue to check its values against the threshold for the defined number of persistence check iterations. In other words, the algorithm determines whether the exceeded threshold was instantaneous or if it occurred because of an incident. Another feature of this algorithm is that it detects the continuation of incidents, alerting an operator of the termination of an incident.

When California algorithm #7 was tested with Los Angeles Freeway data, the reported best performance included a detection rate of 67%, an off-line false alarm rate of 0.134%, and a mean time to detect of 2.91 minutes (*2*).

2.1.1.2.4 California Algorithm #8

With 30 decision nodes, algorithm #8 is more complex than other California algorithms, but it applies only four parameters. The decision tree for Algorithm #8 is shown in Figure 4. The algorithm compares OCCDF, OCCRDF, DOCC, and DOCCTD to their respectively defined thresholds. This algorithm is essentially the same as algorithm #7, but it includes a check for compression waves.

Compression waves form during heavy traffic conditions. They are characterized by a sudden increase in occupancy which propagates at an upstream station within 2 to 5 minutes (*2*).

Algorithm #8 applies DOCC and DOCCTD parameters to test for the presence of compression waves. This algorithm typically repeats its check for a compression wave for 5 minutes. If the compression wave continues for 5 minutes, the algorithm starts again at state 0 (incident free) to check for incidents and compression waves. The algorithm also restarts with state 0 when the compression wave terminates before the end of the 5 minutes. This configuration allows the algorithm to discern between compression waves and incidents. Algorithm #8 also includes persistence check and incident continuation features. Payne et al. (*2*) reduced the complexity of algorithm #8 and managed to decrease the number of decision nodes from 30 to 21 using a tree optimization procedure (Figure 5). Although the decision tree is different, it is the same algorithm.

The reported best performance for California algorithm #8 included a 68% detection rate, an off-line false alarm rate of 0.177%, and an average detection time of 3.04 minutes. These results were based on an analysis using data from the Los Angeles Freeway (*2*).

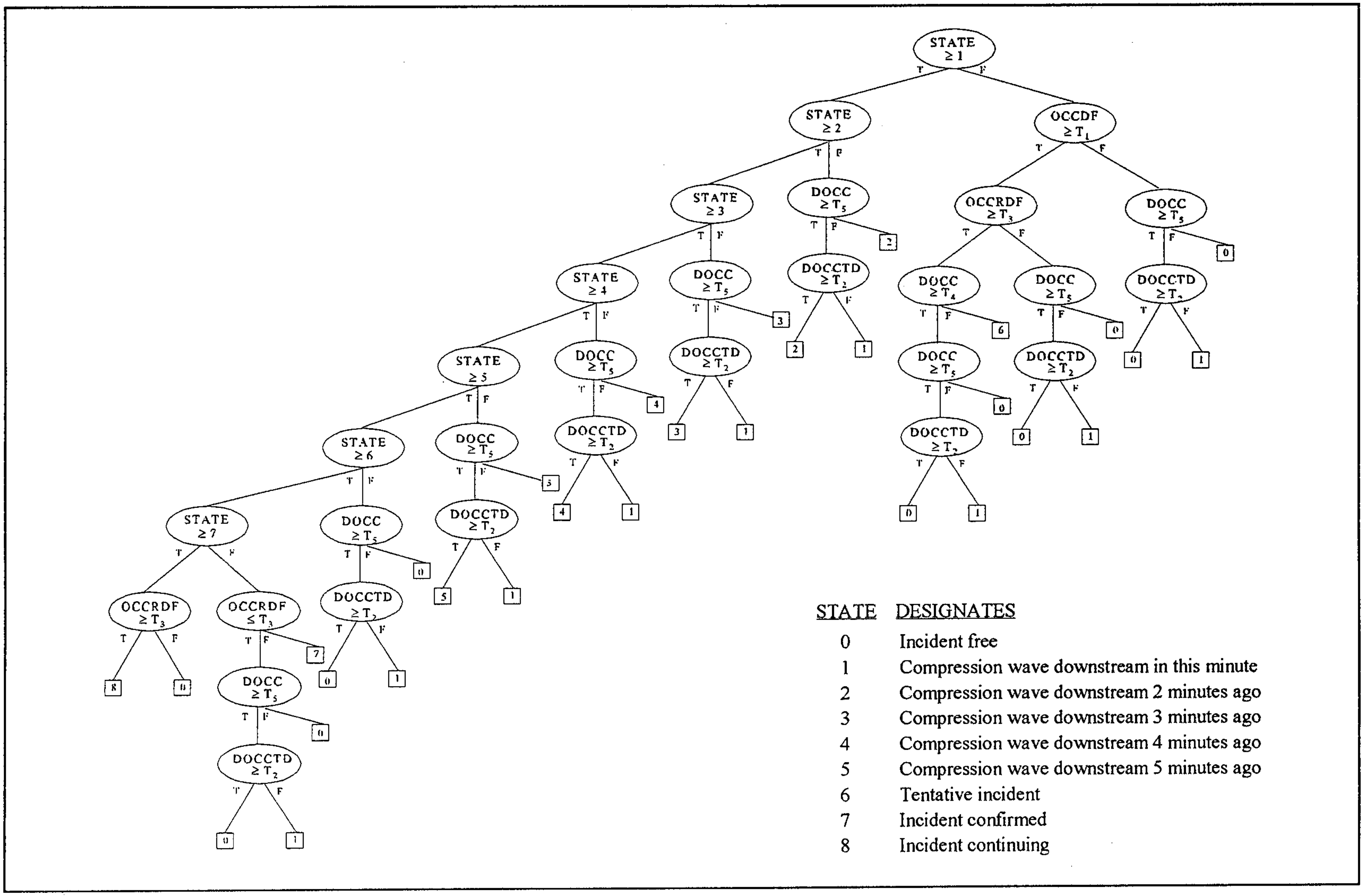
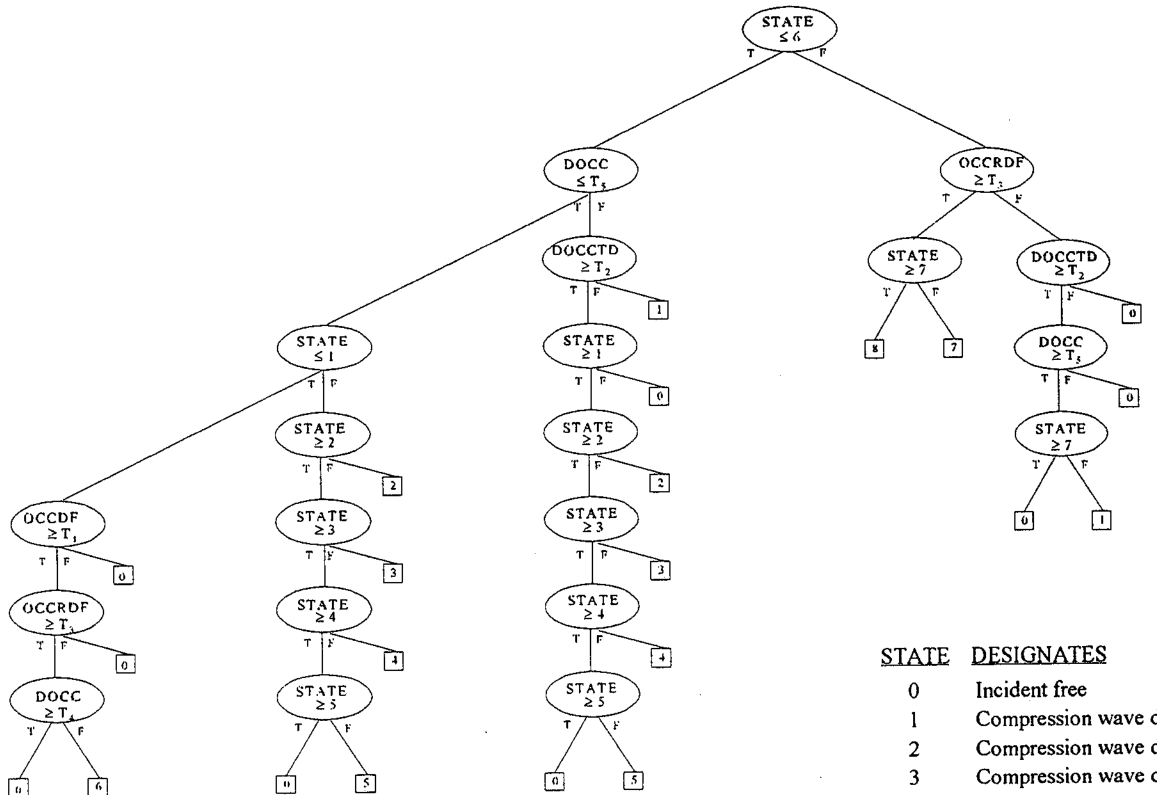


Figure 4. California Algorithm #8 Decision Tree (2)



STATE	DESIGNATES
0	Incident free
1	Compression wave downstream in this minute
2	Compression wave downstream 2 minutes ago
3	Compression wave downstream 3 minutes ago
4	Compression wave downstream 4 minutes ago
5	Compression wave downstream 5 minutes ago
6	Tentative incident
7	Incident confirmed
8	Incident continuing

Figure 5. Modified California Algorithm #8 Decision Tree (*2*)

2.1.1.2.5 California Algorithm #9

Algorithm #9 is essentially equivalent to algorithm #8, but it does not include the persistence check. Figure 6 is the decision tree for Algorithm #9. According to a study using Los Angeles Freeway data, the algorithm's performance consisted of a 71% detection rate, a 1.190% off-line false alarm rate, and a mean-time-to-detect of 0.47 minutes (*2*).

2.1.1.2.6 California Algorithm #10

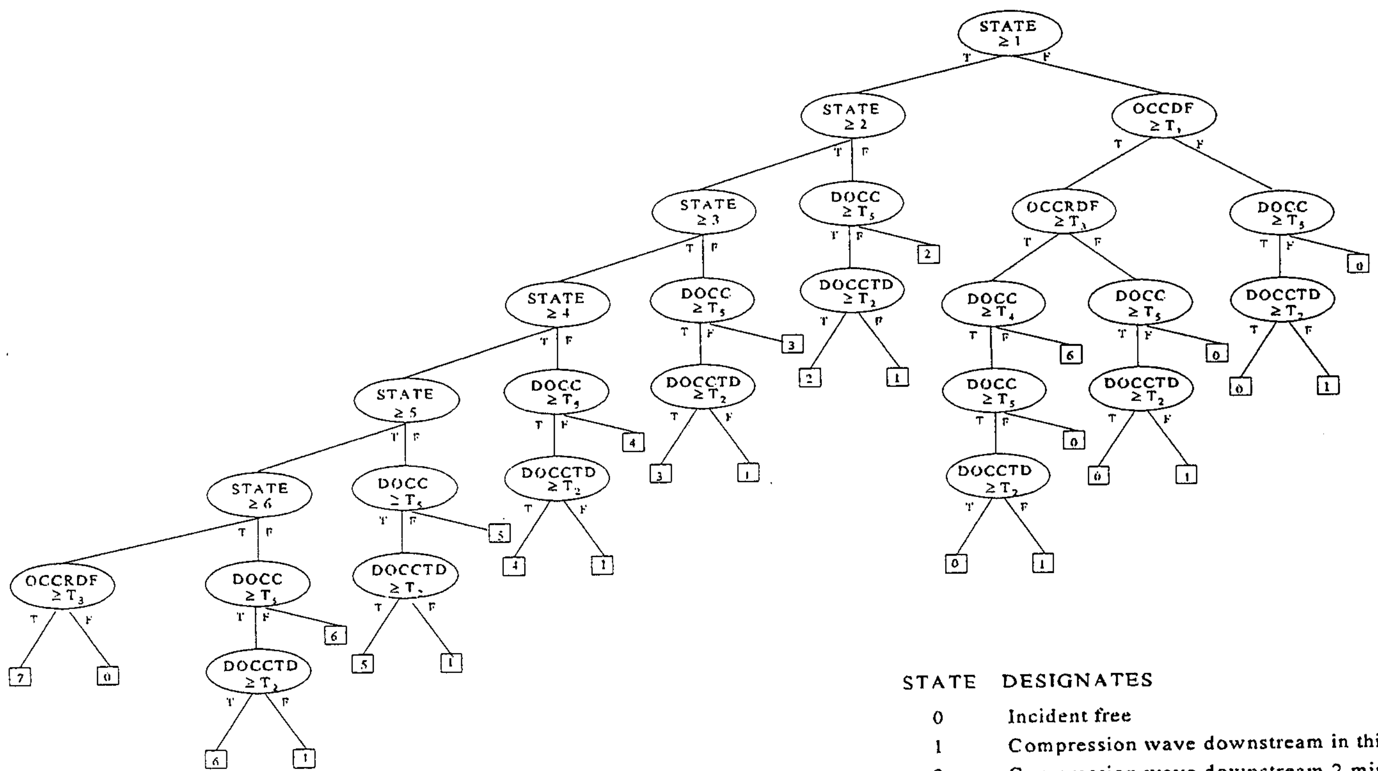
This algorithm is different from the other California algorithms because it includes a speed based feature, the relative temporal difference in speed (SPDTDF), which is computed with the following equation (*2*):

$$SPDTDF(i,t) = \frac{SPD(i,t-2) - SPD(i,t)}{SPD(i,t-2)}$$

where: SPD = speed at the specified time and detector station.

The purpose of including this feature is to detect incidents that occur in light or moderate traffic. Figure 7 shows the structure of algorithm #10. Theoretically, it is better to detect incidents under these conditions using vehicle speeds because occupancies might not increase enough for an algorithm to detect the change in traffic. According to the speed/flow curve (Figure 8), low flows do not necessarily indicate incident conditions. Low flows may indicate slow or fast speeds; therefore, applying speed data to an algorithm should make the algorithm operate more effectively.

The performance of California algorithm #10 was tested with Los Angeles Freeway data. The algorithm had a 51% detection rate, a 0.065% off-line false alarm rate, and a mean of 3.59 minutes to detect incidents (*2*).



STATE	DESIGNATES
0	Incident free
1	Compression wave downstream in this minute
2	Compression wave downstream 2 minutes ago
3	Compression wave downstream 3 minutes ago
4	Compression wave downstream 4 minutes ago
5	Compression wave downstream 5 minutes ago
6	Incident confirmed
7	Incident continuing

Figure 6. California Algorithm #9 Decision Tree (*2*)

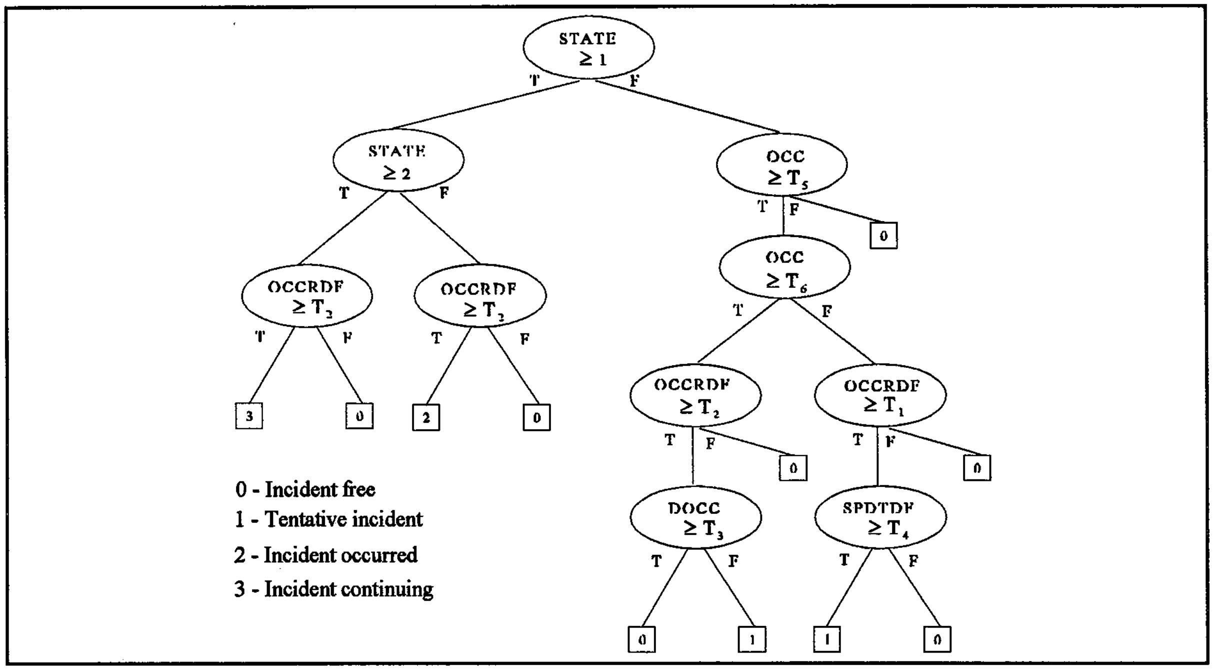


Figure 7. California Algorithm #10 Decision Tree (*2*)

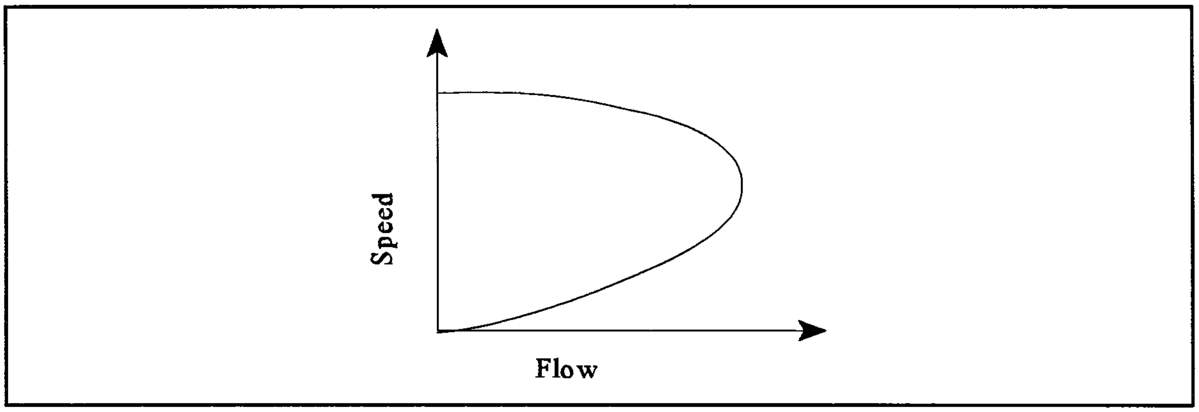


Figure 8. Speed/flow Curve (*4*)

2.1.1.3 All Purpose Incident Detection Algorithm (APID)

The APID algorithm uses five variables which were defined within the California algorithm section. They include OCCDF, OCCRDF, DOCCTD, DOCC, and SPDTDF. This algorithm is similar to California algorithms in its comparison of loop data to a threshold for each parameter. The difference in these algorithms is that the APID algorithm automatically changes which parameters are used and adjusts their thresholds according to existing loop conditions, while the California algorithm thresholds are changed manually and parameter use is constant.

After the APID algorithm determines the traffic flow type (low, medium, or high), it applies the test designed for that particular flow state. For medium volume conditions, a compression wave test is performed, followed with comparisons of OCCRDF and SPDTDF to defined thresholds. If both thresholds are exceeded, a persistence check is performed to determine whether the conditions still exist. If the conditions remain after a specified number of persistence checks, an incident is declared. For high traffic flow, the algorithm checks for a compression wave with DOCCTD data. When the section is clear of compression waves, OCCDF, OCCRDF, and DOCC values are compared with thresholds. It performs persistence checks if thresholds are exceeded.

For all traffic flow conditions, the APID algorithm is essentially the same as California algorithm #8. If the algorithm detects a compression wave, it continues to check for its presence until the maximum defined endurance period expires. When the algorithm tentatively finds an incident, a persistence test compares actual OCCRDF values with a threshold to determine whether an incident occurred.

This algorithm was designed to handle all flow conditions. It was tested with data from the Burlington Skyway in Ontario, Canada, with flows reaching 2000 vphpl. Off-line testing of the algorithm produced an 86% detection rate for detectable incidents, a 0.05% off-line false alarm rate per station, and a mean time to detect of 2.55 minutes (*5*). This included a 2 minute persistence check.

2.1.2 Statistical Algorithms

A statistical algorithm may examine the deviation from the mean for a parameter using a statistical approach to determine whether the change in the traffic variable data was significant. Another approach can determine the statistical probability that an incident occurred based on historical data. Two statistical algorithms include the Standard Normal Deviate and Bayesian algorithms.

2.1.2.1 Standard Normal Deviate (SND)

In general, the standard normal deviate is the number of deviations that a variable is away from the mean of that variable. The mean of the variable is computed with a moving average.

The SND algorithm can apply occupancy or energy (based on volume and speed measurements) data from loop detectors at a single station to detect incidents. For the SND model to work effectively, it depends on the passage of a shock wave over a set of sensors. The SND model is based on the theory that a large change in traffic variables will indicate the occurrence of an incident. SND measures the deviation from the mean with the following equation:

$$SND = \frac{x-\bar{x}}{s}$$

where:

x	=	a given value for the control variable at time t;
$\bar{x}$	=	mean of control variable over previous n sampling periods; and
s	=	standard deviation of control variable over previous n periods.

Theoretically, a large SND value is indicative of a significant change in the state of a traffic variable due to an incident. Evaluating the rate of change of a variable should be more effective than comparing values to constant thresholds since traffic variables may constantly change with time of day and weather conditions.

This algorithm was tested on-line with three and five minute moving average samples from detector stations on the Gulf Freeway in Houston. With a single persistence check and a critical SND value of 4, the five-minute moving average method achieved its best performance in 1979 (*5*). Ninety-two percent of all incidents were detected, the off-line false alarm rate was 1.3%, and the average response time was 1.1 minutes (*6*).

2.1.2.2 Bayesian Algorithm

This algorithm uses Bayesian statistics to determine the probability that an incident occurred. The algorithm applies the relative spatial difference in occupancies (OCCRDF) feature which was previously defined for the California algorithms. This parameter was selected because its values are typically stable, yet there is a considerable difference between its incident and non-incident values (*7*).

This approach requires frequency distributions of adjacent station occupancies for incident and non-incident situations based on historical data for each detector station. The frequency distribution curves and computed probabilities of an incident occurring within each specified section are applied to obtain the optimal threshold for OCCRDF.

The probability of a capacity-reducing incident occurring at a specific detector station at a specified time is computed with the following ratio:

$$\frac{A}{B \cdot C}$$

where: A = average number of incidents occurring in the study section during the total time period;

B = the total number of detectors in the study section; and

C = the number of minutes in the time period.

Probabilities are computed to determine the number of persistence checks required to achieve an appropriate probability of an incident occurring according to a comparison of consecutive OCCRDF values with the defined threshold. The incident probability value was incorporated in computing the OCCRDF threshold. This method will reduce the number of false alarms; however, detection time will increase to achieve high probabilities of detection.

The Bayesian algorithm was tested on-line at the Kennedy Expressway in Chicago during the evening peak period. It applied a persistence check which required the algorithm to determine the probability of an incident from four consecutive data sets. The algorithm detected 100% of the incidents with no false alarms and an average detection time of 3.9 minutes (*7*).

2.1.3 Time-series Algorithms

Algorithms using the time-series approach use historical data to predict future parameter values. These algorithms typically predict values that are one or two time slices ahead. A confidence interval is then computed for future values. If the actual values lie outside the predicted range, an incident is declared. Time-series algorithms usually use occupancy as the traffic parameter. The Auto Regressive Integrated Moving Average (ARIMA) and High Occupancy (HIOCC) algorithms are time-series algorithms.

2.1.3.1 Auto Regressive Integrated Moving-Average (ARIMA) Algorithm

The ARIMA algorithm accounts for the dynamic behavior of traffic variables, such as occupancy, with a linear model. An ARIMA model is calibrated with three steps: preliminary identification, estimation, and diagnostic checking. After the appropriate model is selected, it applies the errors of the predicted and existing traffic parameters from the previous three time slices. It predicts confidence limits one or two time slices ahead, based on real-time estimates of the changes in traffic parameters. The algorithm declares an incident when the actual conditions lie outside the confidence interval.

The algorithm was tested under moderate to heavy flow conditions with data from the Lodge Freeway in Detroit. With variable parameter estimates, the ARIMA [0,1,3] algorithm had a 100% detection rate, a 1.4% on-line false alarm rate, and an average detection time of 0.39 minutes (*8*).

2.1.3.2 High Occupancy (HIOCC) Algorithm

For this algorithm, the computer receives occupancy data from loop detectors every tenth of a second. These data are compiled to determine how many times during one second the detectors were occupied for each detector station; this is defined as the instantaneous occupancy. If the detector station was occupied for more than the defined number of times over one second, a tentative incident is declared. Typically, a threshold of 10 is appropriate (*9*); this means that the detector was occupied for a full second. A persistence check helps reduce false alarms; two iterations producing an instantaneous occupancy value of 10 should generally be sufficient (*9*).

In an off-line test of the HIOCC algorithm with a 2 second persistence check, the algorithm detected all capacity reducing incidents. It achieved detection times between 20 seconds and slightly over 2 minutes (*9*).

2.1.4 Smoothing/filtering Algorithms

The significance of algorithms that use smoothing or filtering techniques is their ability to remove noise from data sets. Smoothing algorithms run data through an equation to smooth outlying data and then apply the smoothed data to the incident detection algorithm. The filtering application uses a linear filter to remove the high-frequency fluctuations that occur in normal traffic, while allowing the low-frequency data (i.e., data representative of incident conditions) to pass. The Minnesota and Double Exponential Smoothing algorithms apply smoothing and filtering techniques.

2.1.4.1 Minnesota Smoothing Algorithm

This algorithm uses linear smoothing before applying the data to a spatial occupancy algorithm. The algorithm smooths occupancy data for specified time periods before and after an incident using a moving average smoother. By smoothing the data, the algorithm is not as likely to mistake wide fluctuations in data for incidents. The following equation averages occupancies from two adjacent detector stations for a specified time period after the incident (*10,11*):

$$y_t = \frac{1}{M}\left[\sum_{k=0}^{M-1} OCC^{u}_{t\pm k} - \sum_{k=0}^{M-1} OCC^{d}_{t\pm k}\right]$$

where:

y_t	=	variable filtered with moving-average linear smoother;
OCC^u	=	unfiltered upstream occupancy during interval t+k;
OCC^d	=	unfiltered downstream occupancy during interval t+k;
t	=	incident occurrence time;
k	=	the interval corresponding to the incident occurrence time; and
M	=	number of averaging intervals before or after t.

The y_t equation applies to the time period that lasts for M intervals after the incident occurs at time t. The temporal difference of y_t before and after t indicates the change in traffic conditions before and after an incident that occurred at time t. The temporal difference (Δy) is computed by subtracting y_t before t from y_t after t. Computing Δy filters abnormal traffic flow that geometric or weather conditions may cause to reduce false alarms.

The maximum of upstream and downstream occupancies averaged over a specified time period, M, before the incident, is determined as follows (*10,11*):

$$m_t = \frac{1}{M}\max\left(\sum_{j=1}^{M} OCC_{t-j}^{u}; \sum_{j=1}^{M} OCC_{t-j}^{d}\right)$$

This normalized occupancy accounts for variations between high-occupancy and low-occupancy stations and changes in occupancy due to the time of day.

The final portion of the algorithm structure involves comparing predefined thresholds with two ratios (RAT1 and RAT2):

$$RAT1 = \frac{y_t^a}{m_t} \qquad\qquad RAT2 = \frac{\Delta y}{m_t}$$

RAT1 applies the smoothed occupancy data after time t to test for congestion. If both ratios exceed their thresholds, an alarm is declared.

According to an analysis of the Minnesota algorithm, it works appropriately with five-minute averaging following an incident to remove high-frequency fluctuations. To achieve a faster detection time, the algorithm was tested with a three-minute moving average following an incident. On-line testing of the Minnesota algorithm on I-35 in Minneapolis produced an 81.5% detection rate with an off-line false alarm rate of 0.34%. It had detection times less than 1.5 minutes after operator detection (*10,11*).

2.1.4.2 Double Exponential Smoothing (DES)

The DES algorithm compares smoothed traffic variable data with thresholds to detect incidents. The algorithm can apply a combination of volume, occupancy, and speed variables using data from single detector stations. The operator or programmer can select which variables to apply.

Algorithm execution involves recalculating the traffic variable data to smooth the data. The data are smoothed by dividing the cumulative error in prediction by the mean absolute deviation. The algorithm continues to recalculate the smoothing values for each execution cycle during the incident detection process. The following equations are applied to compute the smoothed volume, occupancy, and speed values (*5*):

e(x,i,t) = error in prediction $\qquad e(x,i,t) = x(i,t) - D(x,i,t)$

E(x,i,t) = cumulative error in prediction $$E(x,i,t) = E(x,i,t-1) + e(x,i,t)$$

m(x,i,t) = mean absolute deviation $$m(x,i,t) = SFM|e(x,i,t)| + (1-SFM)[m(x,i,t-1)$$

Smoothed variable $$x = \frac{E(x,i,t)}{m(x,i,t)}$$

where:	I	=	vehicle detection station number;
	t	=	incident detection execution cycle;
	x	=	a traffic variable (volume, occupancy, or speed);
	D	=	double smoothing value;
	n	=	number of polling periods within the average blockage clearance duration; and
	SFM	=	mean absolute deviation smoothing factor.

Once the variables are smoothed, the values are compared with defined thresholds to determine whether an incident exists. The algorithm may include a persistence check for a defined number of execution periods specified by the programmer. All of the applied variables must exceed their respective thresholds for the defined number of periods for the algorithm to declare an incident.

Using average blockage clearance durations and historical traffic variable data, initial values of the double smoothing value and mean absolute deviation are computed with equations which are not discussed within this report. They can be found in a paper written by Masters, Lam, and Wong (*5*).

An off-line evaluation using two weeks of data from the Burlington Skyway, with traffic volumes approaching 2000 vphpl, tested the effectiveness of the DES algorithm. The algorithm had a detection rate of 82% of detectable incidents with an off-line false alarm rate of 0.28% per station. The average detection time was 5.05 minutes (*5*).

2.1.5 Modeling Algorithms

The traffic modeling approach applies traffic flow relationships for incident detection. With historical data, traffic flow relationships are determined for a specified number of conditions, including uncongested, congested, and heavily congested. An incident is declared if the data fall in the defined range for incident situations.

2.1.5.1 McMaster Algorithm

The McMaster algorithm detects incidents based on the volume and occupancy data of a single detector station. Figure 9 shows the volume-occupancy relationship divided into four sections which are defined as follows:

Area 1 - Uncongested flow (High volume, low occupancy)
Area 2 - Congested flow (Low volume, low occupancy)

Area 3 - Heavy congestion (Low volume, high occupancy)
Area 4 - Queue discharge flow (High volume, high occupancy)

Area 1 is separated by the lower bound of uncongested data (LUD). Areas 2 and 3 are separated by the critical occupancy (O crit), and the critical volume (V crit) separates areas 2 and 3 from area 4.

To apply the McMaster algorithm, volume-occupancy templates must be created for each detector station. If the observed loop detector data lie in areas 2 or 3 for more than three consecutive intervals, the algorithm declares an incident.

An on-line test was performed with the McMaster algorithm on the Queen Elizabeth Way in Ontario. Results of the testing included a 68% detection rate, 0.0008% off-line false alarm rate (20 false alarms over 64 days), and a 1.4 minute detection time (*13*).

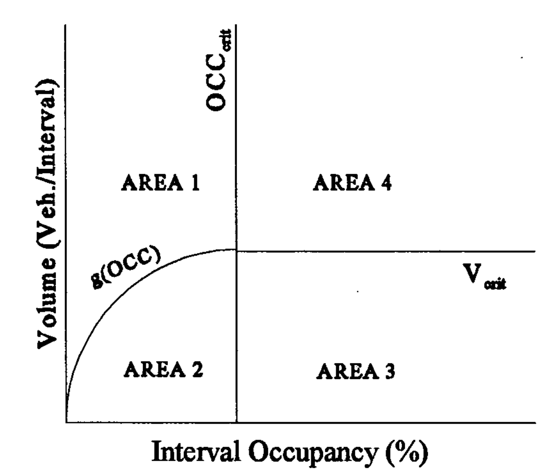


Figure 9. McMaster Algorithm Template (*12*)

2.1.5.2 Dynamic Algorithm

Two macroscopic dynamic models were applied in testing the Dynamic algorithm created by Willsky et al. (*14*), including the multiple model (MM) and the generalized likelihood ratio (GLR) methods. Both methods are based on fundamental speed-density and flow-density relationships which are depicted in Figure 10. Input data are filtered by Kalman filtering.

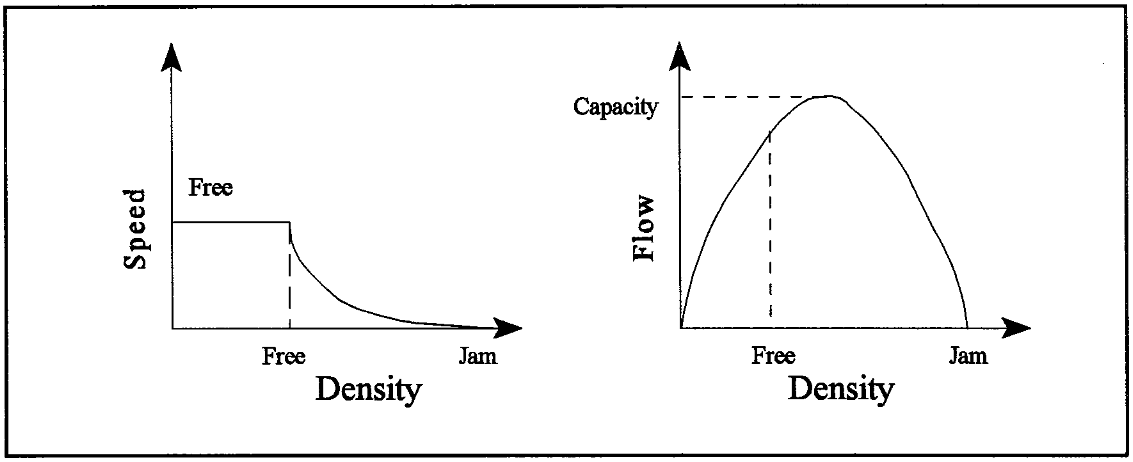


Figure 10. Traffic Flow Relationships in the Dynamic Model Algorithm (*15*)

The multiple model algorithm outputs a conditional probability that the existing speed/density and flow/density conditions are representative of incident conditions. If the conditional probability value exceeds the threshold, an incident is declared. It is possible to apply a persistence check, but it was not used in their report.

The generalized likelihood ratio algorithm is designed to detect abrupt system changes. The algorithm computes a ratio of the likelihood that an incident occurred. An incident is declared when the ratio exceeds the threshold.

According to an off-line evaluation, the algorithm produced no false alarms with a short mean-time-to-detect (no values were reported). When all simulated incidents were detected, the detection time was rather high (*14*).

2.1.6 Low-volume Algorithms

A common problem with incident detection algorithms is their inability to detect incidents during low-volume conditions. It is inappropriate to compare traffic flow conditions, as most algorithms do, during low-volume conditions because the flow is inconsistent. One low-volume technique, Event Scan, is described in this section (*16*).

2.1.6.1 Event Scan Algorithm

This is a microscopic algorithm that was created for the purpose of detecting incidents during low-volume situations. Using speed data from a set of trap detectors, three possible arrival times at the downstream set of detectors are computed for each vehicle passing over the first detector station.

The expected time for a vehicle to arrive at the downstream detector station is computed with the following equation:

$$t_e = t_i + \frac{D}{V}$$

where:	t_e	=	time that the vehicle exits the study section (seconds);
	t_i	=	time that the vehicle enters the study section (seconds);
	D	=	length of study section (feet or meters); and
	V	=	vehicle speed as it enters the study section.

The earliest possible arrival time at the downstream station is computed assuming a maximum speed of 160 km/hr (100 mph) (*16*). The second arrival time at the next station is computed based on the speed measured at the first detector station. The latest arrival time is computed using a 10 percent reduction factor in the measured speed to allow for errors in the measured speed (*16*). If a vehicle does not arrive at the downstream detector within the expected time period, the algorithm declares an incident. Since this algorithm predicts the arrival time at the downstream station for every vehicle, it would be difficult for the algorithm to correctly correspond every predicted arrival time with each vehicle within that section unless volumes are very low.

A simulation study of the Event Scan algorithm with 455 m (1500 ft) detector spacings and traffic volumes of 1000 vph found a detection time ranging from 15 seconds to 50 minutes. Research conducted by Dudek et al. (*16*) proved that the algorithm performed well with 152 m (500 ft) detector spacings and volumes of 100 vph.

2.1.7 Algorithms Using Advanced Techniques

A variety of advanced techniques exist which can be applied to incident detection. Neural networks and fuzzy logic are artificial intelligence techniques which are discussed in this section.

2.1.7.1 Neural Network

The structure of neural networks are designed to emulate the functions of the human brain at a simplified level. They consist of numerous interconnected processing elements (PEs). The PEs act as neurons while their connections model human synapses. The PEs are arranged into an input layer, at least one hidden layer, and an output layer. They are weighted between each layer with the activation functions transforming the weighted sum of input PEs into each PEs output.

While a variety of neural networks exist, Ritchie and cheu (*17*) selected the multi-layer feed-forward neural network to detect incidents. In a feed-forward neural network, the results from one neuron are only input to a layer following the current layer. This type of non-linear neural network is defined as supervised, comparing outputs of the network with target values. If the outputs do not match the target values, weighting values within the network are automatically altered to achieve values which are sufficiently close to the target values.

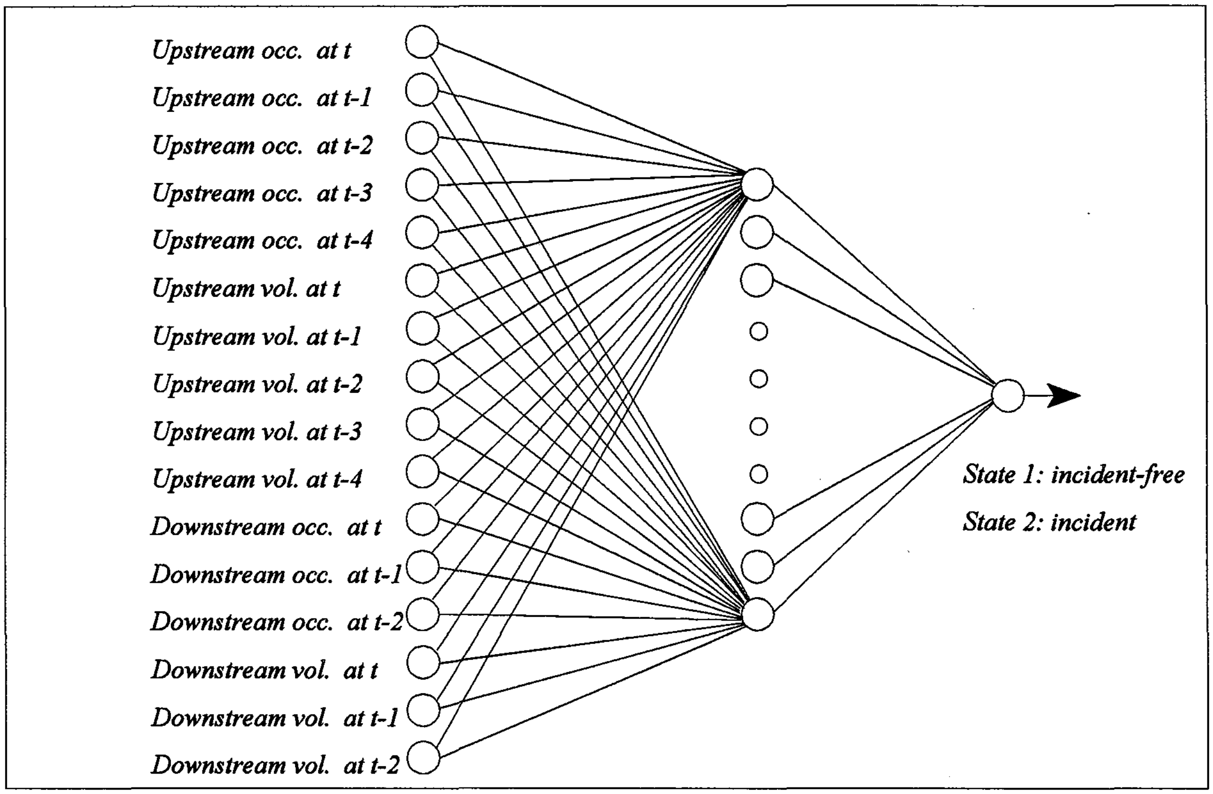


Figure 11. Multi-Layer Feed-Forward Neural Network (*18*)

The neural network attempts to define the existing conditions of the freeway with pattern recognition to detect lane-blocking incidents. Figure 11 shows the basic structure of the neural network with the chosen input features for this network. The network has the ability to form decision boundaries with hyperplanes to improve responses to pattern variations. Using backpropogation, the network can "learn" what conditions are typical for an incident situation.

The neural network application was tested off-line with data from Orange County, California. The neural network had up to a 97% detection rate for incidents where two or more lanes were blocked, and the detection rate reached 78% for incidents blocking one lane. Using a three interval persistence check, the off-line false alarm rate was 0.2% (*18*).

2.1.7.2 California Algorithm #8 with Fuzzy Logic

The basic version of California algorithm #8 truncates the left or right branch of its decision tree at a decision node; it makes a 1 (yes) decision when the data exceeds the threshold or a 0 (no) decision if it does not. The fuzzy version of this algorithm is different in that the fuzzy approach considers all paths and then selects the most appropriate result. The fuzzy algorithm does not provide a strict 0 or 1 solution; instead, it defines the probability (between the values of 0 and 1) of each parameter being low or high. Each node, ij, has a membership function, f_{ij}, which computes the probability value. A general membership function consists of the following equations (*18,19,22,23*):

$$f_{ij}(x) = 0 \qquad if \quad x < a_{ij}$$

$$f_{ij}(x) = \frac{(x-a_{ij})}{(b_{ij}-a_{ij})} \qquad if \quad a_{ij} \leq x < b_{ij}$$

$$f_{ij}(x) = 1 \qquad if \quad b_{ij} \leq x$$

where: x is detector occupancy, and a_{ij} and b_{ij} are individual thresholds. Figure 12 shows the general membership function in a graphical form.

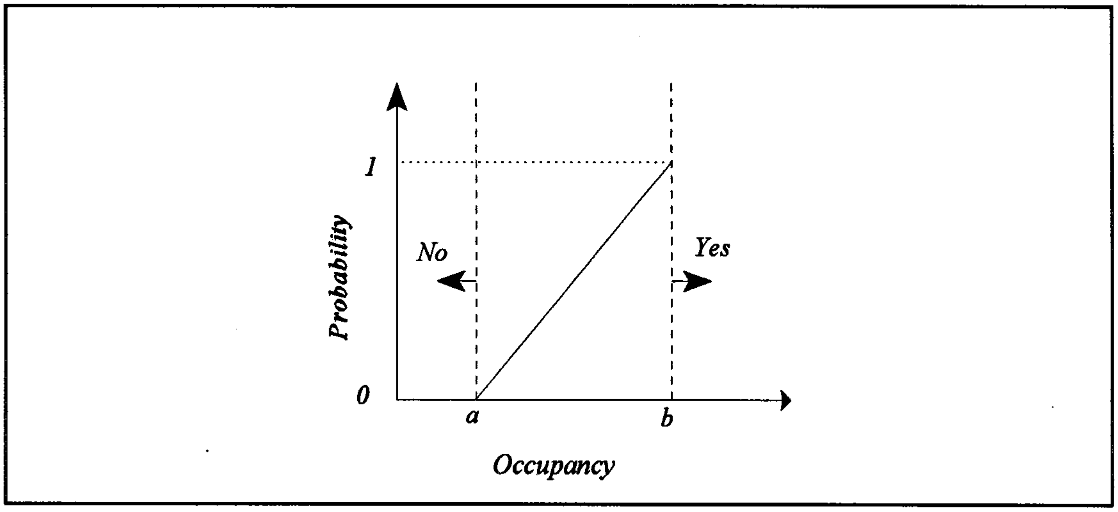


Figure 12. Membership Functions for a Fuzzy System (*19*)

For a binary decision tree, if the membership function for one branch is $f_{ij}(x)$, then the membership function of the other branch is its complement, $1 - f_{ij}(x)$. The Fuzzy California #8 algorithm uses the same parameters as the California algorithm #8, but it assigns a probability at each decision node. Appendix A contains the membership functions for California algorithm #8 with Fuzzy Logic. There are five membership functions, with one for the states and one for each of the parameters: OCCDF, DOCCTD, OCCRDF, and DOCC. The membership functions for the states defines the probability of no incidents, congestion, continuing congestion, tentative incidents, confirmed incidents, and continuing incidents. The OCCDF, DOCCTD, and OCCRDF membership functions define their probabilities of being low or high, with the membership function for DOCC also defining the probability of its value being medium. Based on the previous state and the current probabilities of the states and parameters lying within the defined regions, the most probable conditions are reported. California algorithm #8 with Fuzzy Logic has not been tested in an on-line or off-line evaluation.

2.2 ALGORITHM SELECTION

The following criteria were established for selecting which algorithms to evaluate in this study. First, the algorithm must have the ability to detect an incident within two minutes of the incident's occurrence. The algorithm's structure must be appropriate for the traffic volumes of the San Antonio highway sections under evaluation. Also, the algorithm must run from speed, volume, and/or occupancy loop detector data that are averaged over 20 seconds across all lanes. The algorithm's performance must be sufficient for the existing loop detector spacings which vary throughout the system. Due to time constraints of this study, some algorithms were not selected on the basis that they require a significant amount of historical data to run effectively. This section provides reasons why each algorithm was selected or rejected for this research study.

2.2.1 California Algorithms

Because the California algorithms were evaluated in the same study (*2*), their performance measures may be compared for the selection process. California algorithm #4 performed better than the basic California algorithm. By replacing DOCCTD with DOCC, the false alarm rate and mean-time-to-detect improved. California algorithm #7 was an improvement over #4 with the use of a persistence check; although the detection time increased, the persistence check improved the false alarm rate. The California algorithm #8 improved on algorithm #7 with a check for compression waves, but according to the evaluation, the performance was nearly the same as algorithm #7. California algorithm #9 is equivalent to algorithm #8 but eliminates the persistence check. Algorithm #9 produced a large increase in the false alarm rate. California algorithm #10 uses a different approach, applying the relative temporal difference in speed. With a poor detection time and detection rate, it did not perform as well as the others. Algorithm #8 had the best performance of the California algorithms and was selected for comparison.

2.2.2 All Purpose Incident Detection Algorithm

Although the reported detection time of the APID algorithm exceeded the two minute requirement, this could be reduced by decreasing the time for the persistence check. This algorithm is nearly equivalent to California algorithm #8 except for its initial check to select thresholds according to the current occupancy level. It is unnecessary to test both algorithms in this evaluation considering their similarities, so it was not selected.

2.2.3 Standard Normal Deviate Algorithm

This algorithm computes the SND value which reflects the degree of change of a traffic variable compared to the average. The algorithm is not very sensitive to small fluctuations in traffic data; it would require a significant change in traffic flow to detect an incident. This algorithm is inappropriate to compare with the TxDOT algorithm because it would only detect incidents having a significant impact on traffic.

2.2.4 Bayesian Algorithm

According to a previous study, the algorithm exceeded the two minute requirement. Although its structure could be altered by changing the threshold to achieve a faster detection time, the performance of the algorithm would suffer. Therefore, this algorithm was not chosen for evaluation.

2.2.5 ARIMA Algorithm

Studies proved that the ARIMA algorithm has excellent performance. However, it requires a significant amount of historical data to develop an appropriate model for selected sites; the lack of available historical data will not allow a proper analysis.

2.2.6 High Occupancy Algorithm

The HIOCC algorithm is inapplicable for the TransGuide system because it requires updated loop detector data every tenth of a second while the TransGuide system uses a 20 second polling cycle. Since detector data is not available every tenth of a second, the HIOCC algorithm cannot be tested for this research.

2.2.7 Minnesota Algorithm

The Minnesota algorithm computes a moving average of the difference in upstream and downstream occupancies, before and after a hypothesized incident occurrence time. According to an analysis by Stephanedes et al. (*11*), a five-minute averaging period following the incident is appropriate to remove high-frequency fluctuations and achieve good performance. The algorithm was tested with a three-minute moving average to reduce the detection time. The algorithm performed reasonably well at this level; however, it is not expected that the algorithm would perform well while achieving a two-minute detection time. This algorithm should not be used in the analysis.

2.2.8 Double Exponential Smoothing Algorithm

The structure of the Double Exponential Smoothing algorithm is such that it cannot effectively achieve a two minute detection time requirement. Loop detector data must exceed thresholds for all of the selected parameters. This can often take a significant amount of time to detect incidents if the thresholds are set such that the number of false alarms are limited. Furthermore, these are set thresholds which do not change until physically changed by the operator. This type of a system may be more effective with real-time changes in thresholds; however, its current structure is insufficient for comparison in this study.

2.2.9 McMaster Algorithm

Studies have shown that the McMaster algorithm has excellent performance. Considering that San Antonio has wide variations in detector spacings, the McMaster algorithm's use of a single point detector may prove to be appropriate for this system. Although application of the McMaster algorithm appears promising, it requires ample historical data to define its four conditions, so it cannot be evaluated in this study.

2.2.10 Dynamic Algorithm

While the multiple method and generalized likelihood ratio algorithms performed well in an off-line evaluation, a significant amount of incident data is required to develop models which can recognize incident conditions. It will not be used for comparison.

2.2.11 Event Scan Algorithm

Considering that the Event Scan algorithm is a microscopic algorithm, it is only appropriate to use this algorithm for very low volume conditions. Research by Dudek et. al. (*16*) found that the Event Scan algorithm is applicable to low volumes of about 400 vph. This is a considerably lower volume than existing volumes on San Antonio highways, so the algorithm should not be evaluated in this comparison.

2.2.12 Neural Network

Although the use of neural networks for incident detection appears promising, a significant amount of detector data is needed to train the neural network. This data was unavailable for this analysis due to time constraints, so this algorithm cannot be evaluated in this study.

2.2.13 California Algorithm #8 with Fuzzy Logic

It appears that the California algorithm #8 with fuzzy logic should have better performance than the general California algorithm #8 according to their structures, but the fuzzy algorithm has not been tested to date. Theoretically, this algorithm can apply imprecise data to generate an approximate output. This is appropriate for incident detection because loop detector data is not exact, and traffic conditions may be similar for incident and nonincident situations. This algorithm was chosen for evaluation.

2.2.14 Selected Algorithms

The California algorithm #8 and Fuzzy Logic algorithm were found to be the most appropriate algorithms for the San Antonio TransGuide system. These algorithms will be tested against the TxDOT speed based algorithm to determine which has the best performance on the San Antonio system. The algorithms will be evaluated by applying real data from selected loop detector stations in San Antonio.

2.3 PERFORMANCE EVALUATION

The evaluation is made primarily based on the following performance indicators.

- Detection rate -- ratio of incidents detected out of all incident that occur;
- False alarm rate -- ratio of false alarms out of all decisions (incident and non-incident) made by the system during a specified time period;
- Mean detection time -- the average time required for the system to detect an incident;

In addition to these primary measures, secondary measures are used to evaluate the performance of the alternative algorithms. Examples of the secondary measures include the following factors:

- Data requirements,
- Ease of Installation,
- Ease of Calibration,
- Algorithm Complexity, and
- Potential for self-calibration

The detection rate is defined as

$$DR = \frac{\textit{num. of incidents detected by the algorithm}}{\textit{total num. of incidents}} \times 100\ \%$$

The false alarm rate (FAR) has been defined in two ways. The first definition is used for on-line tests; the second definition is used for off-line tests. In this study, we utilized second definition as a FAR since the test was performed with off-line data. The FAR is given by:

$$FAR = \frac{num.\ of\ incident\text{-}free\ intervals\ which\ give\ false\ alarms}{total\ num.\ of\ incident\text{-}free\ intervals} \times 100\ \%$$

The MTTD for a set of n incidents is defined as:

$$MTTD = \frac{1}{n} \sum_{i=1}^{n} (t_{id} - t_{io})$$

where t_{id} is the time when an incident i is detected, and t_{io} is the time when an actual incident i has occurred.

3.0 STUDY METHODS AND DATA

3.1 METHOD

Algorithm comparisons may be conducted with an off-line or on-line analysis. In an off-line analysis, the algorithms process real or simulated data on a personal computer or workstation. The algorithm results are compared with operator incident logs or with CCTV (closed circuit television) recordings of actual freeway conditions. An on-line analysis is generally conducted with the traffic management center system. The system immediately receives and processes loop detector data. When the algorithms produce alarms, operators verify whether an incident occurred.

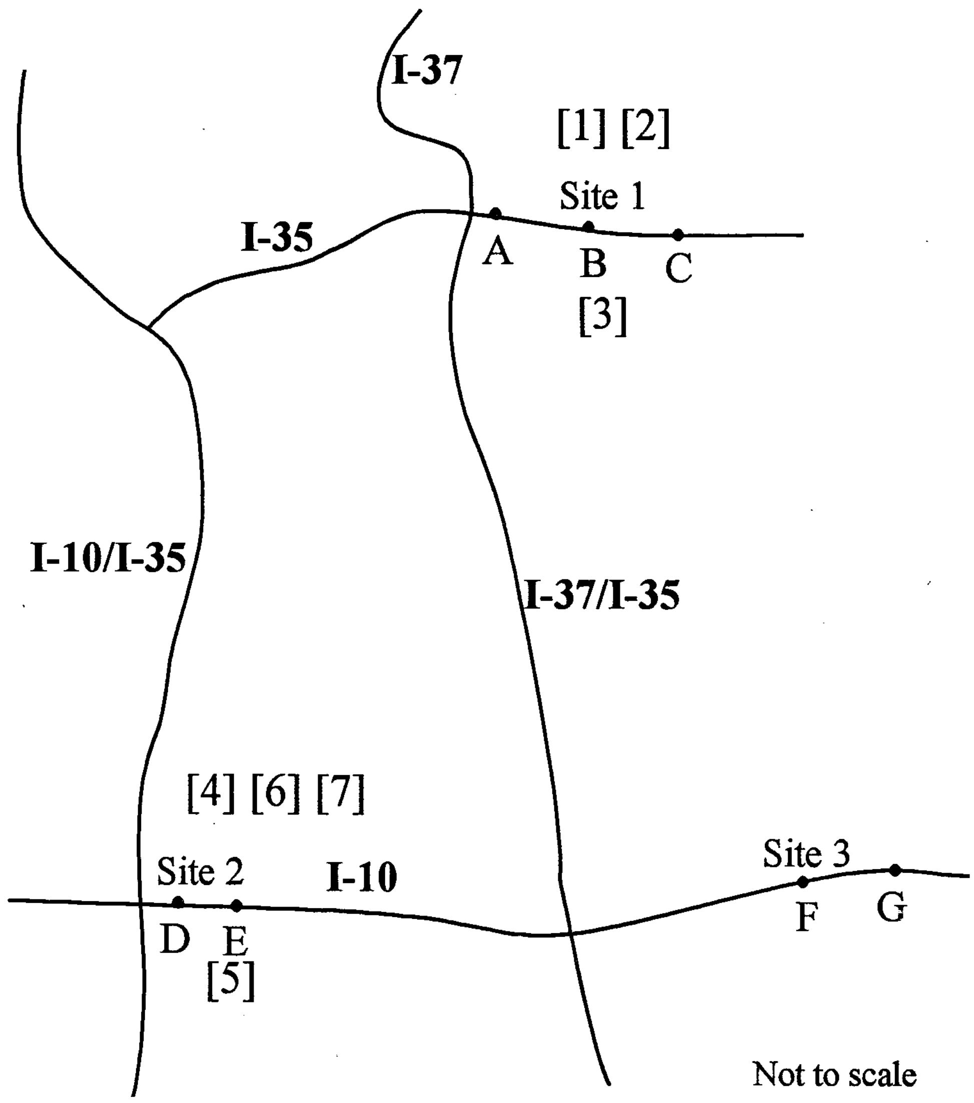
Each method has disadvantages which limit the algorithm analysis. If an off-line analysis compares algorithm results with operator incident logs, the overall results depend on the accuracy of the logs. If the operators did not detect an incident which an algorithm detected, it is recorded as an algorithm false alarm. This problem will not occur with CCTV recordings; all algorithm alarms can be verified by watching the recorded conditions. However, camera recordings are limited because they can only record in one direction. The evaluation area may also be limited by a lack of recording equipment. Another disadvantage of CCTV recording is the amount of time required to view the CCTV tapes, but this time can be reduced by viewing the tapes at advanced speeds. The advantage of the freeway video recording method is that the exact amount of time for an algorithm to detect incidents can be determined. In this case, synchronization of the video camera and the loop detector is necessary.

The advantage of the on-line method is that the existing conditions are immediately checked with CCTVs following an incident alarm; the comparison does not merely depend on the reliability of the operator logs or the chance of recording the incident on video. One disadvantage of this method is that selected threshold sets may only be tested once in the analysis. Also, it is unlikely that exact incident occurrence times are recorded since operators rely on CCTVs and algorithm output to detect incidents. In research, an off-line analysis was performed with real data, and incidents were verified through videos taped at five CCTV viewing areas.

3.1.1 Study location

Three sites were selected for evaluation from Phase I of the San Antonio TransGuide system which includes sections of I-10, I-35, and I-37 in the downtown area of San Antonio. The selected sites and their approximate loop detector locations are shown on the map of Phase I in Figure 13, with the letters denoting the locations of loop detector stations selected for video recording.

Figures 14-16 show the locations of the loop detectors and cameras for each of the three sites. Both highway directions were monitored at all three sites. The loop detectors and cameras



Note: The number in the brackets indicates incident case number.

Figure 13. Selected Loop Detector Locations From Phase I of TransGuide

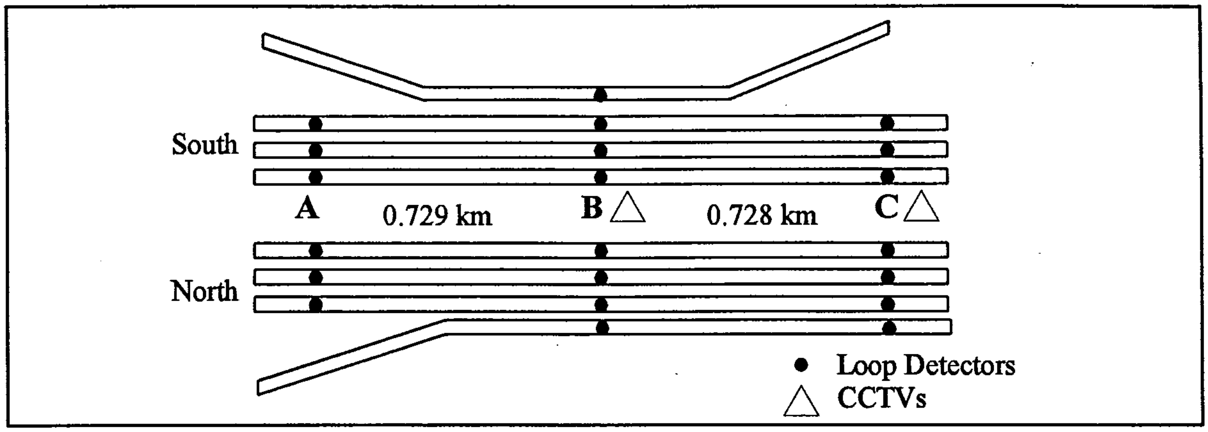


Figure 14. Equipment Locations for Site 1 on I-35

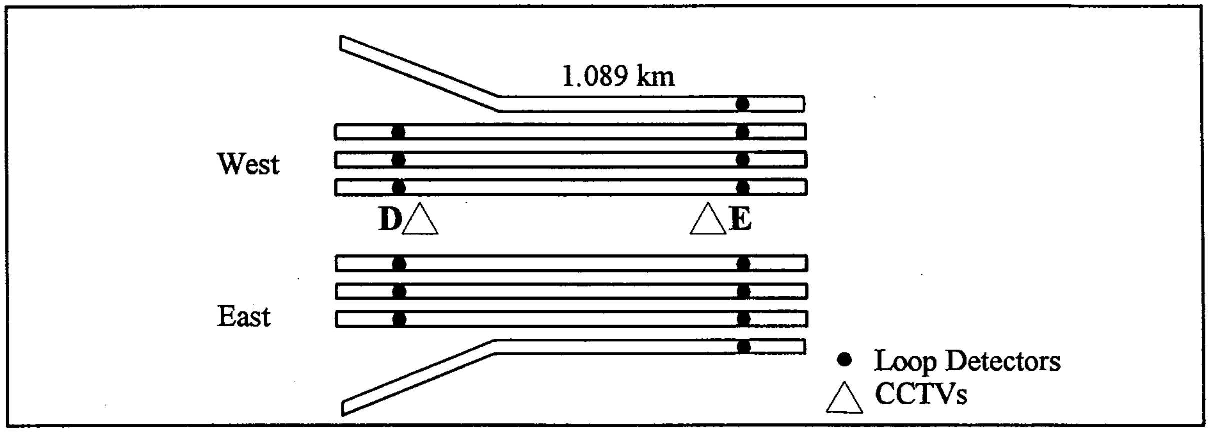


Figure 15. Equipment Locations for Site 2 on I-10

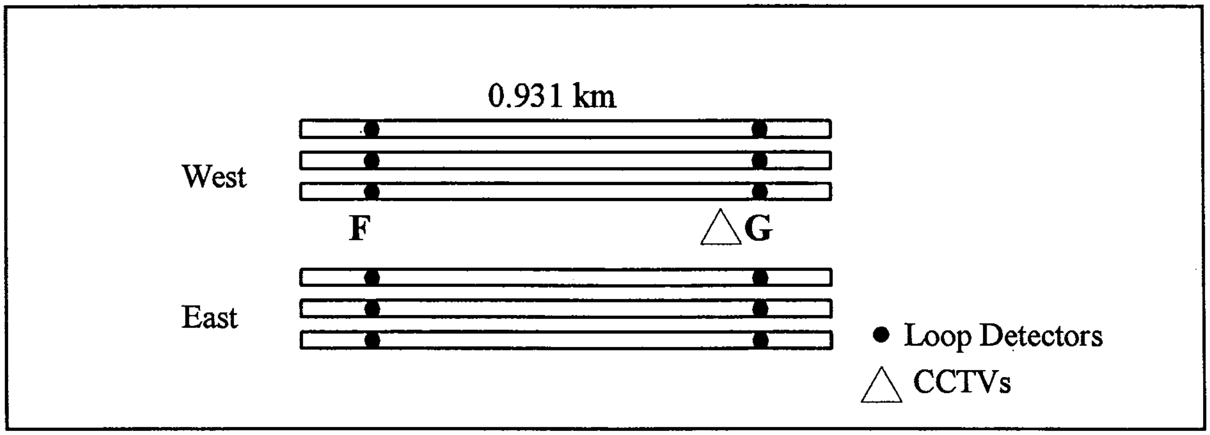


Figure 16. Equipment Locations for Site 3 on I-10

are coded with the same labels as those used at TransGuide, but detector stations were also coded from A to G for simplicity. The loop detectors have the same code number for both sides of the highway with different notations for the change in direction. For example, Station 35N-158.492 is a detector station on Northbound IH-35 at milepoint 158.492.

Site 1 is located slightly east of the IH-35/IH-37/US-281 interchange. The equipment monitoring Site 1 includes three detector stations (35N/S-158.036 [Station A], 35N/S-158.492 [Station B], and 35N/S-158.947 [Station C]) and two cameras (CCTV-0035N-158.560 and CCTV-0035N-158.989). Site 2 along IH-10 is monitored by two loop detector stations (10E/W-572.973 [Station D] and 10E/W-573.654 [Station E]) and two cameras (CCTV-0010W-572.992 and CCTV-0010W-573.645). Site 3 is on IH-10, with two loop detector stations (10E/W-576.264 [Station F] and 10E/W-576.846 [Station G]) and one camera (CCTV-0010E-576.832).

3.1.2 Site Selection

Sites were selected based on relative camera and loop detector locations, as well as historical accident rates. Cameras for the chosen sites have sufficient sight distance such that their viewing areas encompass at least two loop detector stations for the same freeway direction. Selected cameras are not located within sharp horizontal or vertical curves, and their viewing areas are not impeded by obstructions.

According to historical accident data from San Antonio police records, a number of incidents were expected to occur during the study period. Monthly accident averages were computed for each site based on data from 1993 and 1994. The monthly averages for Sites 1-3 were 14.8, 13.6, and 7.8 accidents per month, respectively.

3.2 TRAFFIC PATTERNS

Loop detector data were plotted to determine typical traffic characteristics for the selected sites. These graphs were generated with 15 minute averages of loop detector data. One of the apparent characteristics on San Antonio highways is that speeds are typically constant throughout the day, remaining above 72 km/hr (45 mph) with normal traffic flow conditions. When an incident occurs, speeds drop rapidly below around 40 km/hr (25 mph).

3.2.1 Normal Weekday/Weekend Patterns

Figures 17 and 18 show the normal patterns of three basic traffic variables (speed, volume, and occupancy) of both weekday (Westbound Station D of Site 2 on February 16, 1996) and weekend (Northbound Station A of Site 1 on January 13, 1996), respectively. As shown in figures, the freeway, currently under evaluation, does indicate obvious peaking phenomenon with some level of traffic congestion. As indicated above, one of the apparent characteristics on this specific section in San Antonio is that the operating speed does not fall below 72 km/hr (45 mph) during normal traffic conditions.

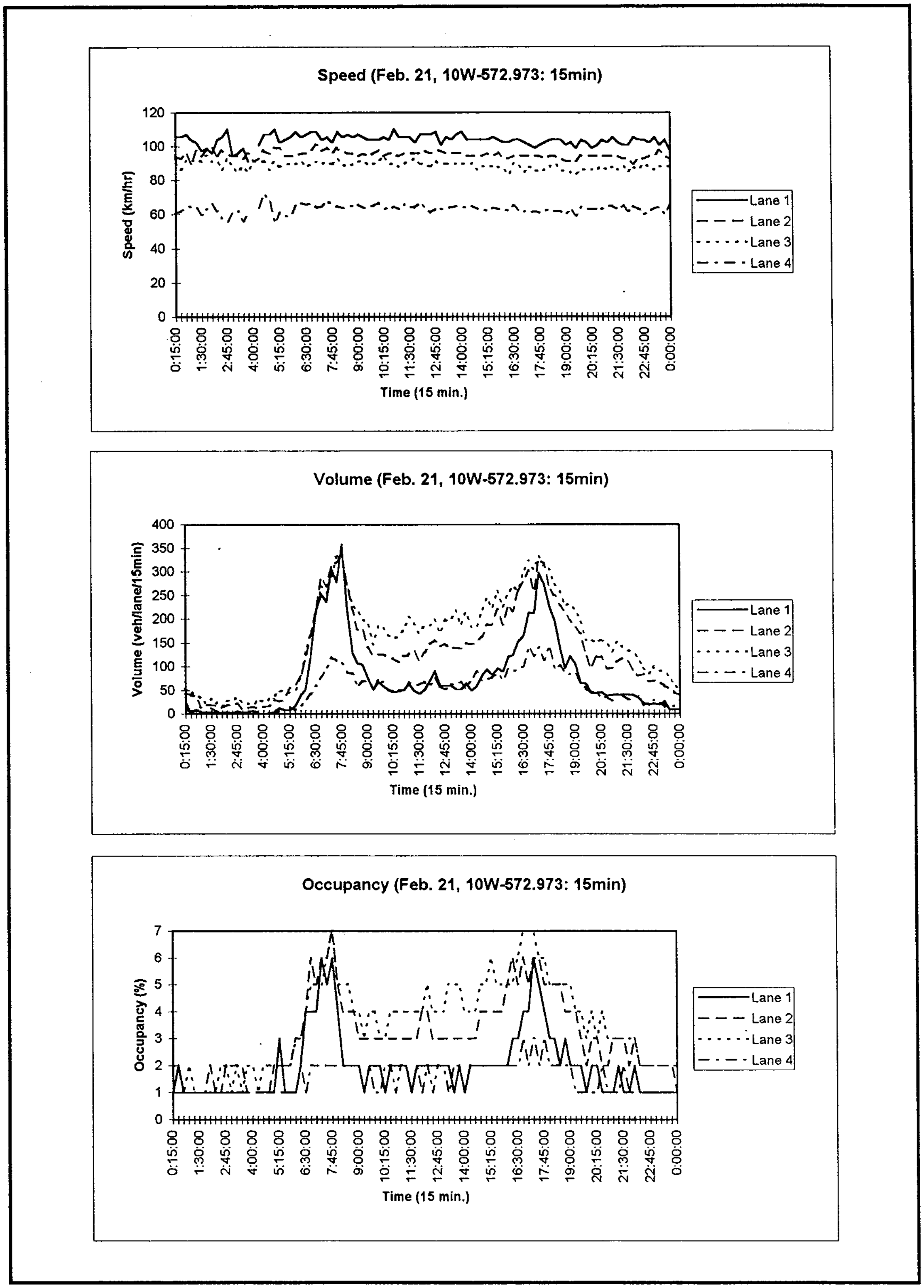


Figure 17. Normal Weekday Patterns

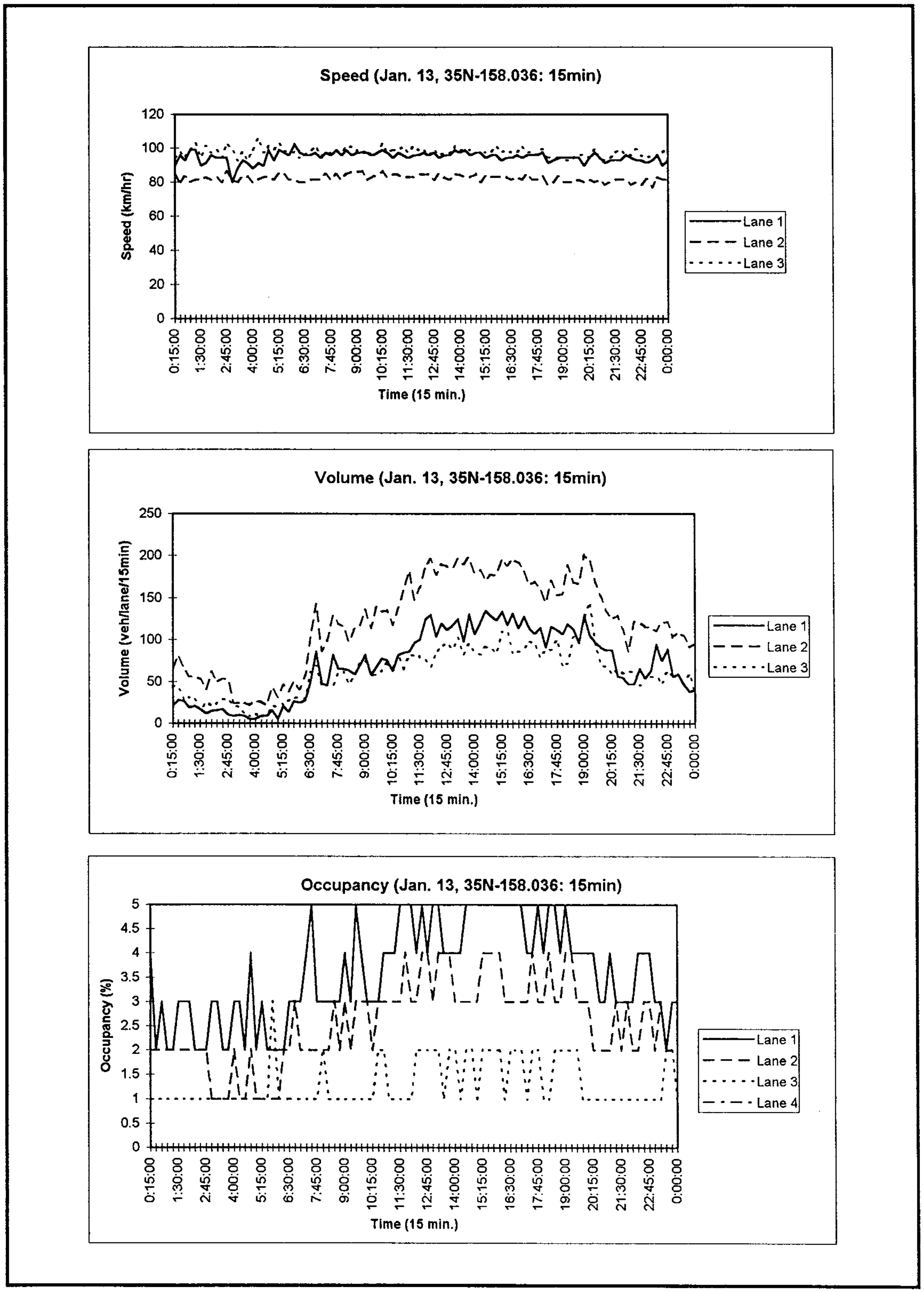


Figure 18. Normal Weekend Patterns

3.2.2 Incident Patterns

Figure 19 shows incident patterns (Eastbound Station D of Site 2 on February 16, 1996) of speed, volume, and occupancy over time. It was observed that during incident periods speeds drop below 40 km/hr (25 mph), occupancies go up more than 35%, and volumes remain as usual.

3.3 TEST CASES

A total of seven incidents were found during the two month study period.

3.3.1 Incident Description

Table 2 provides a brief description of the incidents. The Table lists each incident in a specific case number; the incidents are referred to by case number through the remainder of this report. The location column of the Table defines the detector stations between which the incident occurred. The lane column lists which lanes the incident blocked, with lane 1 being next to the median. The column labeled Time denotes the incident occurrence time.

Table 2. Incidents from Sites 1-3 between January 8 and March 9, 1996.

Case #	Date	Incident Type	Location	Direction	Lanes	Time
1	Tues., Jan. 9	Accident	Station B-A	South	2 and 3	16:07:40
2	Sat., Jan. 13	Accident	Station C-B	South	Next to 3	18:26:10
3	Thurs., Jan. 18	Motorist blocking lane	Station B-C	North	4	9:21:30
4	Thurs., Jan. 18	Debris	Station E-D	West	1 and 2	16:25:50
5	Mon., Jan. 29	Accident	Station E-D	West	3	7:46:30
6	Fri., Feb. 16	Accident	Station D-E	East	4	15:43:30
7	Tues., Feb. 20	Stalled Vehicle	Station E-D	West	3	17:18:00

3.3.1.1 Case 1

This incident occurred between Northbound Station A and B. It takes approximately one or two minutes for detection. This detection time is appropriate because it takes nearly that amount of time for the incident to affect traffic at the upstream station.

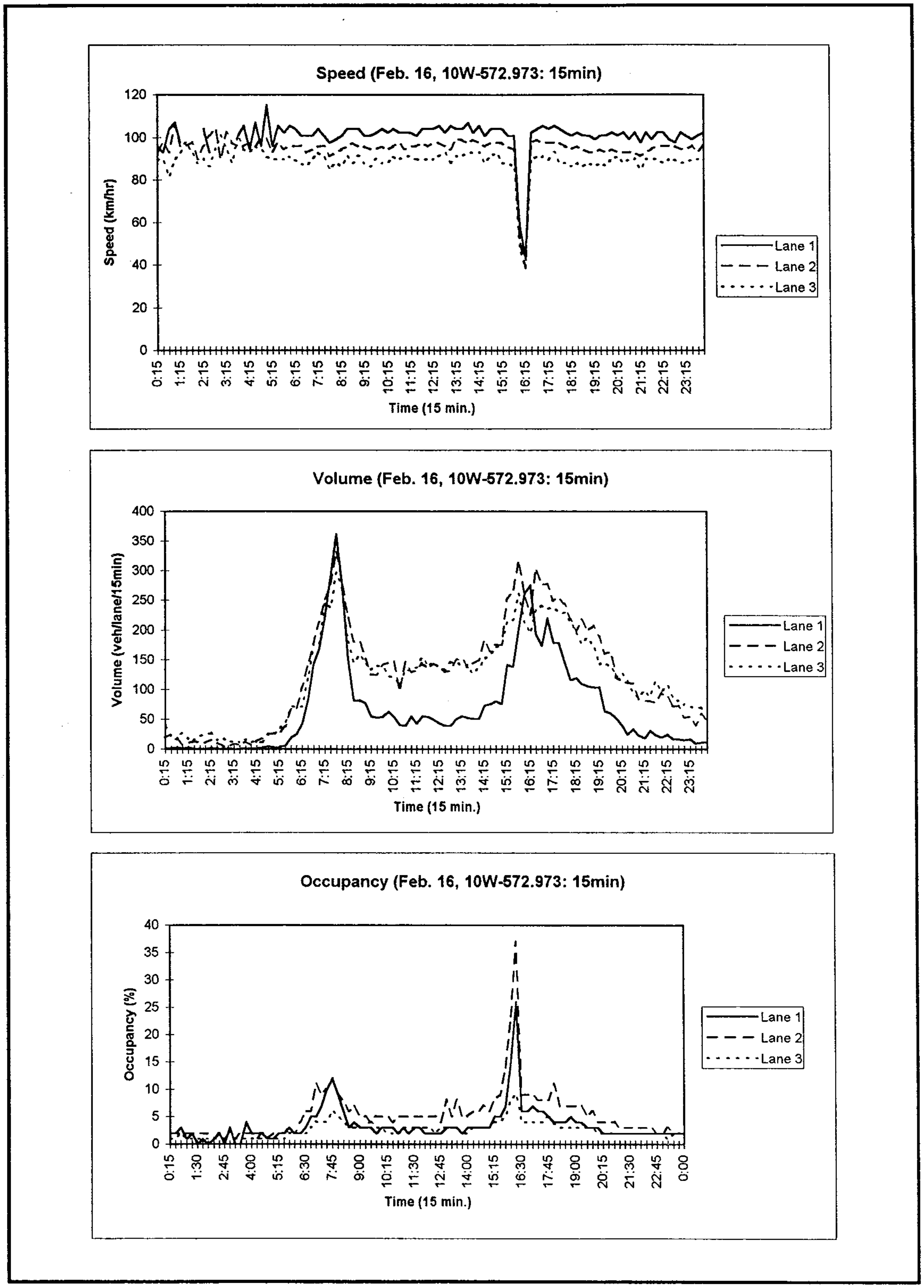


Figure 19. Typical Incident Traffic Patterns

3.3.1.2 Case 2

It was dark at the time that incident #2 occurred in the gore area. Because of these conditions, the incident did not affect traffic until emergency vehicles arrived to handle the incident. A policeman arrived at the scene at 18:32:02 in a vehicle travelling in lane 3. This affected traffic in lane 3 slightly before arriving at the accident site since drivers were clearing the path for him in lane 3. The system detected the conditions about one minute before the policeman arrived.

3.3.1.3 Case 3

For this incident, it did not affect speeds in the three main lanes such that they dropped below 40 km/hr (25 mph). However, the speed, volume, and occupancy parameters were all zero between 9:22:49 and 9:44:49 because of the truck blocking the lane.

3.3.1.4 Case 4

It was difficult to detect this incident because some vehicles drove over the debris while others avoided it. Although the glass debris dropped on the road at 16:25:30, the first queue did not form until approximately 16:38, but it dissipated at 16:46. Once the debris was spotted by the traffic management center, lane controllers advised drivers that the left two lanes were closed ahead. This caused a second queue to propagate at 17:07, forming in the right two lanes first. The algorithms could not detect the incident until it began to affect traffic almost 45 minutes later.

3.3.1.5 Case 5

It was difficult to determine what effect this incident had on traffic at the upstream detector because of the video angle. However, it is known that the incident occurred approximately halfway between the detectors. Because of the incident location, it is likely that it took longer for it to affect traffic at the upstream station and for the system to detect the incident.

3.3.1.6 Case 6

Since this incident occurred directly in front of Station E, it took just a few minutes for the queue to propagate and affect data at the upstream detectors.

3.3.1.7 Case 7

This incident also occurred immediately in front of a detector. In this case, however, the speeds never decreased significantly enough for the speed algorithm to detect the incident, except using the data from the lane in which the incident occurred.

3.3.2 Data Collection Procedure

Data were collected from video cameras and loop detectors from the selected sites. The cameras recorded traffic flow from 7 a.m. until 7 p.m. for two months, between January 8 to March 9, 1996. The speed, volume, and occupancy loop detector data were automatically averaged for 20 second time intervals. The internal camera and computer system clocks were adjusted within the limits of manual synchronization.

3.3.3 Data Reduction Procedure

As shown in Figures 16 and 17, speeds are typically constant throughout the day, remaining above 72 km/hr (45 mph). Based on this assumption, data from the three sites were flagged when speeds dropped below 72 km/hr (45 mph). Camera recordings were only viewed for sections where the data were flagged for more than one minute per lane in an attempt to find incidents.

Two sets of incident-free data were prepared. The first set, which was intended to compare the performance of different incident detection algorithms including the TxDOT algorithm, California #8 algorithm, and California #8 with fuzzy logic algorithm, was selected from the highway sections with less missing data. Where data were missing, values were manually inserted for the missing sets. By averaging data from the other lanes for the specified time, data were created for the missing data sets. For cases where all lanes were missing data for the same period or where one lane's data appeared consistently different from the other lanes, the new data were computed by averaging that lane's data from its polling cycles immediately before and after the missed period. If a lane's data were missing for the whole incident data set, new values were not computed. Instead, this lane was not used in the analysis.

On the contrary, the second dataset was run for only sensitivity analysis of speed-based algorithm. The dataset did not attempt to supersede missing data. Both data sets were run for 12 hour periods (7 a.m. - 7 p.m.).

3.3.4 Data Verification

Loop detector volumes were checked for validity by comparing the values generated by the loops with manual volume counts from video tapes. Data were compared for Station C of Site 1 using January 11 data, counting vehicles for five minute periods. Loop detector and manual volume count values are presented in Tables 3 and 4. Table 5 shows the difference in these values, where a negative number represents the loop detectors counting fewer vehicles than were counted manually. These differences were generally negligible, with no consistent pattern in over-counting or under-counting. However, it appears that the Northbound detector in lane 2 was malfunctioning at 17:05. It reported normal speeds of 88 km/hr (55 mph), yet reported high occupancies of approximately 85% and very low volumes, counting only a few vehicles during each 20 second period. These data appear erroneous. Their use would inhibit the validity of the study results.

During the detector data evaluation, it appeared that occupancy values seemed unreasonable at times, while speeds were stable and reasonable. Considering that this research compares two algorithms which rely only on occupancy data with an algorithm which exclusively relies on speed data, it is expected that the TxDOT Speed algorithm will consistently perform better since its decisions are based on the acceptable data. With unreasonably high occupancies existing in the raw data, California algorithm #8 and the Fuzzy Logic algorithms will produce many more false alarms than the TxDOT algorithm.

It would be unreasonable to compare the results of these algorithms while the input is inappropriate for two of the algorithms but reasonable for the other. To account for this situation, false alarms were computed twice for the California #8 and Fuzzy Logic algorithms. Raw loop detector occupancy data were run through the algorithms, and the total number of false alarms were computed. Then the false alarm results were filtered such that a false alarm was not counted when the occupancy data appeared unreasonable. An unreasonable data region was defined with an equation that is based on traffic flow theory (*20*):

$$Occupancy\,(\%) = \frac{(L_V + L_D)\,Flow}{10\,(Speed)}$$

where: L_V = Average vehicle length; and
L_D = Average detector length.

Assuming an average vehicle length of 5.7 m (19 ft), an average detector length of 1.8 m (6 ft), average volume of 2160 vphpl, and an average speed of 80 km/hr (50 mph), the theoretical occupancy should be approximately 20%. The volume of 2160 vphpl was selected because it was one of the higher volumes found within the raw data. The average 80km/hr (50 mph) speed was selected for the region to reject because it is typical that occupancies are low for these speeds. After verifying that actual data appeared unreasonable when 80 km/hr (50 mph) speeds with corresponding 20% occupancies were exceeded, this was selected as the filtering region. When a false alarm occurred with an occupancy of 20% or greater and a speed of 80 km/hr (50 mph) or more, it was not counted as a false alarm for the California #8 and Fuzzy Logic algorithms with filtering.

Table 3. Loop Detector Volumes over 5 Minute Periods for Station C, Site 1, January 11, 1996

	North				South		
	Lane 1	Lane 2	Lane 3	Lane 4	Lane 1	Lane 2	Lane 3
7:30-7:35	85	104	80	89	176	171	190
7:35-7:40	102	106	83	99	183	175	177
7:40-7:45	89	106	79	99	199	175	180
17:00-17:05	159	120	112	79	102	166	168
17:05-17:10	175	35	132	60	189	162	168
17:10-17:15	170	42	146	68	167	164	133

Table 4. Manually Counted Volumes over 5 Minute Periods for Station C, Site 1, January 11, 1996

	North				South		
	Lane 1	Lane 2	Lane 3	Lane 4	Lane 1	Lane 2	Lane 3
7:30-7:35	84	105	81	90	171	173	187
7:35-7:40	104	130	85	101	184	178	184
7:40-7:45	82	101	97	96	199	163	190
17:00-17:05	155	136	113	85	124	134	143
17:05-17:10	166	174	127	76	180	161	177
17:10-17:15	165	158	133	83	168	176	157

Table 5. Differences in Loop Detector Volumes and Manually Counted Volumes over 5 Minutes for Station C, Site 1, January 11, 1996

	North				South		
	Lane 1	Lane 2	Lane 3	Lane 4	Lane 1	Lane 2	Lane 3
7:30-7:35	1	-1	-1	-1	5	-2	3
7:35-7:40	2	-24	-2	-2	-1	-3	-7
7:40-7:45	7	5	-18	3	0	12	-10
17:00-17:05	4	-16	-1	-6	22	32	25
17:05-17:10	9	-139	5	-16	9	1	-9
17:10-17:15	5	-116	13	-15	-1	-12	-24

4.0 EVALUATION RESULTS

4.1 EVALUATION RESULTS

Raw loop detector data were run in parallel for the three algorithms selected. California algorithm #8 and the Fuzzy Logic algorithm detect incidents between two stations by comparing the occupancies of those stations. The TxDOT algorithm uses data from just one detector; however, it may be able to detect an incident with a detector either upstream or downstream of an incident, depending on its location and conditions. The speed algorithm was run with both detectors, producing two sets of results for one highway section.

Algorithms were run using two data input methods, one using overall lane average data and one using per lane data. For the first method, the computer program averaged data across lanes for each time slice; then the algorithm ran the averaged data. In the second case, the algorithm ran data for each lane individually. If there were three lanes, for example, the algorithm would produce results for each of the three lanes. However, more than one lane may sound an incident alarm at nearly the same time when an incident occurs (incident detection) or when the algorithm misinterprets incident-free conditions (false alarms) as an incident. The reported incident detection time refers to the first lane detecting the incident. Similarly, to compute false alarms, only one alarm is counted if two or more lanes produce alarms at nearly the same time.

The times that the algorithms detected each incident are presented in Table 6, with total detection times in Table 7. For three instances, an algorithm declared a false alarm just prior to the incident, and the false alarm continued during the time that the incident occurred. This situation is denoted by an asterisk in Tables 6 and 7. If the algorithm was unable to detect the incident, it is noted as ND (no detection). When the second incident occurred on January 13, the loop detector in lane 2 for Station C was not producing any data. Since the algorithms could not produce any results, Tables 6 and 7 denote this occurrence as MD (missing data). Detection times for the California #8 and Fuzzy Logic algorithms with filtering are not reported separately in these tables because their results are equivalent to the algorithms without filtering.

Reported speed algorithm detection times refer to the time of detection by upstream detectors adjacent to the incident, except for Case 3 which detected the incident with downstream detectors. Downstream detectors may detect incidents faster when incidents are close to those detector stations. Conversely, upstream detectors are typically better for detecting incidents which cause queues to propagate upstream of the incident.

The algorithm detection times were slow for a number of the incidents. Many of these delays can be explained by conditions of the incident. For Cases 2, 5, 6, and 7, the incidents locations relative to the detectors and the traffic volumes are such that it takes a few minutes for queues to develop and affect upstream detectors.

Incident #2 occurred in the gore area; therefore, the incident did not affect traffic until emergency vehicles arrived to handle the incident. A policeman arrived at the scene at 18:33:02 in a vehicle traveling in lane 3. This affected traffic in lane 3 slightly before arriving at the accident site since drivers cleared a path in lane 3 to provide access for the policeman. The system detected the conditions about one minute before the policeman arrived.

Table 6. Algorithm Detection Times

		Incident Number						
		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Incident Occurrence		16:07:40	18:26:10	9:21:30	16:25:30	7:46:30	15:43:30	17:18:00
Average	Speed (25)	16:09:50	18:32:30	ND	17:23:00	7:53:00	15:50:20	ND
	Calif. 8	16:08:50	18:31:40	ND	17:19:00	7:53:00	15:49:00	*
	Fuzzy	16:08:50	18:35:00	ND	17:23:20	7:55:40	15:50:20	ND
Lane 1	Speed (25)	16:10:10	18:32:50	ND	17:34:40	7:52:40	ND	ND
	Calif. 8	16:09:30	18:32:00	ND	ND	7:52:40	15:48:00	ND
	Fuzzy	16:09:30	18:34:30	ND	ND	7:55:40	15:48:20	ND
Lane 2	Speed (25)	16:09:50	MD	ND	17:34:40	7:52:40	15:49:40	ND
	Calif. 8	16:08:50	MD	ND	17:35:00	7:52:00	15:46:00	ND
	Fuzzy	16:08:50	MD	ND	17:35:00	7:52:00	15:46:00	ND
Lane 3	Speed (25)	16:10:10	18:32:10	9:26:50	17:09:40	ND	15:49:00	17:25:30
	Calif. 8	*	18:31:00	ND	17:07:20	7:52:00	ND	17:20:10
	Fuzzy	*	18:31:00	ND	17:08:20	7:53:20	ND	17:21:50

* False alarm continuing through incident
ND No detection of incident
MD Missing data

Case 3 was not necessarily an incident because it did not require response by emergency vehicles. However, it was considered in the analysis because algorithms should be able to detect the change in the traffic patterns caused by this event.

Case 4 was a difficult incident to detect because some vehicles drove over the debris while others avoided it. Although the glass debris dropped on the road at 16:25:30, the first queue did not form until approximately 16:38, but it dissipated at 16:46. Once the debris was spotted by the traffic management center, lane controllers advised drivers that the left two lanes were closed ahead. This caused a second queue to propagate at 17:07, forming in the right two lanes first. Therefore, it is reasonable that the traffic management center could not detect the incident until it began to affect traffic almost 45 minutes later. Algorithms were tested in detecting this incident, but the detection time was not included in computing the algorithm mean time to detect.

Table 7. Algorithm Time to Detect Incidents

		Incident Number						
		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Average	Speed (25)	2:10	6:20	-	57:30	6:30	6:50	-
	Calif. 8	1:10	5:30	-	53:30	6:30	5:30	*
	Fuzzy	1:10	8:50	-	57:50	9:10	6:50	-
Lane 1	Speed (25)	2:30	6:40	-	1:09:10	6:10	-	-
	Calif. 8	1:50	6:10	-	-	6:10	4:30	-
	Fuzzy	1:50	8:20	-	-	9:10	4:50	-
Lane 2	Speed (25)	2:10	MD	-	1:04:10	6:10	6:10	-
	Calif. 8	1:10	MD	-	1:09:30	5:30	2:30	-
	Fuzzy	1:10	MD	-	1:09:30	5:30	2:30	-
Lane 3	Speed (25)	2:30	6:00	5:20	44:10	-	5:30	7:30
	Calif. 8	*	4:50	-	41:50	5:30	-	2:10
	Fuzzy	*	4:50	-	42:50	6:50	-	3:50

* False alarm continuing through incident
- No detection of incident
MD Missing data

4.2 ALGORITHM PERFORMANCE

This section provides algorithm results of running incident and incident-free detector data. Table 8 presents values for the 10 algorithm cases for the measures of effectiveness defined in the Performance Measure section of Chapter 2.

Mean time to detect values do not include the detection time for Case 4 where there was debris on the road. This was a special case where the debris did not affect all traffic, making the time to detect very long. Including this detection time in the average would skew the mean time to detect for all algorithms. For by lane data inputs, the mean time to detect equals the average of the fastest lane detection times in each case. A different lane may detect the incident first for every case; it is typical for a lane being blocked by the incident to detect the incident first. For all algorithms, by lane detections were always faster than with lane average inputs. Overall, California algorithm #8 detected incidents first for the cases it was able to detect.

According to the compiled results shown in Table 8, the TxDOT Speed algorithm performance was excellent with per lane input. Most of its false alarms occurred during congestion. California algorithm #8 performance was poor using inputs from each lane, with 1463 false alarms. Even after filtering false alarms caused by unreasonable data, the algorithm produced 1213 false alarms. Off-line false alarm rates were computed by dividing false alarms by the total number of decisions made by the algorithms during the 56 cases (113,347 decisions for California #8 and Fuzzy without filtering; with filtering, subtract the number of filtered false alarms from 113,347; 226,694 for TxDOT).

Table 8. Measures of Effectiveness for Each Algorithm

		Detection Rate	Mean Time to Detect	False Alarms	Off-Line FAR
Average	Speed (40 km/hr, 25mph)	71.4%	5:28	13	0.001%
	California #8	71.4%	4:40	164	0.145%
	Calif. #8 with Filter	71.4%	4:40	114	0.101%
	Fuzzy	71.4%	6:30	42	0.037%
	Fuzzy with Filter	71.4%	6:30	11	0.010%
By Lane	Speed (40 km/hr, 25mph)	100%	5:27	41	0.002%
	California #8	85.7%	2:42	1463	1.291%
	Calif. #8 with Filter	85.7%	2:42	1213	1.073%
	Fuzzy	85.7%	2:58	478	0.422%
	Fuzzy with Filter	85.7%	2:58	189	0.167%

4.3 STATISTIC ANALYSIS

To determine whether there was a significant difference in the mean time to detect when using detector data averaged across lanes versus per lane data, an upper-tailed paired t-test was performed (*21*). Two-tailed paired t-tests were performed to compare the mean time to detect for the seven algorithms (*21*); they were compared with per lane inputs and average of lane inputs. Performing this statistical test requires the use of normally distributed data. It could not be determined from this data whether there was a normal distribution because of the limited data. However, it is believed that the data have nearly a normal distribution, with a slight shift to the right. It would have a shift because algorithms typically do not detect incidents in less than a minute. Because of the robustness of this test, it was determined that this statistical test could still be used with the data. Tables 9-11 report the results of the statistical tests.

Table 9. Paired t-Test Comparing Mean Time to Detect for Per Lane and Average of Lanes Results

Algorithm Tested	$t_{calculated}$	α	t_{table}	Result
Speed (40 km/hr, 25mph)	1.190	0.10	1.533	Cannot reject H_0
California #8	1.513	0.10	1.533	Cannot reject H_0
Fuzzy Logic	2.139	0.05	2.132	Reject H_0

Table 10. Paired t-Test Comparing Algorithm Mean Time to Detect using Average of Lanes Input

Algorithms Compared		$t_{calculated}$	$\alpha/2$	t_{table}	Result
Speed (40 km/hr,25mph)	Calif.	2.791	0.05	2.353	Reject H_0
Calif. #8	Fuzzy	2.480	0.05	2.353	Reject H_0
Speed (40 km/hr,25 mph)	Fuzzy	1.140	0.05	2.353	Cannot reject H_0

Table 11. Paired t-Test Comparing Algorithm Mean Time to Detect using Per Lane Input

Algorithms Compared		$t_{calculate}$	$\alpha/2$	t_{table}	Result
Speed (40km/hr)	Calif. #8	2.552	0.05	2.132	Reject H_0
Calif. #8	Fuzzy	1.000	0.05	2.132	Cannot reject H_0
Speed (40 km/hr)	Fuzzy	3.167	0.025	2.776	Reject H_0

The null hypothesis (H_0) stated that the difference in the mean algorithm results was zero (μ_1-μ_2=0). When the results in the tables state 'cannot reject H_0,' it means that there was not sufficient evidence to prove that there was a significant difference in the algorithm results. But if the null hypothesis is rejected, the difference in the performance for the algorithms tested was statistically significant. The smaller the value of α when H_0 is rejected, the stronger the evidence of a difference in algorithm performance. The null hypothesis for upper-tailed tests was tested at 0.10, 0.05, and 0.025 levels. Two-tailed tests were tested at 0.10 and 0.05 levels. If the result was to reject the null hypothesis, the α values reported in the tables correspond to the most conservative (smallest α value) level for which it was true. When the table reports that the null hypothesis was not rejected, the listed α values correspond to the most liberal (largest α value) values that were tested.

Tables 9-11 did not compare the filtered versions of California algorithm #8 and the Fuzzy Logic algorithm since their detection times were equivalent to the unfiltered algorithm results. In Tables 10 and 11, the algorithms were compared using a mean time to detect that did not include the debris incident.

As revealed in Table 9, there is a difference in the mean time to detect between using per lane data and data averaged across lanes for the Fuzzy Logic algorithm. A t-test also compared these two input methods using the total number of false alarms. The null hypothesis was rejected at a level of 0.05 ($t_{calc} = 2.139$, $t_{table} = 2.132$), showing a statistical difference in false alarms for the average of lane versus per lane input.

Table 10 shows that there was a statistically significant difference for the mean time to detect between California algorithm #8 with both the TxDOT Speed algorithm and the Fuzzy Logic algorithm. There was not a significant difference in the detection time for the other algorithms when input data were averaged across lanes.

The results of the paired t-test with per lane input showed a significant difference in mean time to detect between the TxDOT Speed algorithm with California algorithm #8 and with the Fuzzy Logic algorithm. There was not a significant difference in the mean time to detect between California algorithm #8 and the Fuzzy Logic algorithm.

4.4 GENERAL OBSERVATIONS

Determining which algorithm has the overall best performance is a complicated task; while one algorithm's detection rate and mean time to detect are good, that algorithm may produce many false alarms. However, another algorithm which has few false alarms may have a poor detection rate and slow average detection time. Due to the limited data available, it is emphasized that the results may be considerably different if the algorithms were calibrated with large incident cases and incident-free data set.

By running data for each lane, as opposed to the average of the lanes, all algorithms had better performance in detecting incidents; but there were more false alarms. California algorithm #8 had the fastest mean detection time, but it performed poorly by producing a significant number of false alarms. Even after filtering out alarms caused by questionable detector data, it still produced numerous false alarms. The TxDOT algorithms had the best detection rates and false alarm rates. However, the TxDOT algorithm needs to improve its mean time to detect to become the best algorithm.

The Fuzzy Logic algorithm produced moderate results for all the algorithm performance measures. With its general structure being based on California algorithm #8, its results were similar to that algorithm, except for false alarms. Results of the Fuzzy Logic algorithm indicated that it could filter variations in data better than California algorithm #8.

5.0 DETAILED ANALYSIS OF SAN ANTONIO SPEED BASED ALGORITHM

5.1 OVERVIEW

Based on the previous analysis of alternative incident detection algorithms, the TxDOT speed-based algorithm was investigated in detail to increase system responsiveness and reduce false alarms of San Antonio TransGuide system. The analysis was performed with different moving average intervals and threshold values. Seven incident datasets and over two months of incident-free datasets were examined in the analysis.

It should be noted that the speed-based algorithm was run not on a per average lane basis but on a per lane basis. The reason is that a preliminary study of Chapter 4 showed the average lane basis not only takes a longer time to detect but also produces less detection rate.

5.1.1 Different Moving Average Intervals

Currently, TxDOT speed-based algorithm uses six polling cycles as a moving average interval. As mentioned earlier, the study results show that six polling cycles of a moving average interval can not always detect incident within two minutes.

The analysis was designed with different moving average intervals from two to eight polling cycles, i.e., ranging from 40 seconds to 160 seconds, or 0.67 minutes to 2.67 minutes.

5.1.2 Different Threshold Values

Currently, the TransGuide system uses 40 km/hr (25 mph) as a threshold value to detect incidents. This analysis indicates that 40 km/hr (25 mph) is a low value and may cause a longer time to detect. In order to increase system responsiveness, the analysis was performed with different threshold values of 40 km/hr (25 mph), 48 km/hr (30 mph), and 56 km/hr (35 mph).

5.2 EVALUATION

5.2.1 Increase System Responsiveness

Seven incident dataset were run with different moving average intervals and speed thresholds to determine the optimum interval size and threshold value which minimize mean time to detect. It was observed that more than one lane sounded an incident alarm at nearly the same time when an incident occurred (incident detection) or when the algorithm misinterpreted incident-free conditions (false alarms) as an incident. The reported incident detection time refers to the first lane detecting the incident. The sensitivity analysis results were plotted in Figure 20.

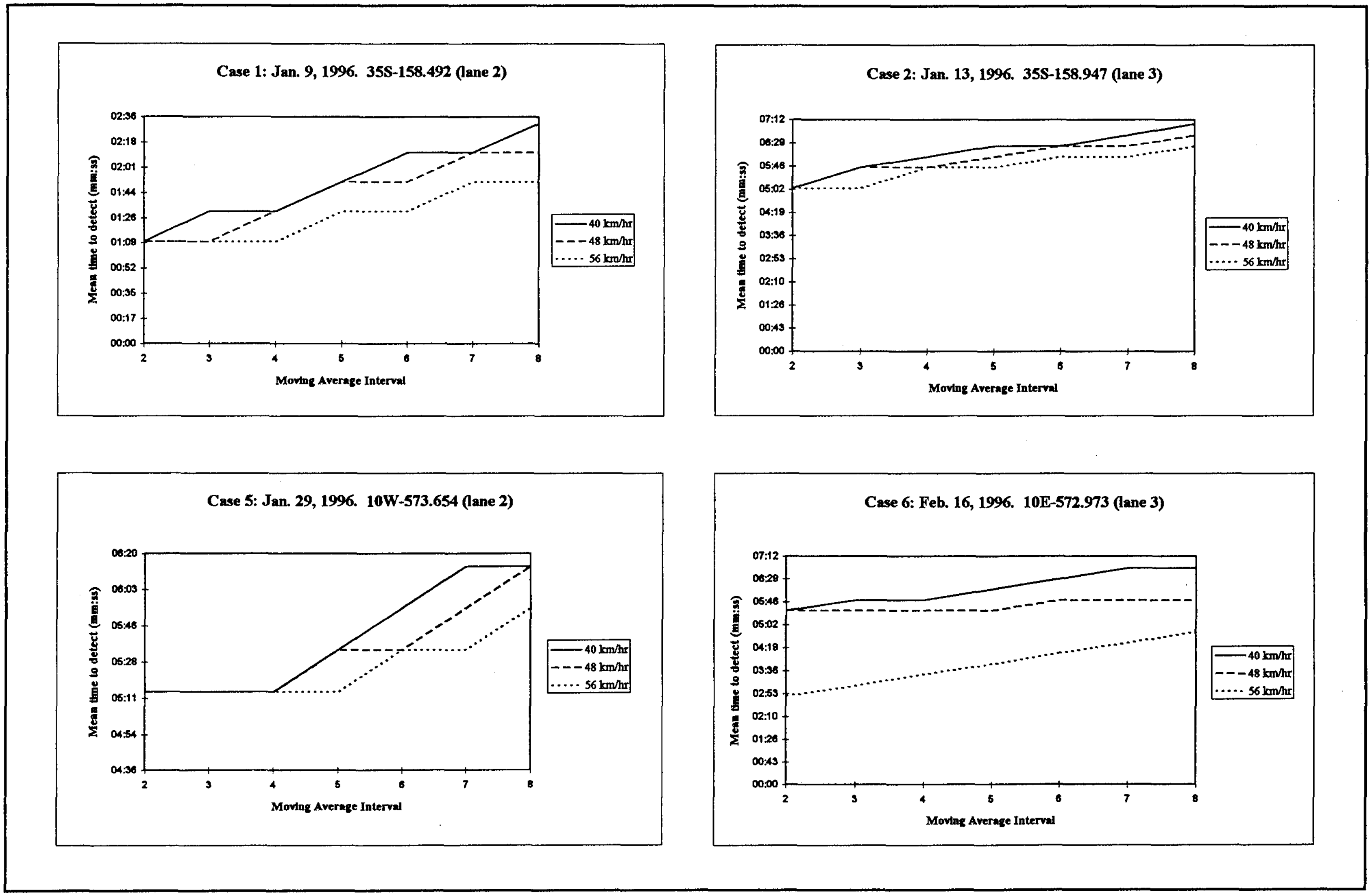


Figure 20. Sensitivity of Mean Time To Detect

As shown in Figure 20, mean time to detect can be reduced significantly with different moving average intervals and threshold values. These figures show the relationship between the moving average interval versus mean time to detect with different speed threshold values. As previously envisioned, as the speed thresholds lower and/or moving average intervals increase, more time to detect incident is required. It is noted that the results of only four accident cases were plotted in the report since the other three cases out of seven incidents were not detected immediately. That is, case 3 of motorist blocking lane, case 4 of debris, and case 7 of stalled vehicle were not serious enough to affect the traffic flow during the study evaluation.

5.2.2 Reduce False Alarms

Two different datasets were analyzed; one consisted of incident data, and the other consisted of over two months of incident-free data. It should be noted that since more than one lane sounded an incident alarm at nearly the same time when an incident occurred (incident detection) or when the algorithm misinterpreted incident-free conditions (false alarms) as an incident, the reported incident detection time of Figure 20 and Tables 12-15 refers to the first lane detecting the incident. However, to compute false alarms, every alarm was counted whenever lanes produced alarms at nearly the same time unless they were continuous false alarms.

Incident data were run first to count the number of false alarms. The results were obtained from the off-line evaluation of 12 hours of 20 second speed data which included incidents. It indicated that most of the alarms occur during incident periods which are attributed to the traffic speed fluctuations. Tables 12-15 show that most false alarms can be removed with the system operator's monitoring. That is, if the operator turns off the incident alarms after it is confirmed, the system no longer yields false alarms. This is the reason that moving average speeds, even during incident periods, show relatively high fluctuations. Incident-free data were also run to measure number of false alarms with different moving average intervals and speed threshold values. Appendix C shows the total number of false alarms, the daily average of false alarms, and the false alarm rates according to the different moving average intervals and speed threshold values. It is found that the moving average interval and threshold value should be selected such that the number of false alarms can be minimized. That is, the optimum moving average interval and speed threshold value can be determined differently according to the location characteristics. In Table 16, the moving average interval and speed threshold value were summarized by every direction from seven stations selected. The recommended moving average intervals and speed threshold values for each direction of seven locations are emphasized in bold.

As the moving average interval and threshold value are lowered, the less mean time is required to detect. The moving average interval and threshold value shown in bold can reduce mean time to detect. The question is whether this can reduce number of false alarms or not. It is believed that the average daily false alarms, which come from each lane, could be further reduced with site specific modifications and would reasonably lower such that it could be acceptable for system operators.

Table 12. False Alarm, Mean Time To Detect - Case 1.

Location: 35S-158.492 Jan. 9, 1996 Accident lane 2&3
Actual Time of Incident Occurred = 16:07:40

Lane	Detected Time Threshold Value			Window Size	Mean Time To Detect			Actual Num. of False Alarms			Num. of False Alarms with Operator Monitoring		
	40 km/hr	48 km/hr	56 km/hr		40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
1	16:09:11	16:09:11	16:09:11	2	0:01:31	0:01:31	0:01:31	4	4	4	0	0	0
	16:09:31	16:09:31	16:09:11	3	0:01:51	0:01:51	0:01:31	4	4	4	0	0	0
	16:09:31	16:09:31	16:09:31	4	0:01:51	0:01:51	0:01:51	4	4	4	0	0	0
	16:09:51	16:09:51	16:09:31	5	0:02:11	0:02:11	0:01:51	5	5	5	0	0	0
	16:10:11	16:09:51	16:09:51	6	0:02:31	0:02:11	0:02:11	4	4	4	0	0	0
	16:10:11	16:10:11	16:09:51	7	0:02:31	0:02:31	0:02:11	4	4	4	0	0	0
	16:10:30	16:10:11	16:09:51	8	0:02:50	0:02:31	0:02:11	4	4	4	0	0	0
2	16:08:50	16:08:50	16:08:50	2	0:01:10	0:01:10	0:01:10	3	3	4	0	0	0
	16:09:11	16:08:50	16:08:50	3	0:01:31	0:01:10	0:01:10	5	5	5	0	0	0
	16:09:11	16:09:11	16:08:50	4	0:01:31	0:01:31	0:01:10	5	5	5	0	0	0
	16:09:31	16:09:31	16:09:11	5	0:01:51	0:01:51	0:01:31	5	5	5	0	0	0
	16:09:51	16:09:31	16:09:11	6	0:02:11	0:01:51	0:01:31	4	4	4	0	0	0
	16:09:51	16:09:51	16:09:31	7	0:02:11	0:02:11	0:01:51	4	4	4	0	0	0
	16:10:11	16:09:51	16:09:31	8	0:02:31	0:02:11	0:01:51	4	4	4	0	0	0
3	16:09:11	16:09:11	16:08:50	2	0:01:31	0:01:31	0:01:10	7	5	6	0	0	1
	16:09:31	16:09:11	16:09:11	3	0:01:51	0:01:31	0:01:31	5	4	5	0	0	1
	16:09:31	16:09:31	16:09:11	4	0:01:51	0:01:51	0:01:31	5	4	5	0	0	1
	16:09:51	16:09:31	16:09:31	5	0:02:11	0:01:51	0:01:51	5	4	4	0	0	0
	16:10:11	16:09:51	16:09:31	6	0:02:31	0:02:11	0:01:51	5	4	4	0	0	0
	16:10:30	16:10:11	16:09:31	7	0:02:50	0:02:31	0:01:51	5	4	4	0	0	0
	16:10:51	16:10:30	16:09:51	8	0:03:11	0:02:50	0:02:11	5	4	4	0	0	0
4	16:11:11	16:09:31	16:09:11	2	0:03:31	0:01:51	0:01:31	7	12	11	0	0	1
	16:11:11	16:09:51	16:09:31	3	0:03:31	0:02:11	0:01:51	5	9	10	0	0	1
	16:11:31	16:11:11	16:09:51	4	0:03:51	0:03:31	0:02:11	5	6	7	0	0	0
	16:11:31	16:11:11	16:10:11	5	0:03:51	0:03:31	0:02:31	3	5	4	0	0	0
	16:11:51	16:11:11	16:10:30	6	0:04:11	0:03:31	0:02:50	3	5	3	0	0	0
	16:11:51	16:11:11	16:10:51	7	0:04:11	0:03:31	0:03:11	3	3	3	0	0	0
	16:11:51	16:11:11	16:10:51	8	0:04:11	0:03:31	0:03:11	3	4	3	0	0	0

Table 13. False Alarm, Mean Time To Detect - Case 2.

Location: 35S-158.947 Jan. 13, 1996 Accident next to lane 3
Actual Time of Incident Occurred = 18:26:10

Lane	Detected Time Threshold Value			Window Size	Mean Time To Detect			Actual Num. of False Alarms			Num. of False Alarms with Operator Monitoring		
	40 km/hr	48 km/hr	56 km/hr		40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
1	18:31:54	18:31:34	18:31:34	2	0:05:44	0:05:24	0:05:24	1	1	1	0	0	0
	18:31:54	18:31:54	18:31:54	3	0:05:44	0:05:44	0:05:44	1	1	1	0	0	0
	18:32:13	18:32:13	18:31:54	4	0:06:03	0:06:03	0:05:44	1	1	1	0	0	0
	18:32:33	18:32:13	18:31:54	5	0:06:23	0:06:03	0:05:44	1	1	1	0	0	0
	18:32:53	18:32:13	18:32:13	6	0:06:43	0:06:03	0:06:03	1	1	1	0	0	0
	18:33:14	18:32:33	18:32:13	7	0:07:04	0:06:23	0:06:03	1	1	1	0	0	0
	18:33:34	18:32:53	18:32:33	8	0:07:24	0:06:43	0:06:23	1	1	1	0	0	0
2	Missing Data			2	N/A			N/A			N/A		
				3									
				4									
				5									
				6									
				7									
				8									
3	18:31:14	18:31:14	18:31:14	2	0:05:04	0:05:04	0:05:04	4	4	6	1	1	2
	18:31:54	18:31:54	18:31:14	3	0:05:44	0:05:44	0:05:04	5	5	6	0	0	1
	18:32:13	18:31:54	18:31:54	4	0:06:03	0:05:44	0:05:44	6	6	6	0	0	0
	18:32:33	18:32:13	18:31:54	5	0:06:23	0:06:03	0:05:44	5	5	5	0	0	0
	18:32:33	18:32:33	18:32:13	6	0:06:23	0:06:23	0:06:03	5	5	5	0	0	0
	18:32:53	18:32:33	18:32:13	7	0:06:43	0:06:23	0:06:03	5	5	5	0	0	0
	18:33:14	18:32:53	18:32:33	8	0:07:04	0:06:43	0:06:23	5	5	4	0	0	0

Table 14. False Alarm, Mean Time To Detect - Case 5.

Location: 10W-573.654 Jan. 29, 1996 Accident lane 3
Actual Time of Incident Occurred = 7:46:30

Lane	Detected Time Threshold Value 40 km/hr	48 km/hr	56 km/hr	Window Size	Mean Time To Detect 40 km/hr	48 km/hr	56 km/hr	Actual Num. of False Alarms 40 km/hr	48 km/hr	56 km/hr	Num. of False Alarms with Operator Monitoring 40 km/hr	48 km/hr	56 km/hr
1	7:51:44	7:51:44	7:51:44	2	0:05:14	0:05:14	0:05:14	7	7	7	0	0	0
	7:51:44	7:51:44	7:51:44	3	0:05:14	0:05:14	0:05:14	8	8	8	0	0	0
	7:51:44	7:51:44	7:51:44	4	0:05:14	0:05:14	0:05:14	9	9	9	0	0	0
	7:52:04	7:51:44	7:51:44	5	0:05:34	0:05:14	0:05:14	9	9	9	0	0	0
	7:52:24	7:52:04	7:52:04	6	0:05:54	0:05:34	0:05:34	9	9	9	0	0	0
	7:52:24	7:52:24	7:52:04	7	0:05:54	0:05:54	0:05:34	9	9	9	0	0	0
	7:52:44	7:52:44	7:52:24	8	0:06:14	0:06:14	0:05:54	9	9	9	0	0	0
2	7:51:44	7:51:44	7:51:44	2	0:05:14	0:05:14	0:05:14	3	3	4	0	0	0
	7:51:44	7:51:44	7:51:44	3	0:05:14	0:05:14	0:05:14	3	3	4	0	0	0
	7:51:44	7:51:44	7:51:44	4	0:05:14	0:05:14	0:05:14	3	3	2	0	0	0
	7:52:04	7:52:04	7:51:44	5	0:05:34	0:05:34	0:05:14	3	2	2	0	0	0
	7:52:24	7:52:04	7:52:04	6	0:05:54	0:05:34	0:05:34	3	2	2	0	0	0
	7:52:44	7:52:24	7:52:04	7	0:06:14	0:05:54	0:05:34	2	2	2	0	0	0
	7:52:44	7:52:44	7:52:24	8	0:06:14	0:06:14	0:05:54	2	2	2	0	0	0
3	7:54:44	7:53:25	7:51:44	2	0:08:14	0:06:55	0:05:14	0	2	9	0	0	0
	7:54:44	7:53:44	7:51:44	3	0:08:14	0:07:14	0:05:14	0	1	4	0	0	0
	ND	7:54:04	7:52:04	4	N/A	0:07:34	0:05:34	0	1	3	0	0	0
	ND	7:54:24	7:52:24	5	N/A	0:07:54	0:05:54	0	1	3	0	0	0
	ND	7:54:44	7:52:44	6	N/A	0:08:14	0:06:14	0	1	2	0	0	0
	ND	7:54:44	7:53:04	7	N/A	0:08:14	0:06:34	0	0	1	0	0	0
	ND	7:54:44	7:53:04	8	N/A	0:08:14	0:06:34	0	0	1	0	0	0

Table 15. False Alarm, Mean Time To Detect - Case 6.

Location: 10E-572.973 Feb. 16, 1996 Accident
Actual Time of Incident Occurred = 15:43:30

Lane	Detected Time Threshold Value 40 km/hr	48 km/hr	56 km/hr	Window Size	Mean Time To Detect 40 km/hr	48 km/hr	56 km/hr	Actual Num. of False Alarms 40 km/hr	48 km/hr	56 km/hr	Num. of False Alarms with Operator Monitoring 40 km/hr	48 km/hr	56 km/hr
1	16:02:19	15:49:19	15:48:19	2	0:18:49	0:05:49	0:04:49	1	5	6	0	0	0
	16:02:19	15:49:39	15:48:59	3	0:18:49	0:06:09	0:05:29	1	3	3	0	0	0
	16:02:39	15:49:59	15:48:59	4	0:19:09	0:06:29	0:05:29	1	3	3	0	0	0
	16:02:59	15:50:19	15:49:19	5	0:19:29	0:06:49	0:05:49	1	2	2	0	0	0
	16:03:18	15:50:19	15:49:19	6	0:19:48	0:06:49	0:05:49	1	2	2	0	0	0
	16:03:18	15:50:39	15:49:39	7	0:19:48	0:07:09	0:06:09	1	2	2	0	0	0
	16:03:18	15:55:39	15:49:59	8	0:19:48	0:12:09	0:06:29	1	1	2	0	0	0
2	15:48:59	15:48:59	15:46:38	2	0:05:29	0:05:29	0:03:08	6	5	3	0	0	0
	15:49:59	15:48:59	15:48:38	3	0:06:29	0:05:29	0:05:08	2	3	2	0	0	0
	15:49:59	15:48:59	15:48:38	4	0:06:29	0:05:29	0:05:08	2	3	2	0	0	0
	15:49:59	15:49:19	15:48:38	5	0:06:29	0:05:49	0:05:08	1	2	2	0	0	0
	15:50:19	15:49:39	15:48:59	6	0:06:49	0:06:09	0:05:29	1	2	2	0	0	0
	15:50:19	15:49:59	15:48:59	7	0:06:49	0:06:29	0:05:29	1	2	0	0	0	0
	15:50:19	15:49:59	15:48:59	8	0:06:49	0:06:29	0:05:29	1	2	0	0	0	0
3	15:48:59	15:48:59	15:46:19	2	0:05:29	0:05:29	0:02:49	5	6	7	0	1	4
	15:49:19	15:48:59	15:46:38	3	0:05:49	0:05:29	0:03:08	4	4	1	0	0	0
	15:49:19	15:48:59	15:46:59	4	0:05:49	0:05:29	0:03:29	2	4	0	0	0	0
	15:49:39	15:48:59	15:47:18	5	0:06:09	0:05:29	0:03:48	2	3	0	0	0	0
	15:49:59	15:49:19	15:47:39	6	0:06:29	0:05:49	0:04:09	2	1	0	0	0	0
	15:50:19	15:49:19	15:47:58	7	0:06:49	0:05:49	0:04:28	2	2	0	0	0	0
	15:50:19	15:49:19	15:48:19	8	0:06:49	0:05:49	0:04:49	1	1	0	0	0	0

Table 16. Reasonable Moving Average Intervals and Threshold Values

Moving Average Interval	Speed Threshold Values		
	40 km/hr (25 mph)	48 km/hr (30 mph)	56 km/hr (35 mph)
2	D-E (0.6), E-W (0.5), F-E (0.3), F-W (0.2), G-E (0.1), G-W(0.2)	E-W (0.8), F-E (0.5), F-W (0.3), G-E (0.2), G-W (0.5)	F-E (0.7), F-W (0.7), G-E (0.7)
3	A-N (0.4), C-S (0.8), D-E (0.2), E-E (0.4), E-W (0.2), F-E (0.2), F-W(0.1), G-E (0.1), ***G-W (0.0)***	A-N (0.7), D-E (0.6), E-E (0.8), E-W (0.4), F-E (0.2), F-W (0.2), G-E (0.1), G-W (0.1)	E-W (0.7), F-E (0.2), F-W (0.2), G-E (0.3), G-W (0.6)
4	***A-N (0.0)***, B-N (0.9), B-S (0.6), C-N (0.8), C-S (0.8), ***D-E (0.1)***, ***E-E (0.3)***, ***E-W(0.1)***, ***F-E (0.1)***, ***F-W (0.0)***, ***G-E (0.0)***, G-W (0.0)	A-N (0.1), B-S (0.8), D-E (0.3), E-E (0.5), E-W (0.1), F-E (0.1), F-W (0.0), G-E (0.1), G-W (0.1)	A-N (0.8), D-E (0.6), E-E (0.7), E-W (0.3), F-E (0.1), F-W (0.1), G-E (0.2), G-W (0.3)
5	A-N (0.0), ***A-S (0.7)***, ***B-N (0.7)***, ***B-S (0.5)***, ***C-N (0.7)***, ***C-S (0.5)***, D-E (0.1), E-E (0.2), E-W (0.0), F-E (0.0), F-W (0.0) ,G-E (0.0), G-W (0.0)	A-N (0.1), B-S (0.5), C-S (0.9), D-E (0.2), ***E-E (0.3)***, E-W (0.1), F-E (0.0), F-W (0.0), G-E (0.1), G-W (0.1)	A-N (0.4), B-S (0.9), D-E (0.3), E-E (0.5), E-W (0.1), F-E (0.1), F-W (0.1), G-E (0.2), G-W (0.2)
6	A-S (0.6), B-N (0.6), B-S (0.3), C-N (0.7), C-S (0.4), D-E (0.0), ***D-W(0.7)***, E-E (0.1), E-W (0.0), F-E (0.0), F-W (0.0), G-E (0.0), G-W (0.0)	A-N (0.1), A-S (0.8), B-N (0.9), B-S (0.3), C-S (0.7), D-E (0.2), E-E (0.2), E-W (0.0), F-E (0.0), F-W (0.0), G-E (0.1), G-W (0.0)	A-N (0.2), B-S (0.6), D-E (0.2), E-E (0.4), E-W (0.1), F-E (0.0), F-W (0.1), G-E (0.2), G-W (0.1)

Note: The number in blanket represents the average daily false alarms per direction. The first letter (A-G) relates to the site location. The second letter (N,S,E,W) Indicates direction.
The sites bolded with direction are located within the cell of recommended moving average interval and threshold value.

5.3 TRADE-OFF ANALYSIS

Trade-offs always exist between how to reduce the mean time to detect and how to reduce the number of false alarms when any automatic incident detection algorithms have to be used. In order to provide better guidance for future operational evaluation, a graph analysis method was performed to examine how to select the optimum moving average interval and threshold speed when using the speed-based incident detection algorithms.

The trade-offs between mean time to detect and number of false alarms were provided in Figures 21-24. The number of false alarms are represented in average daily false alarms per direction. From this analysis, the optimum combination of moving average interval and threshold value can be determined. For example, Figure 21 indicates that the incident can be detected within two minutes either with a moving average interval of 5 and 40 km/hr (25 mph) threshold value, or with a moving average interval of 6 and 48 km/hr (30 mph) speed threshold. Furthermore, the combinations of decreasing the moving average interval up to four intervals with 40 km/hr (25 mph) can detect incident more quickly, although it will increase number of false alarms slightly for the incidents being evaluated. As mentioned in Chapter 4, for cases 2, 5, and 6, the accident locations relative to the detectors and the traffic volumes are such that it takes a few minutes for queues to develop and affect upstream detectors.

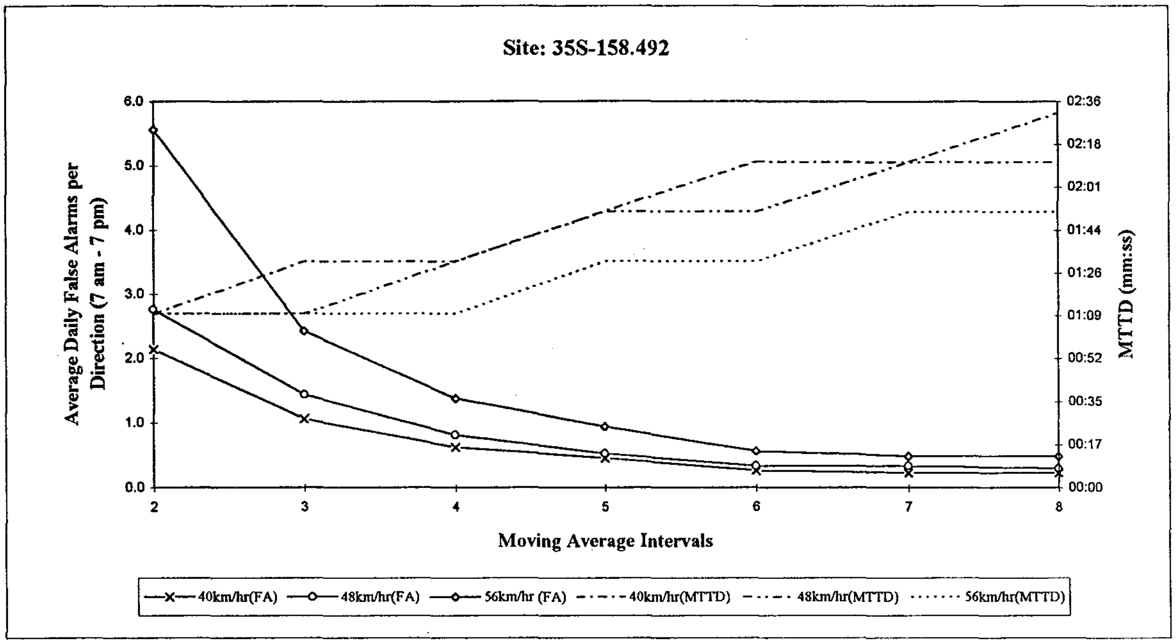


Figure 21. Average Daily False Alarms Vs. MTTD - Case 1

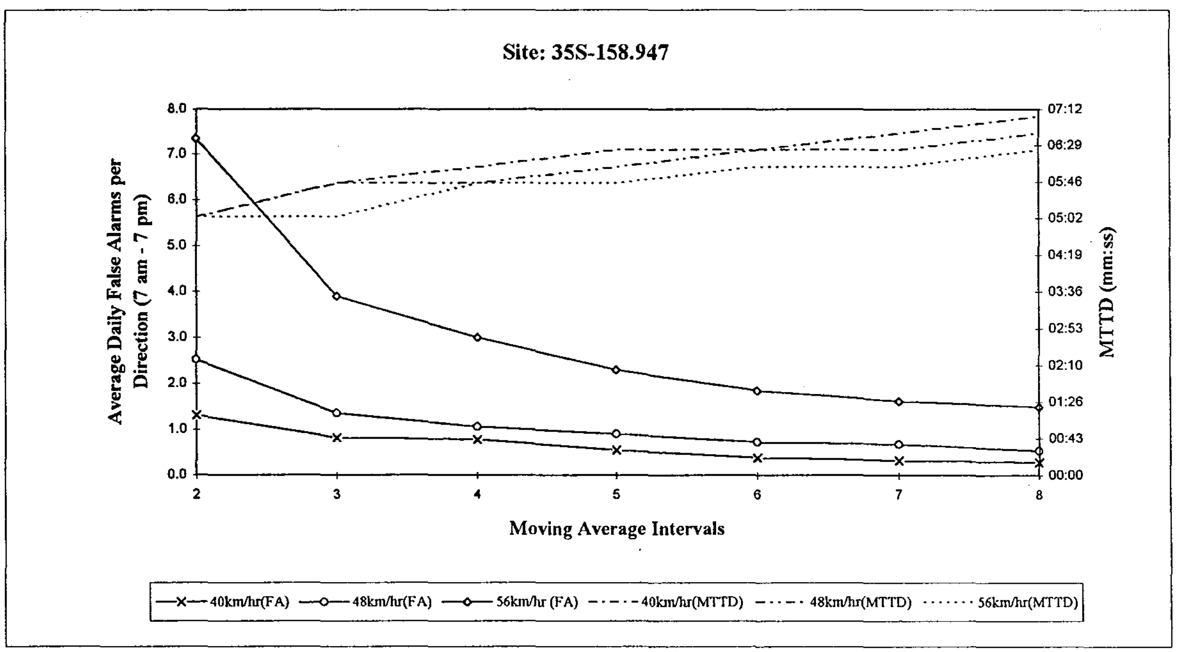


Figure 22. Average Daily False Alarms Vs. MTTD - Case 2

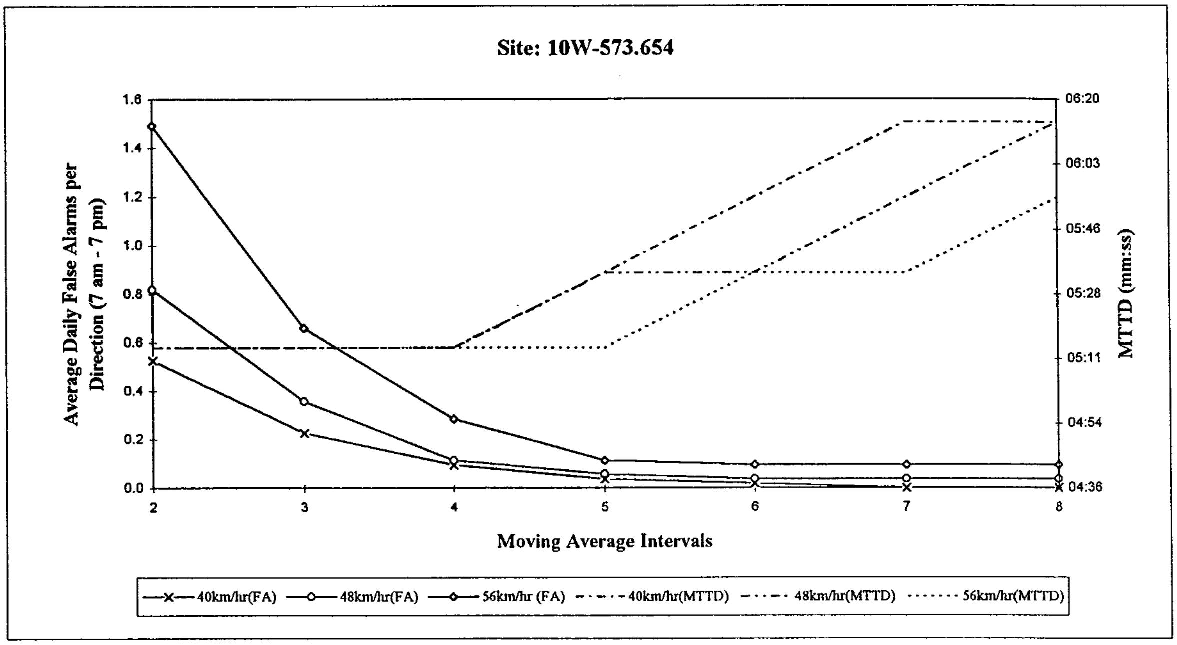


Figure 23. Average Daily False Alarms Vs. MTTD - Case 5

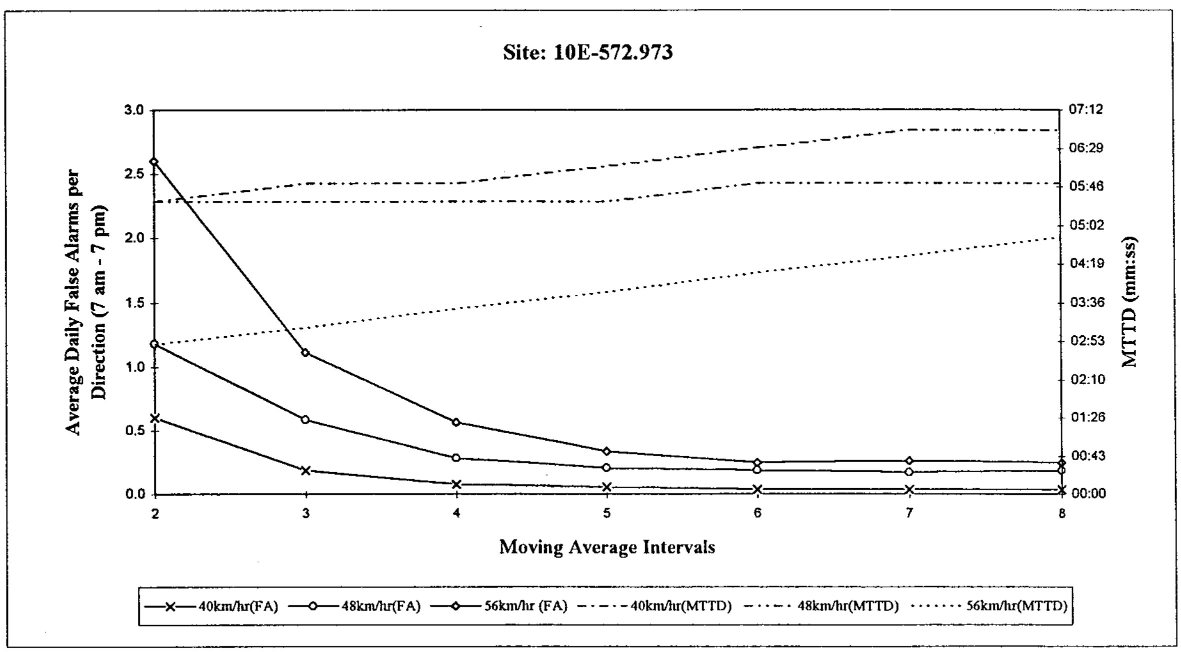


Figure 24. Average Daily False Alarms Vs. MTTD - Case 6

6.0 CONCLUSIONS AND RECOMMENDATIONS

The effectiveness of freeway incident management systems depends upon agency operating policies and system response strategies. In order to reduce incident response time, control strategies should be used to increase the operational efficiency and traffic safety. This research has evaluated incident detection algorithms with several real traffic data collected from the TxDOT San Antonio TransGuide traffic management system. The analysis of the TxDOT San Antonio speed-based algorithm was performed to further increase incident detection system responsiveness and reduce the total number of false alarms of the freeway traffic management system.

6.1 CONCLUSIONS

This study has found that the TxDOT San Antonio incident detection algorithm worked well as compared to other algorithms being used in other systems. This is based on the performance evaluation criteria on the mean time to detect, false alarm rate, and data verification simplicity. However, other incident detection algorithms evaluated in this study may also have potential with more data available for calibration. This study also indicates the importance of taking advantage of both the operational procedures and automatic incident detection algorithms in order to enhance system responsiveness of freeway traffic management systems.

Even with very limited incident cases, this study has shown the speed-based algorithm works well to provide adequate automatic incident detection capability. Furthermore, the speed-based incident detection algorithm can be improved with variable a moving average interval and selecting a specific threshold speed value for the specific locations.

6.2 RECOMMENDATIONS

In order to further improve the overall system operations, it is also recommended that the operator should monitor and flag the "end of incident" manually through CCTV monitoring during the period of known incident occurrence to reduce secondary alarms for the same incident. Although the existing TxDOT algorithm had few false alarms within this analysis, it is likely that it would produce more false alarms in a more congested area. Since Phase II of San Antonio's TransGuide system will be implemented within a more congested area, it will be desirable to continue to refine the algorithm.

In addition, the TransGuide system should develop methods or algorithms that can detect and screen out erroneous loop detector data. Since the erroneous data typically produce high occupancies and low volumes which have the same characteristics of incidents, the use of such data will increase the false alarm rates of algorithms that apply these parameters. The data collection process should discard the invalid data so that it will not be run through the incident detection algorithms.

It also appears appropriate to develop a database system which manages loop detector data as well as incident alarm logs. It is hard to distinguish between recurrent congestion and non-recurrent congestion conditions using current methodologies. Advanced technologies such as neural network, fuzzy logic, and catastrophe theory should be tested as a means to distinguish between recurrent and non-recurrent congestion conditions. For example, advanced technologies such as neural network and numerical analysis can learn normal situations based on observed traffic data, helping to overcome the difficulty of calibrating threshold values.

7.0 REFERENCES

1. Chang, G.L.,Y.L. Li, H.J. Payne, and S.G. Ritchie. *Incident Detection Issues Task A Report: Automatic Freeway Incident Detection*. Report No. FHWA-R-024-93. Federal Highway Administration, U.S. Department of Transportation, Washington D.C., October 1993.
2. Payne, H.J., E.D. Helfenbein, and H.C. Knobel. *Development and Testing of Incident Detection Algorithms, Volume 2: Research Methodology and Detailed Results*. Report No. FHWA-RD-76-20. Federal Highway Administration, U.S. Department of Transportation, Washington D.C., April 1976.
3. Payne, H.J. and S.C. Tignor. Freeway Incident Detection Algorithms Based on Decision Trees with States. *Transportation Research Record 682*. Transportation Research Board, National Research Council, Washington D.C., 1978, pp. 30-37.
4. Gerlough, D.L. and M.J. Huber. *Traffic Flow Theory: A Monograph.* Special Report 165. Transportation Research Board, National Research Council, Washington D.C., 1975.
5. Masters, P.H., J.K. Lam, and K. Wong. Incident Detection Algorithms for COMPASS - An Advanced Traffic Management System. *Vehicle Navigation and Information Systems Conference Proceedings*. Society of Automotive Engineers, Inc. Warrendale, Pennsylvania, October 1991, pp. 295-311.
6. Dudek, C.L. and C.J. Messer. Incident Detection on Urban Freeways. *Transportation Research Record 495*. Transportation Research Board, National Research Council, Washington D.C., 1974, pp. 12-24.
7. Levin, M. and G.M. Krause. Incident Detection: A Bayesian Approach. *Transportation Research Record 682*. Transportation Research Board, National Research Council, Washington D.C., 1978, pp. 52-58.
8. Ahmed, S.A. and A.R. Cook. Time Series Models for Freeway Incident Detection. *Transportation Engineering Journal*. American Society of Civil Engineers, New York, New York. November 1980, pp. 731-745.
9. Collins, J.F., C.M. Hopkins, and J.A. Martin. Automatic Incident Detection-TRRL Algorithms HIOCC and PATREG. *TRRL Supplementary Report 526.* Transport and Road Research Laboratory, Crowthorne, Berkshire, 1979.
10. Stephanedes, Y.J. and A.P. Chassiakos. Application of Filtering Techniques for Incident Detection. *Journal of Transportation Engineering*, Vol. 119, No. 1. American Society of Civil Engineers, New York, New York. January/February 1993, pp. 13-26.
11. Stephanedes, Y.J., A.P. Chassiakos, and P.G. Michalopoulos. Comparative Performance Evaluation of Incident Detection Algorithms. *Transportation Research Record 1360.* Transportation Research Board, National Research Council, Washington D.C., 1992, pp. 50-57.
12. Gall, A.I. and F.L. Hall. Distinguishing Between Incident Congestion and Recurrent Congestion: A Proposed Logic. *Transportation Research Record No. 1232.* Transportation Research Board, National Research Council, Washington, D.C., 1993, pp.

1-8.
13. Hall, F.L. On-line Testing of the McMaster Incident Detection Algorithm Under Recurrent Congestion. *Transportation Research Record No. 1394.* Transportation Research Board, National Research Council, Washington, D.C., 1993, pp. 1-7.
14. Willsky, A.S., E.Y. Chow, S.B. Gershwin, C.S. Greene, P.K. Houpt et al. Dynamic Model-Based Techniques for the Detection of Incidents on Freeways. *IEEE Transactions on Automatic Control,* Vol. AC-25, No. 3. Institute of Electrical and Electronic Engineers, Piscataway, New Jersey, June 1980, pp. 347-359.
15. McShane, W.R. and R.P. Roess. *Traffic Engineering.* Prentice Hall, Englewood Cliffs, New Jersey, 1992.
16. Dudek, C.L. et al. Detecting Freeway Incidents Under Low-Volume Conditions. *Transportation Research Record 533.* Transportation Research Board, National Research Council, Washington D.C., 1975, pp. 34-47.
17. Ritchie, S.G. and R.L. Cheu. *Neural Network Models for Automated Detection of Non-Recurring Congestion.* PATH Research Report UCB-ITS-PRR-93-5. Irvine, California, June 1993.
18. Ritchie, S.G., R.L. Cheu, S.I. Khan, B. Abdulhai, A.E. Parkany et al. A Comprehensive System for Incident Detection on Freeways and Arterials. Irvine, California, 1994.
19. Chang, E.C. and K. Huarng. *Incident Detection using Advanced Technologies.* Prepared for 72nd TRB Annual Meeting. Washington, D.C., January 1993.
20. May, A.D. *Traffic Flow Fundamentals.* Prentice Hall, Englewood Cliffs, New Jersey, 1990.
21. Devore, J.L. *Probability and Statistics for Engineering and the Sciences,* 3rd edition. Brooks/Cole Publishing, Pacific Grove, California, 1991.
22. Chang, E.C. and Kunhuang Huarng, Application of Advanced Techniques for Freeway Incident Detection. 1992 Annual Transportation Research Board Meeting, Washington D.C., January 1993.
23. Chang, E.C. and Su-Hua Wong. Improved Freeway Incident Detection Using Fuzzy Set Theory. 1994 Annual Transportation Research Board Meeting, Washington D.C., January 1994.

APPENDIX A

MEMBERSHIP FUNCTIONS FOR CALIFORNIA ALGORITHM #8 WITH FUZZY LOGIC

A-1. Membership Functions for OCCDF

If OCCDF $\leq$ OCCDF T_1 then OCCDF is low.

If OCCDF $T_1 <$ OCCDF $\leq$ OCCDF T_2
then the probability of OCCDF being low = $\dfrac{OCCDF\ -\ OCCDF\ T_1}{OCCDF\ T_1 -\ OCCDF\ T_2}$
and the probability of OCCDF being high = *1 - P (OCCDF low).*

If OCCDF > OCCDF T_2 then OCCDF is high.

A-2. Membership Functions for DOCCTD

If DOCCTD $\leq$ DOCCTD T_1 then DOCCTD is low.

If DOCCTD $T_1 <$ DOCCTD $\leq$ DOCCTD T_2
then the probability of DOCCTD being low = $\dfrac{DOCCTD\ -\ DOCCTD\ T_1}{DOCCTD\ T_1 -\ DOCCTD\ T_2}$
and the probability of DOCCTD being high = *1 - P (DOCCTD low).*

If DOCCTD > DOCCTD T_2 then DOCCTD is high.

A-3. Membership Functions for OCCRDF

If OCCRDF $\leq$ OCCRDF T_1 then OCCRDF is low.

If OCCRDF $T_1 <$ OCCRDF $\leq$ OCCRDF T_2
then the probability of OCCRDF being low = $\dfrac{OCCRDF\ -\ OCCRDF\ T_1}{OCCRDF\ T_1 -\ OCCRDF\ T_2}$
and the probability of OCCRDF being high = *1 - P (OCCRDF low).*

If OCCRDF > OCCRDF T_2 then OCCRDF is high.

A-4. Membership Functions for DOCC

If DOCC $\leq$ DOCC T_1 then DOCC is low.

If DOCC $T_1 <$ DOCC $\leq$ DOCC T_2
then the probability of DOCC being low = $\dfrac{DOCC\ -\ DOCC\ T_2}{DOCC\ T_1 -\ DOCC\ T_2}$
and the probability of DOCC being medium = *1 - P (DOCC low).*

If DOCC $T_2 <$ DOCC $\leq$ DOCC T_3
then the probability of DOCC being medium = $\dfrac{DOCC\ -\ DOCC\ T_3}{DOCC\ T_2 -\ DOCC\ T_3}$
and the probability of DOCC being high = *1 - P (DOCC medium).*

If DOCC > DOCC T_3 then DOCC is high.

A-5. Membership Functions for States

If the state $\leq$ 1 then the probability of the state being incident-free = *1 - State.*
and the probability of the state being congested = $\dfrac{State}{4}$.

If 1 < state $\leq$ 4 then the probability of the state being congested = $\dfrac{State}{4}$.

If 4 < state $\leq$ 5 then the probability of the state being congested = *5 - State.*
and the probability of the state being continued congestion = *State - 4.*

If 5 < state $\leq$ 6 then the probability of the state being continued congestion = *6 - State.*
and the probability of the state being a tentative incident = *State - 5.*

If 6 < state $\leq$ 7 then the probability of the state being a tentative incident = *7 - State.*
and the probability of the state being a confirmed incident = *State - 6.*

If the state > 7 then the then the state confirms an incident.

A-6. State Output Conditions

If the last state = confirmed incident and OCCRDF is high
then the new state is incident continuing.

If the last state = confirmed incident and OCCRDF is low
then the new state is incident-free.

If the last state = tentative incident and OCCRDF is high
then the new state is incident confirmed.

If the last state = tentative incident, OCCRDF is low, and DOCC and DOCCTD are high
then the new state is incident-free.

If the last state = tentative incident, OCCDRF and DOCCTD are low and DOCC is high
then the new state is congested.

If the last state = tentative incident, OCCRDF is low and DOCC is not high
then the new state is incident-free.

If the last state = continuing congestion, DOCC is high and DOCCTD is high
then the new state is incident-free.

If the last state = continuing congestion and DOCC is not high
then the new state is incident-free.

If the last state = congestion, DOCC is high and DOCCTD is high
then the new state is continuing congestion.

If the last state = congestion and DOCC is not high
then the new state is continuing congestion.

If the last state = incident-free, OCCDF and OCCRDF are high and DOCC is medium
then the new state is incident-free.

If the last state = incident-free, OCCDF and OCCRDF are high and DOCC is low
then the new state is tentative incident.

If the last state = incident-free, OCCDF is high, OCCRDF is low, and DOCC is not high
then the new state is incident-free.

If the last state = incident-free, OCCDF is low and DOCC is not high
then the new state is incident-free.

If the last state = incident-free, DOCC is high and DOCCTD is high then the new state is incident-free.

If the last state = incident-free, DOCC is high and DOCCTD is low then the new state is congestion.

APPENDIX B

INCIDENT-FREE DATA SETS SELECTED FOR ALGORITHM TESTING

Table B-1. January Incident-Free Data Sets Selected for Algorithm Testing

	North A-B	South B-A	North B-C	South C-B	East D-E	West E-D	East F-G	West G-F
January 8			◆			◆	◆	
January 9								
January 10								
January 11					□		◆	
January 12			□				◆	
January 13							◆	◆
January 14								
January 15							◆	◆
January 16			□					
January 17							◆	◆
January 18		◆				◆		
January 19								
January 20								
January 21								
January 22			◆			◆		◆
January 23						◆		
January 24								
January 25						◆		
January 26	◆						◆	
January 27								
January 28								
January 29			◆				◆	◆
January 30			◆				◆	
January 31			◆	◆			◆	◆

◆ = 7 am - 7 pm (12 hrs)
□ = Congestion Period (1 hr)

Table B-2. February Incident-Free Data Sets Selected for Algorithm Testing

	North A-B	South B-A	North B-C	South C-B	East D-E	West E-D	East F-G	West G-F
February 1								
February 2								
February 3								
February 4								
February 5								
February 6						◆		
February 7			◆			◆	◆	◆
February 8								
February 9			◆					
February 10								
February 11								
February 12								
February 13								
February 14								
February 15			◆			◆	◆	
February 16			◆				◆	
February 17								
February 18								
February 19								
February 20			◆				◆	◆
February 21			◆				◆	
February 22								
February 23								
February 24								
February 25								
February 26								
February 27			◆				◆	◆
February 28								
February 29								

Table B-3. March Incident-Free Data Sets Selected for Algorithm Testing

	North A-B	South B-A	North B-C	South C-B	East D-E	West E-D	East F-G	West G-F
March 1			◆					
March 2								
March 3								
March 4								
March 5						◆		
March 6			◆					
March 7								
March 8			◆			◆		
March 9								

APPENDIX C

TOTAL NUMBER OF FALSE ALARMS OF INCIDENT-FREE DATASET

Table C-1. Total Number of False Alarms

35N-158.036

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	71	122	274	1.3	2.3	5.2	0.0598%	0.1027%	0.2306%
3	22	36	103	0.4	0.7	1.9	0.0185%	0.0303%	0.0867%
4	5	14	41	0.1	0.3	0.8	0.0042%	0.0118%	0.0345%
5	1	7	21	0.0	0.1	0.4	0.0008%	0.0059%	0.0177%
6	1	5	11	0.0	0.1	0.2	0.0008%	0.0042%	0.0093%
7	1	4	7	0.0	0.1	0.1	0.0008%	0.0034%	0.0059%
8	1	3	5	0.0	0.1	0.1	0.0008%	0.0025%	0.0042%

35S-158.036

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	164	286	576	3.1	5.4	10.9	0.1380%	0.2407%	0.4848%
3	77	122	255	1.5	2.3	4.8	0.0648%	0.1027%	0.2146%
4	52	73	135	1.0	1.4	2.5	0.0438%	0.0614%	0.1136%
5	36	54	93	0.7	1.0	1.8	0.0303%	0.0455%	0.0783%
6	32	44	73	0.6	0.8	1.4	0.0269%	0.0370%	0.0614%
7	29	47	57	0.5	0.9	1.1	0.0244%	0.0396%	0.0480%
8	27	36	52	0.5	0.7	1.0	0.0227%	0.0303%	0.0438%

35N-158.492

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	80	123	230	1.5	2.2	4.2	0.0673%	0.1035%	0.1936%
3	54	76	110	1.0	1.4	2.1	0.0455%	0.0640%	0.0926%
4	50	58	74	0.9	1.1	1.4	0.0421%	0.0488%	0.0623%
5	38	56	60	0.7	1.1	1.1	0.0320%	0.0471%	0.0505%
6	34	48	52	0.6	0.9	1.0	0.0286%	0.0404%	0.0438%
7	32	36	44	0.6	0.7	0.8	0.0269%	0.0303%	0.0370%
8	30	34	40	0.6	0.6	0.8	0.0253%	0.0286%	0.0337%

35S-158.492

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	118	152	306	2.1	2.8	5.6	0.0993%	0.1279%	0.2576%
3	56	76	129	1.1	1.4	2.4	0.0471%	0.0640%	0.1086%
4	33	43	73	0.6	0.8	1.4	0.0278%	0.0362%	0.0614%
5	24	28	50	0.5	0.5	0.9	0.0202%	0.0236%	0.0421%
6	14	18	30	0.3	0.3	0.6	0.0118%	0.0152%	0.0253%
7	12	18	26	0.2	0.3	0.5	0.0101%	0.0152%	0.0219%
8	12	16	26	0.2	0.3	0.5	0.0101%	0.0135%	0.0219%

Table C-1. Total Number of False Alarms (Cont'd)

35N-158.036

Number of False Alarms

Window Size	Total 25	Total 30	Total 35	Daily Average 25	Daily Average 30	Daily Average 35	False Alarm Rate 25	False Alarm Rate 30	False Alarm Rate 35
2	71	122	274	1.3	2.3	5.2	0.0598%	0.1027%	0.2306%
3	22	36	103	0.4	0.7	1.9	0.0185%	0.0303%	0.0867%
4	5	14	41	0.1	0.3	0.8	0.0042%	0.0118%	0.0345%
5	1	7	21	0.0	0.1	0.4	0.0008%	0.0059%	0.0177%
6	1	5	11	0.0	0.1	0.2	0.0008%	0.0042%	0.0093%
7	1	4	7	0.0	0.1	0.1	0.0008%	0.0034%	0.0059%
8	1	3	5	0.0	0.1	0.1	0.0008%	0.0025%	0.0042%

35S-158.036

Number of False Alarms

Window Size	Total 25	Total 30	Total 35	Daily Average 25	Daily Average 30	Daily Average 35	False Alarm Rate 25	False Alarm Rate 30	False Alarm Rate 35
2	164	286	576	3.1	5.4	10.9	0.1380%	0.2407%	0.4848%
3	77	122	255	1.5	2.3	4.8	0.0648%	0.1027%	0.2146%
4	52	73	135	1.0	1.4	2.5	0.0438%	0.0614%	0.1136%
5	36	54	93	0.7	1.0	1.8	0.0303%	0.0455%	0.0783%
6	32	44	73	0.6	0.8	1.4	0.0269%	0.0370%	0.0614%
7	29	47	57	0.5	0.9	1.1	0.0244%	0.0396%	0.0480%
8	27	36	52	0.5	0.7	1.0	0.0227%	0.0303%	0.0438%

35N-158.492

Number of False Alarms

Window Size	Total 25 mph	Total 30 mph	Total 35 mph	Daily Average 25 mph	Daily Average 30 mph	Daily Average 35 mph	False Alarm Rate 25 mph	False Alarm Rate 30 mph	False Alarm Rate 35 mph
2	80	123	230	1.5	2.2	4.2	0.0673%	0.1035%	0.1936%
3	54	76	110	1.0	1.4	2.1	0.0455%	0.0640%	0.0926%
4	50	58	74	0.9	1.1	1.4	0.0421%	0.0488%	0.0623%
5	38	56	60	0.7	1.1	1.1	0.0320%	0.0471%	0.0505%
6	34	48	52	0.6	0.9	1.0	0.0286%	0.0404%	0.0438%
7	32	36	44	0.6	0.7	0.8	0.0269%	0.0303%	0.0370%
8	30	34	40	0.6	0.6	0.8	0.0253%	0.0286%	0.0337%

35S-158.492

Number of False Alarms

Window Size	Total 25 mph	Total 30 mph	Total 35 mph	Daily Average 25 mph	Daily Average 30 mph	Daily Average 35 mph	False Alarm Rate 25 mph	False Alarm Rate 30 mph	False Alarm Rate 35 mph
2	118	152	306	2.1	2.8	5.6	0.0993%	0.1279%	0.2576%
3	56	76	129	1.1	1.4	2.4	0.0471%	0.0640%	0.1086%
4	33	43	73	0.6	0.8	1.4	0.0278%	0.0362%	0.0614%
5	24	28	50	0.5	0.5	0.9	0.0202%	0.0236%	0.0421%
6	14	18	30	0.3	0.3	0.6	0.0118%	0.0152%	0.0253%
7	12	18	26	0.2	0.3	0.5	0.0101%	0.0152%	0.0219%
8	12	16	26	0.2	0.3	0.5	0.0101%	0.0135%	0.0219%

Table C-1. Total Number of False Alarms (Cont'd)

35N-158.947

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	80	115	203	1.5	2.1	3.7	0.0673%	0.0968%	0.1709%
3	51	73	109	1.0	1.4	2.1	0.0429%	0.0614%	0.0918%
4	45	60	79	0.8	1.1	1.5	0.0379%	0.0505%	0.0665%
5	38	55	72	0.7	1.0	1.4	0.0320%	0.0463%	0.0606%
6	35	51	63	0.7	1.0	1.2	0.0295%	0.0429%	0.0530%
7	32	46	54	0.6	0.9	1.0	0.0269%	0.0387%	0.0455%
8	30	45	52	0.6	0.8	1.0	0.0253%	0.0379%	0.0438%

35S-158.947

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	72	139	404	1.3	2.5	7.3	0.0606%	0.1170%	0.3401%
3	43	72	207	0.8	1.4	3.9	0.0362%	0.0606%	0.1742%
4	41	56	159	0.8	1.1	3.0	0.0345%	0.0471%	0.1338%
5	29	48	122	0.5	0.9	2.3	0.0244%	0.0404%	0.1027%
6	20	38	98	0.4	0.7	1.8	0.0168%	0.0320%	0.0825%
7	17	36	86	0.3	0.7	1.6	0.0143%	0.0303%	0.0724%
8	15	28	79	0.3	0.5	1.5	0.0126%	0.0236%	0.0665%

10E-572.973

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	33	65	143	0.6	1.2	2.6	0.0278%	0.0547%	0.1204%
3	10	31	59	0.2	0.6	1.1	0.0084%	0.0261%	0.0497%
4	4	15	30	0.1	0.3	0.6	0.0034%	0.0126%	0.0253%
5	3	11	18	0.1	0.2	0.3	0.0025%	0.0093%	0.0152%
6	2	10	13	0.0	0.2	0.2	0.0017%	0.0084%	0.0109%
7	2	9	14	0.0	0.2	0.3	0.0017%	0.0076%	0.0118%
8	2	10	13	0.0	0.2	0.2	0.0017%	0.0084%	0.0109%

10W-572.973

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	886	1189	1798	16.1	21.6	32.7	0.7458%	1.0008%	1.5135%
3	385	539	1028	7.3	10.2	19.4	0.3241%	0.4537%	0.8653%
4	146	268	617	2.8	5.1	11.6	0.1229%	0.2256%	0.5194%
5	64	154	362	1.2	2.9	6.8	0.0539%	0.1296%	0.3047%
6	38	89	233	0.7	1.7	4.4	0.0320%	0.0749%	0.1961%
7	18	51	154	0.3	1.0	2.9	0.0152%	0.0429%	0.1296%
8	13	34	107	0.2	0.6	2.0	0.0109%	0.0286%	0.0901%

Table C-1. Total Number of False Alarms (Cont'd)

10E-573.654

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	68	91	161	1.2	1.7	2.9	0.0572%	0.0766%	0.1355%
3	21	41	75	0.4	0.8	1.4	0.0177%	0.0345%	0.0631%
4	14	28	38	0.3	0.5	0.7	0.0118%	0.0236%	0.0320%
5	9	16	25	0.2	0.3	0.5	0.0076%	0.0135%	0.0210%
6	7	11	19	0.1	0.2	0.4	0.0059%	0.0093%	0.0160%
7	6	11	13	0.1	0.2	0.2	0.0051%	0.0093%	0.0109%
8	5	7	11	0.1	0.1	0.2	0.0042%	0.0059%	0.0093%

10W-573.654

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	29	45	82	0.5	0.8	1.5	0.0244%	0.0379%	0.0690%
3	12	19	35	0.2	0.4	0.7	0.0101%	0.0160%	0.0295%
4	5	6	15	0.1	0.1	0.3	0.0042%	0.0051%	0.0126%
5	2	3	6	0.0	0.1	0.1	0.0017%	0.0025%	0.0051%
6	1	2	5	0.0	0.0	0.1	0.0008%	0.0017%	0.0042%
7	0	2	5	0.0	0.0	0.1	0.0000%	0.0017%	0.0042%
8	0	2	5	0.0	0.0	0.1	0.0000%	0.0017%	0.0042%

10E-576.264

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	18	26	38	0.3	0.5	0.7	0.0152%	0.0219%	0.0320%
3	10	10	13	0.2	0.2	0.2	0.0084%	0.0084%	0.0109%
4	3	3	5	0.1	0.1	0.1	0.0025%	0.0025%	0.0042%
5	2	2	3	0.0	0.0	0.1	0.0017%	0.0017%	0.0025%
6	0	0	1	0.0	0.0	0.0	0.0000%	0.0000%	0.0008%
7	0	0	1	0.0	0.0	0.0	0.0000%	0.0000%	0.0008%
8	0	0	1	0.0	0.0	0.0	0.0000%	0.0000%	0.0008%

10W-576.264

Number of False Alarms

	Total			Daily Average			False Alarm Rate		
Window Size	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	10	17	37	0.2	0.3	0.7	0.0084%	0.0143%	0.0311%
3	5	8	12	0.1	0.2	0.2	0.0042%	0.0067%	0.0101%
4	1	2	7	0.0	0.0	0.1	0.0008%	0.0017%	0.0059%
5	1	2	7	0.0	0.0	0.1	0.0008%	0.0017%	0.0059%
6	1	1	5	0.0	0.0	0.1	0.0008%	0.0008%	0.0042%
7	1	1	3	0.0	0.0	0.1	0.0008%	0.0008%	0.0025%
8	1	1	4	0.0	0.0	0.1	0.0008%	0.0008%	0.0034%

Table C-1. Total Number of False Alarms (Cont'd)

10E-576.846

Number of False Alarms

Window Size	Total			Daily Average			False Alarm Rate		
	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	7	12	39	0.1	0.2	0.7	0.0059%	0.0101%	0.0328%
3	6	6	18	0.1	0.1	0.3	0.0051%	0.0051%	0.0152%
4	2	4	11	0.0	0.1	0.2	0.0017%	0.0034%	0.0093%
5	2	3	10	0.0	0.1	0.2	0.0017%	0.0025%	0.0084%
6	2	3	10	0.0	0.1	0.2	0.0017%	0.0025%	0.0084%
7	2	3	9	0.0	0.1	0.2	0.0017%	0.0025%	0.0076%
8	2	2	9	0.0	0.0	0.2	0.0017%	0.0017%	0.0076%

10W-576.846

Number of False Alarms

Window Size	Total			Daily Average			False Alarm Rate		
	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr	40 km/hr	48 km/hr	56 km/hr
2	9	28	84	0.2	0.5	1.5	0.0076%	0.0236%	0.0707%
3	1	7	33	0.0	0.1	0.6	0.0008%	0.0059%	0.0278%
4	1	4	15	0.0	0.1	0.3	0.0008%	0.0034%	0.0126%
5	1	3	8	0.0	0.1	0.2	0.0008%	0.0025%	0.0067%
6	1	2	7	0.0	0.0	0.1	0.0008%	0.0017%	0.0059%
7	1	2	4	0.0	0.0	0.1	0.0008%	0.0017%	0.0034%
8	0	1	2	0.0	0.0	0.0	0.0000%	0.0008%	0.0017%