A Complete Review of Incident Detection Algorithms & Their Deployment: What Works and What Doesn't

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16. Abstract

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APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimetres	mm
ft	feet	0.305	metres	m
yd	yards	0.914	metres	m
mi	miles	1.61	kilometres	km
		AREA		
in^2	square inches	645.2	millimetres squared	mm^2
ft^2	square feet	0.093	metres squared	m^2
yd^2	square yards	0.836	metres squared	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	kilometres squared	km^2
		VOLUME		
fl oz	fluid ounces	29.57	mililitres	mL
gal	gallons	3.785	Litres	L
ft^3	cubic feet	0.028	metres cubed	m^3
yd^3	cubic yards	0.765	metres cubed	m^3

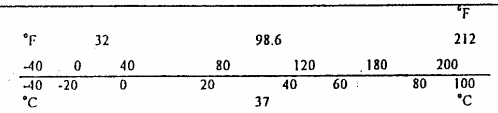
NOTE: Volumes greater than 1000 L shall be shown in m^3

		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams	Mg
		TEMPERATURE (exact)		
°F	Fahrenheit temperature	5(F-32)/9	Celcius temperature	°C

* SI is the symbol for the International System of Measurement

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimetres	0.039	inches	in
m	metres	3.28	feet	ft
m	metres	1.09	yards	yd
km	kilometres	0.621	miles	mi
		AREA		
mm^2	millimetres squared	0.0016	square inches	in^2
m^2	metres squared	10.764	square feet	ft^2
ha	hectares	2.47	acres	ac
km^2	kilometres squared	0.386	square miles	mi^2
		VOLUME		
mL	millilitres	0.034	fluid ounces	fl oz
L	litres	0.264	gallons	gal
m^3	metres cubed	35.315	cubic feet	ft^3
m^3	metres cubed	1.308	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams	1.102	short tons (2000 lb)	T
		TEMPERATURE (exact)		
°C	Celcius temperature	1.8C+32	Fahrenheit temperature	°F



A REVIEW OF INCIDENT DETECTION TECHNOLOGIES, ALGORITHMS AND THEIR DEPLOYMENTS: WHAT WORKS AND WHAT DOESN'T

Abstract: The purpose of this report is to assess the strengths and limitations of available sensor technologies and their corresponding processing algorithms. The performance of an incident detection system is determined on two levels: data collection technologies and data processing algorithms. Variations in sensor-and-algorithm schemes result in a variety of solutions for incident detection. In this report, three categories (roadway-based, probe-based and driver-based) incident detection technologies and their corresponding algorithms are reviewed and evaluated. The capability, accuracy, reliability and cost of available sensor technologies are emphasized. A variety of algorithms associated with these technologies are also investigated in terms of their performance and ease of implementation. Responses to a nationwide online survey of traffic management centers (TMCs) and traffic operations centers (TOCs) across the U.S. provide first-hand information regarding experiences and problems of implementation. The report includes consideration of incident detection on arterial roads and the use of section-related data in incident detection.

Keywords: Incident detection, incident management, traffic detection/sensor technology, incident detection algorithm

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INTRODUCTION

I.1 Problem Statement

Roadway incidents refer to non-recurring events resulting in traffic congestion or disruption, including accidents, breakdowns, debris, spilled loads, inclement weather, unscheduled maintenance and construction activities, and other unusual or special events affecting roadways. During an incident, the normal capacity of the roadway is restricted and queues and delays often result. Incidents are major contributors to delay and have far-reaching consequences for safety, congestion, pollution, and the cost of travel (Mahmassani *et al.*, 1998). Previous investigations indicate that incidents are one of the major causes of loss of time and increases in avoidable costs in transportation networks in the U.S. For example, it was estimated that more than 60% of urban freeway congestion was caused by incidents and that this indicator will increase to 70% or higher by the year 2005 (Lindley, 1987). The Texas Transportation Institute (TTI) estimated that incidents accounted for between 52% and 58% of total delay at a cost of $68 billion in 75 urban areas (Schrank and Lomax, 2002). Prompt and reliable incident detection is vital in reducing incident congestion, post-incident delay and the potential for additional incidents.

Incident management is a crucial function in the design and deployment of Advanced Transportation Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS). It primarily includes incident detection, verification, response, and clearance. Incident detection is a crucial step in incident management; it affects consequent actions and determines the reliability and efficiency of the whole system. The procurement of real-time incident detection information is an integral element of and supports the realization of many other functions in traffic management. Nevertheless, incident detection is one of the weakest links in implementing the advanced traffic control and management concepts that have surfaced over the last decade (Michalopoulos *et al.*, 1993a; Mahmassani and Hass, 2001).

I.2 Motivation and Significance

Considerable effort has been devoted to improving incident detection in past decades, including the deployment of many new detection/sensor technologies and the development of a variety of processing algorithms. Most automatic incident detection algorithms were developed for freeways; only a few have been suggested for arterial systems. At both levels, however, Automated Incident Detection systems have generally not performed well when actually implemented, in terms of the standard performance measures of detection rates (DR), false alarm rates (FAR) and mean time to detect (MTTD). Currently, many traffic management centers have resorted to labor- and equipment-intensive video surveillance of their major roadways. Others rely on screening cellular phone reports of accidents, assuming that two or three phone calls describing an incident at the same location means that an incident has indeed occurred.

Recently, there has been a trend away from data processing algorithms based on traditional surveillance systems (e.g., loop detector systems) toward considering other

emerging traffic detection/sensor technologies, including vehicle-to-roadside communications (VRC) or automatic vehicle identification (AVI) (including toll transponders) and automatic vehicle location (e.g., GPS and cellular telephone geolocation systems). The development of new sensor technologies has led to renewed interest in automatic incident detection, especially for arterials. In this report, the capabilities and costs of new traffic detection/sensor technologies that have significant potential to improve the performance of incident detection are investigated.

I.3 Incident Detection System Architecture

The performance of an incident detection system is determined on two levels: data collection and data processing, as illustrated in *Figure I-1*. Data collection refers to the detection/sense/surveillance technologies that are used to obtain traffic flow data. Data processing refers to the algorithms used for detecting and classifying incidents through analyzing the traffic parameters from detectors or sensors for the purpose of alerting observers of the occurrence, severity, and location of an incident. Combined, the two levels provide a technical platform on which a variety of algorithms can be designed and applied. The "mixing and matching" of data collection technologies and data processing methodologies results in a variety of solutions for incident detection.

Opportunities exist on both levels -- data collection technologies and data processing algorithms -- to improve the reliability and effectiveness of incident detection systems. Historically, most efforts were devoted to the development and improvement of algorithms. Moreover, most algorithms were established based on the measurements from loop detectors or loop emulators, partially because loop detector systems have been the most widely used nationwide and are of relatively low cost compared to other detection technologies. Numerous studies using loop detector data (generally flow and occupancy at one or two points in a detection section) resulted in many loop-based automatic incident detection (AID) algorithms. Although these algorithms have varied data requirements, structural complexity and ease of implementation, few offer satisfactory performance in application and hence they seldom have been successfully implemented in a traffic management center (TMC) or traffic operations center (TOC). A nationwide survey of TMC/TOC operators indicates that more than half of the respondents are not satisfied with their AID system because of frequent malfunctions, high false alarm rates, troublesome calibration and implementation, inconvenient installation and maintenance, performance instability, and/or long detection/verification time (see *Chapter 2* for the details). Most algorithms were developed (and calibrated) based on specific spatial and temporal traffic conditions (i.e., certain roadway segments and times of day). The most widely recognized algorithms (e.g., the California algorithm series, the McMaster algorithm, the high occupancy or HIOCC algorithm, etc.), seem to be non-transferable; many have been shelved in favor of more manual procedures. The lack of success is

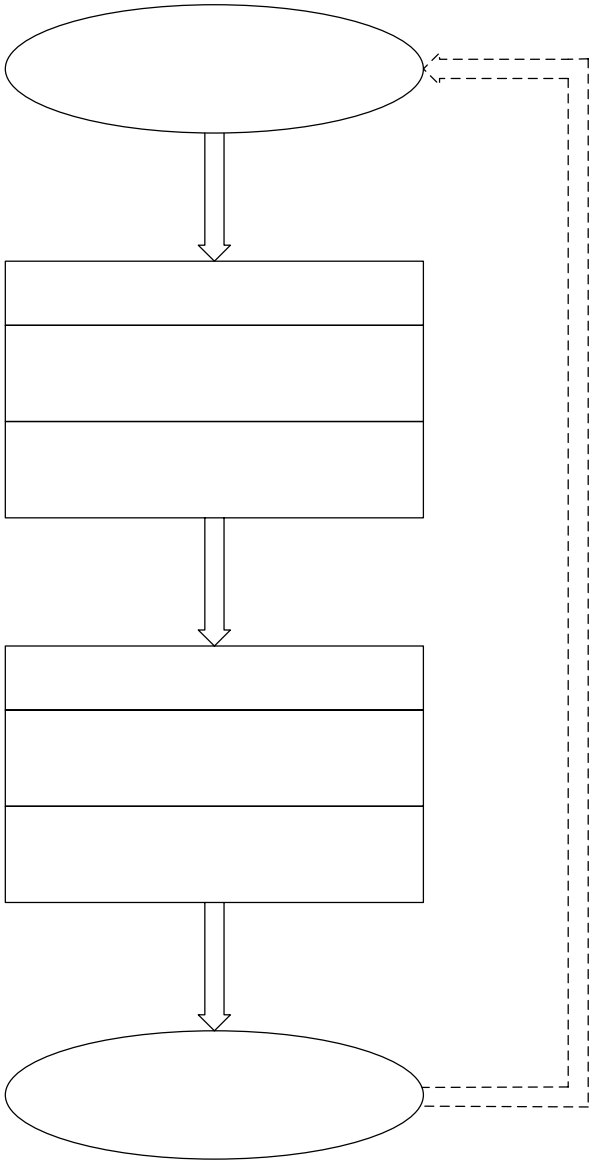

Figure I-1 Incident detection systems conceptually

generally related to limited traffic information coverage and poor data reliability from loop detectors or loop-emulating surveillance systems.

I.4 Objective

This study focuses on the comparison and evaluation of available sensor technologies and their corresponding processing algorithms on both freeways and arterials. The strengths and limitations of both conventional and newly developed algorithms are investigated and identified, based on a thorough literature review and a nationwide survey.

Recommendations for developing and implementing an incident detection system are given in terms of operational performance, data requirement, ease of implementation, ease of calibration, and implementation and maintenance cost.

I.5 Principal Tasks

The tasks of this project include reviewing existing freeway and arterial incident detection algorithms, collecting and analyzing information about the usage of these algorithms from traffic management centers (TMCs) and traffic operations centers (TOCs) across the country, assessing performance of the algorithms, reviewing potential new technologies, considering the costs of different sensors and different data types, identifying incident detection parameter calibration procedures, and recommending an appropriate approach or set of algorithms that can be used by a TMC or TOC.

CHAPTER 1: REVIEW OF FREEWAY AND ARTERIAL INCIDENT DETECTION ALGORITHMS

This chapter reviews the principles of incident detection algorithms; the performance of several of the most widely used algorithms is evaluated in *Chapter 3*. Much effort in past decades has been put into developing and improving incident detection algorithms and systems to satisfy the demands of traffic and incident management systems under a variety of traffic conditions. It was asserted more 15 years ago that incident detection algorithms that detect all congestion-producing incidents without generating a large number of false alarms had yet to be perfected (FHWA, 1985). Although much progress has been made, this statement is still true.

1.1 Overview of Incident Detection Algorithms

Incident detection algorithms may be grouped into two categories: automatic and non-automatic. Automatic algorithms refer to those algorithms that automatically trigger an incident alarm when traffic condition data received from field sensors satisfy certain preset conditions; non-automatic algorithms or procedures are based on human witness reports (i.e., driver-based "sensors") (refer to *Chapter 4*). The former constitute the main part of the existing algorithms. Experience shows that most automatic algorithms operate imperfectly in a real, in contrast to a simulated, traffic environment. (Refer to *Chapter 2*). Recently, more attention has been paid to driver-based procedures, e.g. drivers' wireless phone reports. These are capable of providing quick detection and identification, rich and interactive descriptions, and broad spatial and temporal coverage with less initial investment and operation and maintenance cost (Xie and Parkany, 2002).

Using another classification system, incident detection algorithms may be divided into two functional categories: freeway algorithms and arterial algorithms. Historically, most automatic algorithms were developed for use in freeway incident detection and few are readily transferable to arterial roadways. Less effort has been devoted to incident detection on arterials.

The incident detection literature contains many comparisons and evaluations of detection algorithms. In addition, there are several independent literature reviews including a comprehensive evaluation of a variety of incident detection algorithms. In this chapter, before reviewing a range of representative freeway and arterial incident detection algorithms, we first consider the contributions from previous literature reviews[1]. Most of these reviews are focused on evaluations of freeway incident detection algorithms based on loop detector or loop-detector-like (emulated) data. Therefore, since state-of-the-art reviews of fixed detector based algorithms have been well covered in these earlier studies, roadway-based algorithms are outlined only briefly in this study. Then, probe-based and driver-based algorithms are discussed more fully in the subsequent two sections. In the last section, arterial-specific algorithms are summarized.

[1] The reported performance of the reviewed algorithms in these literature reviews are incorporated into *Chapter 3*.

1.2 Previous Literature Reviews

There are at least six comprehensive studies focusing on or containing a state-of-the-art literature review of existing incident detection algorithms (Subramaniam, 1991; Stephanedes *et al.*, 1992; Balke, 1993; Mahmassani *et al.*, 1998; Peterman, 1999; Black and Sreedevi, 2001[1]). The conclusions of these reviews are summarized briefly in the following section. The typical algorithm acronyms (such as California algorithm No. 7 and APID) are provided here in the summary. The algorithms are described in more detail in Section 1.3. Comparison of algorithms are provided in Section 3.2, Performance of Incident Detection Algorithms. For more detailed information, readers are referred to the original articles and reviews.

1.2.1 Subramaniam's Review

Subramaniam (1991) categorized incident detection algorithms, which were mostly developed in the 1970s and 1980s, into 5 types: 1) pattern recognition (including California algorithm No. 7 and APID algorithm), 2) statistical processing (including SND algorithm, Bayesian algorithm, ARIMA algorithm, smoothing algorithm, DES algorithm, HIOCC algorithm, filtering algorithm, and dynamic algorithm), 3) Catastrophe theory (or McMaster algorithm), 4) neural networks, 5) and video image processing (used in INVAID-TRISTAR System). Their performances are compared in terms of their own reported measures of effectiveness (MOEs). The data required to support these algorithms are derived from either inductive loop detectors (ILDs) or video image processors (VIPs).

1.2.2 Stephanedes *et al.*'s Review

Stephanedes *et al.* (1992) reports on a comparative performance evaluation of the most widely accepted conventional freeway automatic incident detection (AID) algorithms as well as a proposed low-pass filter (LPF) algorithm, the Minnesota algorithm. Three types of AID algorithms were compared: comparative logic (i.e., the California algorithm series), statistical forecasting (i.e., standard normal deviation algorithm, double exponential algorithm, ARIMA algorithm, and HIOCC algorithm), and macroscopic traffic analysis (i.e., the McMaster algorithm, dynamic algorithm, and fictitious volume algorithm[2]). These algorithms were found to suffer from certain limitations: 1) the unsatisfactory quality of raw data (i.e., inductive loop detector (ILD) data) and the use of raw data with only limited filtering; and 2) the lack of effectiveness in distinguishing incidents from bottleneck congestion or other incident-like traffic situations. The best algorithms of the comparative logic and time series types were selected in terms of DR-FAR curves and compared to the Minnesota algorithm using a data set collected on Interstate 35 in Minneapolis, Minnesota.

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[1] Black (1997) initially conducted a literature review of automatic incident detection algorithms for the ITS Decision Database in PATH; then, Black and Sreedevi (2001) updated the content to reflect recent progress and added the sections of "Performance Index" and "Factors Affecting the Performance of Detection Algorithms". It is accessible at http://www.path.berkeley.edu/~leap/TTM/Incident_Manage/Detection/aida.html (June 2004).

[2] The algorithm name of "fictitious volume" is given by authors Stephanedes et al. to the algorithms, proposed by Cremer (1981) to improve detection performance by modeling the attenuation of the road capacity with an additional (fictitious) volume input at the location of the incident.

Based upon this evaluation, Stephanedes *et al.* (1992) concluded that raw detector (i.e., ILD) data are often inappropriate for incident detection if traffic noise cannot be filtered out. This is a weakness characterizing comparative algorithms—when corrupted by noise, incident patterns in the traffic data may not be detected easily by a comparative algorithm. Similarly, fluctuations produced by noise sources are often detected as incidents. As a result, the only traffic patterns easily identified are those occurring under severe incident conditions and satisfying every test of an algorithm. Statistical forecasting algorithms employing filtering offer some improvement in this regard, however, their transferability is greatly limited. The major weakness of all of these algorithms lies in their inability to distinguish incidents from similar traffic patterns.

1.2.3 Balke's Review

Balke's (1993) work on the evaluation of incident detection algorithms was focused on both theory and practice. Algorithms were evaluated in terms of their reported performance, data requirements, ease of implementation, ease of calibration, and operational experience.

In the first part of his research report, existing incident algorithms were reviewed in terms of their underlying theoretical basis. The five groups were: comparative algorithms (i.e., California basic, California No. 7, California No. 8, and APID algorithm), statistical algorithms (i.e., SND algorithm and Bayesian algorithm), time-series algorithms (i.e., ARIMA algorithm), smoothing or filtering algorithms (i.e., DES algorithm and LPF algorithm), and modeling algorithms (i.e., McMaster algorithm). In the second part of the study, in-depth information about incident detection performance and implementation issues extracted from site visits to selected freeway management systems in North America was offered. These freeway management systems were located in: Los Angeles, Seattle, Northern Virginia, Long Island, Minneapolis, Chicago, and Toronto. At the time of these visits, four of the above sites (i.e., Los Angeles, Northern Virginia, Chicago and Toronto) were currently using automatic algorithms to detect incidents while the other management centers (i.e., Seattle, Long Island and Minneapolis) had all discontinued automatic algorithm usage. The results from the theoretical evaluations and on-site investigations indicated that: 1) most of freeway management centers were using a modified version of the California algorithm except for Toronto where the McMaster algorithm was being employed; 2) generally, the operators did not depend heavily on the automatic algorithms to alert them to the presence of incidents; 3) for the most part, the operators relied on other mechanisms, such as radio reports or closed-circuit television (CCTV) monitoring, to alert them to incidents on freeways; and 4) of those systems that have discontinued algorithm use, improper calibration appears to be the most prevalent reason why the algorithms generated a high number of false alarms. Furthermore, it was believed that the algorithms could not be properly calibrated unless an incident occurred in every detection zone.

A qualitative assessment was also provided to evaluate the ease with which each algorithm could be calibrated and implemented in the proposed design of the TxDOT surveillance and control system. The assessment was conducted in terms of judgments relating to the complexity of the design and structure of the algorithm and the amount of processing required by each algorithm. More of these results are presented in Chapter 3.

1.2.4 Mahmassani *et al.*'s Review

Mahmassani *et al.* (1999) investigated both incident detection technologies and algorithms. The advantages and disadvantages of a variety of sensors, including video image processing (VIP), were identified and compared. The potential use of cellular phones for incident detection was also proposed. In the algorithm review, existing incident detection algorithms were classified into 5 main categories: 1) comparative algorithms; 2) statistical algorithms; 3) time-series algorithms; 4) theoretical algorithms; and 5) advanced algorithms. The relationships or trade-offs among performance measures for conventional incident detection algorithms were also identified. Sensor fusion and algorithm fusion were proposed to enhance the reliability and performance of an incident detection system when data requirements cannot be fully satisfied.

1.2.5 Peterman's Review

After reviewing a variety of incident detection algorithms, Peterman (1999) conducted a calibration and evaluation of three recognized fixed detector-based algorithms, including the California No. 8 algorithm, the McMaster algorithm, and the Minnesota algorithm and compared them to the Texas algorithm[1], using a data set including traffic and incident data collected by TransGuide (San Antonio). A Monte Carlo technique was applied to quickly calibrate all of the compared algorithms. Peterman showed that an algorithm that outperforms others in the calibration process does not necessarily provide the best performance when applied to real data.

1.2.6 Black and Sreedevi's Review

Black and Sreedevi (2001) summarized the following important aspects of automatic incident detection algorithms: 1) measures of effectiveness; 2) principles and operation theory; 3) data requirements; and 4) performance. They proposed a performance index (PI) that combines the values of DR, FAR and MTTD in an integrated functional form. A lower PI value indicates better performance. In their classification, analogous to Mahmassani *et al.*'s taxonomy (1999), the existing algorithms fall into five groups: 1) comparative algorithms; 2) statistical algorithms; 3) time series algorithms; 4) traffic and theoretical algorithms; and 5) advanced algorithms. Classification group provides the data requirements and reported performance for the algorithms.

1.2.7 Summary

Each of the above reviewers had slightly different evaluation scopes, classification schemes, and performance results. Although the algorithms have different structural complexity, data requirements, and calibration and implementation methods, most of them function based on data from fixed in-road or roadside sensors on freeways and their performance is heavily affected by the raw data quality, which is a function of the detection accuracy and reliability of sensors.

[1] Texas algorithm is a relatively simple algorithm based on an examination of 3-min aggregated detector occupancy data.

None of these reviews emphasizes either arterial-applicable algorithms or algorithms based on types of traffic sensors other than fixed-point detectors. In addition, the evaluation studies for incident detection techniques carried out in the early 1990s did not cover the recent progress of newly developed algorithms. Thus, although the comprehensive literature review on incident detection algorithms in this chapter will include brief descriptions of the classic roadway-based, fixed-sensor algorithms, it will focus on newly-developed algorithms, probe data-based algorithms, non-automatic algorithms (i.e., driver-based anecdotal reports), and algorithms applicable to arterials.

1.3 Roadway-Based Algorithms

Different algorithms have different data requirements, principles, and complexity. Since the traffic and incident management community realized the importance of comparing and selecting these algorithms for further improvement and potential implementation, several state-of-the-art literature reviews on incident detection have been conducted and summarized above. The traditional incident detection algorithms that have been commonly recognized are summarized in this section. These algorithms are grouped into seven categories in terms of their principles: 1) comparative algorithms; 2) statistical algorithms; 3) time series algorithms; 4) filtering/smoothing algorithms; 5) traffic modeling algorithms; 6) artificial intelligence algorithms; and 7) image processing algorithms. All of these algorithms use loop detector or loop-emulating data collected at points along the roadway and all are applied to freeways.

1.3.1 Comparative Algorithms

Comparative algorithms are designed to compare the value of measured traffic parameters (i.e., volume, occupancy or speed) to a pre-established threshold value. An incident alarm is prompted when the measured traffic parameter exceeds an established threshold. Comparative algorithms include the decision tree (DT) algorithms (Payne, 1976; Payne *et al.*, 1976; Payne and Knobel, 1976; Tignor and Payne, 1977; Payne and Tignor, 1978; Levin and Krause, 1979a, b), the pattern recognition (PATREG) algorithm (Collins *et al.*, 1979), and the APID algorithm (Masters *et al.*, 1991).

The DT algorithms, or so-called California algorithms, are the most widely known comparative algorithms. This type of algorithm is based on the principle that an incident is likely to cause a significant increase in upstream occupancy while simultaneously reducing occupancy downstream. The following occupancy differences of two adjacent fixed detector locations in a decision tree structure are analyzed: 1) the absolute difference in occupancy between the upstream and downstream detectors; 2) the relative difference in occupancy between upstream and downstream detectors compared to the upstream occupancy; and 3) the relative difference in occupancy between upstream and downstream detectors compared to the downstream occupancy. In the California algorithm family, the modified #7 and #8 algorithms were shown to have the best performance (Payne and Tignor, 1978; Balke, 1993). California #7 replaces the temporal downstream occupancy difference in the above third test with the present downstream occupancy measurement. California #8 has the most complicated form (it involves 21 individual tests) in that it incorporates refining functions to deal with compressive waves.

The PATREG algorithm was developed by the Transport and Road Research Laboratory (TRRL) as part of their Automatic Incident Detection (AID) system. It works in conjunction with the HIOCC algorithm (discussed later in the section 1.3.3 *Time Series Algorithms*) to detect traffic disturbances following an incident. The algorithm estimates vehicle speeds by tracing and measuring travel times of particular traffic patterns between detectors. The algorithm compares these speed values to pre-established thresholds and triggers an alarm when they fall below the thresholds during a pre-set number of consecutive intervals.

The All-Purpose Incident Detection (APID) algorithm was developed for use in the COMPASS advanced traffic management system implemented in Metropolitan Toronto. It incorporates and expands the major elements of the California algorithms into a single structure. The algorithm includes the following major parts: 1) a general incident detection algorithm for use under heavy traffic conditions; 2) a light volume incident detection algorithm; 3) a medium volume incident detection algorithm; 4) an incident termination detection routine; 5) a routine for testing for the presence of compression waves; and 6) a routine for testing for the persistence of incident conditions. A primary feature of the algorithm, compared to the California algorithms, is that different algorithms are used under different traffic conditions.

1.3.2 Statistical Algorithms

The statistical algorithms use standard statistical techniques to determine whether observed detector data differ statistically from estimated or predicted traffic characteristics. The standard normal deviate (SND) algorithm (Dudek *et al.*, 1974) and Bayesian algorithm (Levin and Krause, 1978; Tsai and Case, 1979) are two representative types of statistical incident detection algorithms.

The SND algorithm was developed by the Texas Transportation Institute (TTI) in the early 1970s for use in the initial surveillance and control center in Houston, TX. The algorithm computes the SND of the traffic control measure, which is the number of deviations a particular value of a variable deviates from the mean of that particular variable. Its working principle is based on the premise that a sudden change in a measured traffic variable suggests that an incident has occurred. The algorithm compares 1-minute average occupancy measurements to archived occupancy values of the mean and SND that define thresholds for detecting incidents. An SND value greater than the critical value indicates the presence of an incident. Two successive intervals are used to make a consistency test.

The Bayesian algorithm uses Bayesian statistical techniques to compute the likelihood that an incident signal is caused by a lane-blocking incident. The algorithm makes use of the relative difference of the occupancies used in the California algorithms as the traffic measure, but computes the conditional probability using Bayesian statistics. Bayesian theory assumes that frequency distributions of the upstream and downstream occupancies during incident and incident-free conditions can be developed. Three databases are identified for satisfying the requirement of the Bayesian algorithm: 1) traffic occupancy and volume data

during incident conditions; 2) traffic occupancy and volume data during incident-free conditions; and 3) archived data on the type, location, and severity of incidents.

1.3.3 Time Series Algorithms

Time series algorithms assume that traffic normally follows a predictable pattern over time. They employ time series models to predict normal traffic conditions and detect incidents when detector measurements deviate significantly from model outputs. Several different techniques have been used to predict time-dependent traffic for incident detection, including the autoregressive integrated moving-average (ARIMA) model (Ahmed and Cook, 1977, 1980, 1982) and high occupancy (HIOCC) algorithm (Collins *et al.*, 1979).

The ARIMA model assumes that differences in a traffic variable measured in the current time slice (t) and the same traffic variable in the previous time slice ($t-1$) can be predicted by averaging the errors between the predicted and observed traffic variable from the past three time slices. These errors are expected to follow a normal pattern under incident-free conditions while an abnormal error indicates a potential incident occurrence. This model is used to develop short-term forecasts and confidence intervals of traffic variables. Incidents are detected if the observed occupancy values fall outside the established confidence interval.

The HIOCC algorithm also monitors detector data for changes over time, but relies on 1-second occupancy data. The algorithm is designed to examine the individual pulses from the detectors and seek several consecutive seconds of high detector occupancy in order to identify the presence of stationary or slow-moving vehicles over individual detectors. A computer scans detector occupancy data every tenth of a second and several consecutive values of instantaneous occupancies are then examined to see if they exceed a predetermined threshold.

1.3.4 Smoothing/Filtering Algorithms

Smoothing and filtering techniques are designed to remove short-term noises or inhomogeneities from traffic data that cause false alarms and hence permit true traffic patterns to be more visible so as to more readily detect true incidents (Balke, 1993). Smoothing is a mathematical technique for producing a weighted average of a given traffic variable. Filtering algorithms use a linear filter that allows the low-frequency components of the detector data to pass while removing the undesirable high-frequency portions of the detector data. The representative smoothing/filtering algorithms consist of the double exponential smoothing (DES) algorithm (Cook and Cleveland, 1974), low-pass filter (LPF) algorithms (Stephanedes *et al.*, 1992; Stephanedes and Chassiakos, 1993a, b; Chassiakos and Stephanedes, 1993), and the discrete wavelet transform and linear discriminant analysis (DWT-LDA) algorithm (Samant and Adeli, 2000; Adeli and Samant, 2000).

The DES algorithm weights past and present volume, occupancy and speed observations for forecasting short-term traffic conditions that are expected to closely resemble true traffic conditions. This algorithm is expressed mathematically as a double exponential smoothing function, with a smoothing constant, which weights past observations. Incidents are detected using a tracking signal, which is the algebraic sum (to the present minute) of all the

previous errors between the predicted and observed traffic variable. Under incident-free conditions, the tracking signal should dwell around zero since predicted and observed traffic conditions should be similar.

The LPF algorithm series, which are widely known as the Minnesota algorithms or the DELOS (detector logic with smoothing) algorithms, remove sharp or high frequency fluctuations that are characteristic of noise in the data while allowing wide or low frequency fluctuations typically associated with incident conditions to pass through the pre-set filter. The algorithm is based on a simple comparison of the occupancy levels at two adjacent detector stations. In these algorithms, two filters on two levels, respectively employing 3-minute and 5-minute moving average occupancies (Stephanedes *et al.*, 1992), using three types of smoothing techniques, i.e., statistical median occupancies (Stephanedes and Chassiakos, 1993a), or applying exponential smoothing occupancies (Stephanedes and Chassiakos, 1993b), were applied to better distinguish incident and bottleneck congestion and hence reduce the false alarm rate. A more comprehensive discussion and evaluation on these smoothing algorithms can be found in Chassiakos and Stephanedes (1993).

The DWT-LDA algorithm was designed to extract incident features from traffic patterns while eliminating false alarms. The designers of this algorithm used it as a traffic preprocessor to provide better volume and occupancy inputs for an adaptive conjugate gradient neural network model for incident detection. The DWT technique, which was originally developed in signal and image processing, is first applied to filter raw traffic data, and the finest resolution coefficients representing random fluctuations of traffic are discarded. Then, the LDA component is used on the filtered signal for further feature extraction reducing the dimensionality of input data of the incident detection model and hence the computational processing effort.

1.3.5 Traffic Modeling Algorithms

Traffic modeling approaches for incident detection apply traffic flow theory to describe and predict traffic behavior under incident conditions. Discrimination between incident and incident-free traffic by this type of model is based on the comparison between observed traffic parameters and parameter values estimated by the models. The traffic modeling algorithms include the dynamic model (Willsky *et al.*, 1980), the catastrophe theory model and modifications (Gall and Fall, 1989; Persaud and Hall, 1989; Persaud *et al.*, 1990; Forbes and Hall, 1990; Forbes, 1992; Hall *et al.*, 1993), and the low-volume (LV) incident detection algorithm (Fambro and Ritch, 1979; 1980).

The dynamic model was developed to apply macroscopic traffic flow models to capture the dynamic nature of traffic. The fundamental speed-density and flow-density relationships are used as the basic theory in this incident detection algorithm. The algorithm uses two statistical hypothesis testing techniques to examine the flow-density relationships in observed traffic data: the Multiple Model (MM) method and the Generalized Likelihood Ratio (GLR) method. The conditional probability of the validity of the observed data compatible with the flow-density model indicative of incident conditions is determined by the MM method. The GLR method is also used to measure the likelihood that the observed flow-density pattern is

indicative of an incident condition. In this algorithm, measured point detector data must be converted from a time-based average to a space-based average.

The catastrophe theory model, or the so-called McMaster model, is based on a two-dimensional analysis of traffic data. Catastrophe theory takes its name from the sudden discrete changes that occur in one variable while other related variables exhibit smooth and continuous changes (Black and Sreedevi, 2001). The McMaster algorithm is based on the premise that speed changes sharply when traffic changes between a congested state and an uncongested state, while flow and occupancy change smoothly. The algorithm uses historical data to determine the flow-occupancy relationship and further identify different congested and uncongested traffic states with speed variation. In the flow-occupancy template, four areas are identified representing different traffic profiles. Two tests are applied to detect incidents. The first test determines whether traffic at a detector station is congested. If congestion is detected, the second test is used to identify the cause of the congestion through evaluating the traffic state at a downstream detector station.

Most existing algorithms cannot deal with incident detection under low volume conditions very well, because incidents seldom cause severe or detectable congestion under these traffic conditions. To address this problem, the LV algorithm was designed specifically for detecting incidents under low volume conditions, using an input-output analysis of individual vehicles on a section of roadway. The algorithm predicts the departure time of an entering vehicle in terms of its speed and entering time. Based on the projected and actual exiting time, vehicles can be classified into three accounting states: exiting count is less than the projected count (indicating an incident), exiting count is equal to the projected one (indicating no incident), and exiting count is more than the projected one (indicating an unknown situation).

1.3.6 Artificial Intelligence Algorithms

Artificial intelligence refers to a set of procedures that apply inexact or "black box" reasoning and uncertainty in complex decision-making and data-analysis processes. The artificial intelligence techniques applied in automatic incident detection include neural networks (Ritchie and Cheu, 1993; Cheu and Ritchie, 1995; Stephanedes and Liu, 1995; Dia and Rose, 1997; Abdulhai and Ritchie, 1999; Adeli and Samant, 2000), fuzzy logic (Chang and Wang, 1994; Lin and Chang, 1998), and a combination of these two techniques (Hsiao *et al.*, 1994; Ishak and Al-Deek, 1998).

Neural networks are data processing structures used to simulate the thought process and reasoning of the human brain. They consist of a number of simple processing elements (PEs) with parallel interconnections. The PEs receive input information, weighted by the strength of associated connection values, then make computations using a transfer function, and finally send output to other connected PEs in the next layer. The commonly used neural network algorithms for incident detection include multi-layer feed forward neural networks (MLF) and probabilistic neural networks (PNN). The MLF-based algorithm has three fundamental layers: input layer, hidden layer, and output layer. The inputs for PEs on the input layer generally include volume, occupancy, and/or speed at both upstream and downstream detectors. The PNN-based algorithm has the capability of incorporating prior

probabilities of incident occurrence, road conditions, and misclassification cost for incident detection. The neural network algorithms require substantial training through trial-and-error processes to optimize weights in order to identify uncongested and congested traffic, both recurring and nonrecurring. In order to reduce the high dimensionality of a common neural network model and improve its computational efficiency, Adeli and Samant (2000) proposed using an adaptive conjugate gradient neural network (ACGNN) with a two-stage discrete wavelet transform and linear discriminant analysis preprocess (as described as the DWT-LDA algorithm in this chapter) for incident detection to improve detection efficiency and performance.

In addition, Ivan and his colleagues (Ivan *et al.*, 1995; Ivan and Chen, 1997; Ivan, 1997; Ivan and Sethi, 1998) applied neural networks to fuse loop detector and probe vehicle data for arterial incident detection. In these applications, neural networks are designed to work in two forms: 1) combining the raw traffic data; or 2) integrating incident the detection results (or incident occurrence probabilities) from a loop detector-based model and a probe vehicle-based model.

Fuzzy logic is another artificial intelligence technique used for incident detection. It provides a mechanism for applying inexact or imprecise data to a set of rules. It has been applied to eliminate strict decision thresholds and use membership functions to represent the degree of probability of the presence of an incident. Decisions on incident or incident-free states are allowed even though traffic data may be inexact or missing. The ability to make decisions based on incomplete data has the potential to significantly improve the performance of incident detection algorithms.

Fuzzy logic combined with neural networks (Hsiao *et al.*, 1994) was applied to improve the performance of incident detection over either single technique. Ishak and Al-Deek (1998) applied a fuzzy neural network, a clustering algorithm that maps a set of input patterns to a set of categories, to improve the performance of incident detection. This method has the capability of overcoming the so-called stability-plasticity dilemma problem of the MLF-type neural networks.

1.3.7 Image Processing Algorithms

Two types of image processing algorithms have been used for incident detection. In the first instance, the image-processing unit (consisting of a surveillance video camera and an image processing computer program) may be used as a loop detector or another fixed detector to provide traffic measures, such as volume, occupancy, speed, and/or queue length. The image-processing program extracts traffic variables from video images. In the second method, the image-processing program interprets the entire video image to find stationary or slow-moving vehicles, so as to detect incidents. A representative algorithm is the Autoscope incident detection algorithm (AIDA) (Michalopoulos, 1991; Michalopoulos *et al.*, 1993).

The AIDA algorithm takes advantage of temporal variations of traffic characteristics in addition to spatial ones. It looks for rapid traffic breakdowns, comparing speed and occupancy with the preset thresholds for determining congestion levels. AIDA was later

improved to include ancillary information provided by video detection. The information includes stopped vehicles and shock wave signature recognition. One of advantages of the image processing-based incident detection technique is that a detected incident in the field of view of a video camera can be verified visually in a short time. It is also capable of monitoring traffic and detecting incidents outside of through lanes, e.g., shoulders, intersections, or ramps, and under both low and high volume traffic conditions.

Other categories of recently emerging incident detection methods/algorithms, e.g., probe-based algorithms, driver-based algorithms, and arterial incident detection algorithms, will be reviewed and discussed in the remaining part of this chapter.

1.4 Probe-Based Algorithms

As described in the last section, most traditional automated incident detection algorithms use roadway-based *point* data. There are several disadvantages to using point data for incident detection. The algorithms using loop data suffer from high rates of false alarms (Stephanedes *et al.*, 1992; Petty *et al.*, 1997; Mahmassani *et al.*, 1998). One disadvantage is the tendency of loop detectors to malfunction. Anecdotal evidence indicates that as many as half of the loop detectors in a system may be inoperable at any given time (Ygnace *et al.*, 2000). An inherent disadvantage of point-based sensors (even the new loop-emulators such as video, radar or infrared) is that they collect only spot traffic data. It may be difficult to ascertain true traffic conditions using data at only individual points on a roadway. Besides the difficulties involved with implementing most point-based incident detection algorithms, there are specific problems with road-based systems: 1) the installation and maintenance interrupts traffic, and may even require road closure; 2) the placement of roadway detectors or the data collection frequency is critical to the accuracy and reliability of point data used for determining an incident, however, these settings are not readily determined.

Probes, such as toll transponders and GPS receivers mounted on vehicles, are becoming increasingly prevalent for electronic toll collection, congestion pricing and fleet management applications. Using travel times and other spatial traffic measures collected by probes, better information about traffic conditions with wider roadway coverage can be obtained. In this section, recently developed algorithms based on probe data will be reviewed and discussed. Given that these probe-based algorithms were designed in accordance with the operation principles and data availability of their corresponding probe sensors, the sensor used will be identified prior to the description of each algorithm. Detailed information on a variety of traffic probe technologies is provided in *Chapter 4*. In the following, the probe-based algorithms are discussed in approximately the chronological order of development. *Table 1-1* summarizes the operational features of the probe based incident detection algorithms. With the exception of the ADVANCE algorithms developed in Chicago in the early '90s, these probe-based algorithms have been developed for freeway incident detection. Reviews of these algorithms are not found in typical incident detection reviews such as the six presented

Table 1-1 Operational features of the probe-based incident detection algorithms

Algorithm Name		Probe Sensor Technology	Penetration Rate	Traffic Environment	Experiment Type	Data Requirement	Detection Interval
MIT	Headways algorithm Lane switches algorithm Lane-monitoring algorithm	AVI/ETC	50%	Freeway	MITSIM-based simulation	Travel time and headway by lane Lane switches Volumes by lane	≈ 0.8 min
ADVANCE	Travel time algorithm	GPS or AVI	30 or fewer probe reports per interval	Arterial	INTRAS-based simulation	Travel time	7 min
	Dynamic measures algorithm	GPS and map matching	1 probe per interval		Field in the suburbs of Chicago, IL	Total travel time, running time, and 1-sec position	N/A
TTI		Cellular probe system[1]	5-min headway	Freeway	Field in Houston, TX	Travel time	15 min
UCB		CDPD radio	7-min headway	Freeway	Field in Hayward, CA	Speed and acceleration	0.5 min
TRANSMIT		AVI/ETC	1-min headway[2]	Freeway	Field in metropolitan NYC	Travel time	15 min
Waterloo	Confidence limit algorithm Speed and confidence limit algorithm Dual confidence limit algorithm	AVI/ETC	10%	Freeway	INTEGRATION-based simulation	Travel time	≈ 0.3 min

[1] In this cellular probe system, drivers were asked to provide travel time through reporting their passed reference points via cellular phone calls. It served as a prelude to the subsequent AVI system in Houston, TX.
[2] The average 1-min headway of probe vehicles in the TRANSMIT system is estimated by the authors in terms of the data provided by Niver *et al.* (2000).

at the beginning of the chapter. More about performance measures including detection interval/time-to-detect related to these algorithms is found in Chapter 3.

1.4.1 MIT Algorithms

Parkany and Bernstein (1993; 1995) conducted an initial exploration of the use of electronic toll transponders (referred to as vehicle-to-roadside communication, or VRC, in their papers) to detect incidents. They analyzed the capabilities of two types of toll transponders, i.e., "read-only" and "read-write," for incident detection. "Read-only" means a roadside reader can read information from probe transponders or tags while "read-write" allows both obtaining information from and writing information on transponders. Three transponder-based incident detection logics (named headways algorithm, lane switches algorithm, and lane-monitoring algorithm) were proposed utilizing read-only transponders, however, it was posited that these algorithms "could be enhanced with read-write technology" (Parkany and Bernstein, 1995).

In their study, the MITSIM simulator was used to simulate a three-lane highway and generate transponder data as well as comparable loop detector data. It was assumed that 50% of vehicles in the simulation were equipped with toll transponders. The distance interval between two adjacent readers was set as 0.75 mile.

The principle of the headways algorithm is that both temporal and spatial discrepancies of travel times and headways may be observed when traffic varies from incident-free to incident conditions. It includes three sequential comparison tests. The first two tests are temporal tests while the third makes a spatial comparison. The first test determines if there is significant difference in travel time between two AVI readers, where slower travel time indicates a possibility of an incident. The second test considers longer headways scanned by a downstream reader that may indicate an incident. In the third test, different headways detected by different readers may suggest an incident in that headways are longer in the vicinity of an incident and then decrease downstream of the incident. If all three tests exceed corresponding pre-set thresholds, an incident is declared. One disadvantage of this algorithm is that it may be insensitive to incidents occurring close to reader locations.

Being able to identify lane change information of probe vehicles using subsequent readers results in the lane switches algorithm. It is based on the principle that a number of lane switch maneuvers detected from one reader to the next may indicate unstable traffic conditions caused by an incident. The algorithm attempts to determine the percentage of probe vehicles switching lanes between readers using lane-specific, vehicle-specific data. If this result exceeds a certain threshold, an incident is identified. Here, the authors counted a lane switch when a vehicle is driven from one lane to another lane. The authors suggested counting switches across two lanes as two switches rather than one may improve the algorithm performance.

The lane-monitoring algorithm is designed to monitor vehicle passage on each lane at reader locations. The principle behind this algorithm is that if fewer vehicles pass than expected on a certain lane and more vehicles pass than expected on any other lanes an incident may be indicated on the first lane. This algorithm employs an average smoothing

technique over several detection intervals (e.g., 2 or 3 intervals) to eliminate traffic fluctuation and hence prevent false alarms.

All of these proposed algorithms make use of vehicle identification to determine traffic pattern variations between roadside readers. Their performances may be improved by a higher probe penetration rate and a smaller distance interval between neighboring transponder readers.

1.4.2 ADVANCE Algorithms

In the ADVANCE operational test, Sethi *et al.* (1995) and Sermons and Koppelman (1996) developed arterial incident detection algorithms based on probe positioning and timing data, using a discriminant analysis technique. All of the algorithms are designed to eliminate false alarms while keeping detection rates at a high level. In discriminant analysis, analogous to multiple-variable linear regression, a linear relationship of predictor variables describing traffic flow characteristics is developed to distinguish incident and incident-free conditions. The result of discriminant analysis for incident detection is dependent on the measured traffic variables and the prior probability of an incident. The prior probability needs to be specified in terms of prior data analysis, reflecting "the expected share of observations (detection periods on a link) during which an incident is likely to occur" (Sethi *et al.*, 1995).

The travel time algorithm proposed by Sethi *et al.* (1995) utilizes both the incident link and the adjacent upstream link travel time and average speed measures. Common on-board location and communication devices, such as GPS, AVI or toll transponders, can satisfy this data requirement. The two variables used are compared to historical averages for each link to infer if an incident occurs on this link. It was found that traffic measures for the incident link were most useful for incidents located in the downstream portion of the link while traffic measures for the next upstream link worked well for incidents occurring in the upstream or middle portion of the link.

Sermons and Koppelman (1996) made use of three categories of GPS measures in the dynamics measure algorithm: 1) total link travel time; 2) total time and running time; and 3) 1-sec vehicle position (from which the coefficient of speed variation, acceleration noise or deviation, and Greenshield's quality of flow measure (1955) can be derived). These measures have different levels of measurement detail, increasing in turn from total travel time to 1-sec vehicle position data. The principle behind these GPS data based algorithms is that probe vehicles passing an incident have higher total time, running time, and coefficient of speed variation. In their study, single probe reports of the above dynamic measures were used independently for classification of traffic conditions, i.e., incident or incident-free conditions. As expected, algorithm performance improves as the level of measurement detail increases.

1.4.3 TTI Algorithm

The Texas Transportation Institute (TTI), in conjunction with the Texas Department of Transportation, conducted a pilot study to test the feasibility of using probe vehicle travel

time to detect incidents on freeways (Balke *et al.*, 1996). Two hundred trained commuters equipped with cellular phones were asked to report their position as they passed reference locations to a communications center through a wireless phone call.[1] Operators at the communications center entered the probe's identification number and the report time, and then the travel progress of the probe vehicle was tracked and its travel time between two adjacent reference points was estimated. The cellular probe system served as a prelude to the AVI system installed on freeway facilities in Houston.

In this pilot study, average 5-min headway between probe vehicles was approximately generated through carefully selecting the probe drivers' departure time. Reference points were located at key interchanges evenly spaced in the network and the average distance between each reference location was approximately 5 mi. Considering hourly variations in travel times, a 15-min time interval was used for monitoring probe vehicle travel time reports.

The TTI incident detection algorithm is based on the premise that incidents cause travel time to increase significantly over the normal travel time under incident-free conditions at the same time of day and day of week. Its function was developed using the statistical principle of standard normal deviates (SND), which indicates confidence intervals of travel time variation under incident-free conditions. The algorithm tests if travel time is longer than the following threshold value determined by historical data:

$$\bar{t}_i + (SND)(s_i) \tag{1.1}$$

where $\bar{t}_i$ is the historical average travel time for a given time-of-day interval i and s_i represents the standard deviation of the average travel time in the same time interval. If the reporting travel time derived from probe vehicles exceeds the predetermined threshold, an incident alarm is declared. In their study, preliminary results showed that the TTI algorithm with a low penetration rate does worse than most of the common loop-based incident detection algorithms.

1.4.4 UCB Algorithm

Petty *et al.* (1997) proposed a probe-based algorithm using vehicle-equipped radio transponders that communicate with existing cellular phone base stations via the standard cellular digital packet data (CDPD) protocol. This technology is currently used for fleet management, e.g., by taxi or logistics companies to track their individual vehicles' location and to perform scheduling. The CDPD radio is ubiquitous on most freeways and major arterials in the current roadway networks. In this system, probe data transmitted to a base station and then forwarded to a TMC for traffic monitoring and incident detection.

In their study, probe vehicle headways were estimated as approximately 6-8 minutes, which can be translated to probe penetration rates being approximately 0.08-0.1% of the vehicle population.

[1] The commuters were also asked to report incidents occurring on their trips for the performance evaluation of the TTI algorithm.

The assumption behind this algorithm is that a vehicle may slow down when it passes an incident. Vehicles upstream of an incident should be in a slow-moving queue and when they pass the incident they should speed up to normal driving speed or even free- flow speed. It can also be observed that vehicles rapidly decelerate from normal driving speed or free-flow speed to stop-and-go traffic. Therefore, this probe-based approach was designed to detect and locate an incident through monitoring speed and acceleration variations of the traffic stream.

In order to distinguish traffic fluctuations from bottleneck congestion, a standard moving average filter of width of 20 sec is used to filter the probe measurements in this algorithm. Then, the profiles of speed and acceleration are monitored. If acceleration value falls above a certain threshold (a) through a certain speed (v_i), an incident is detected, as explained in *Figure 1.1*.

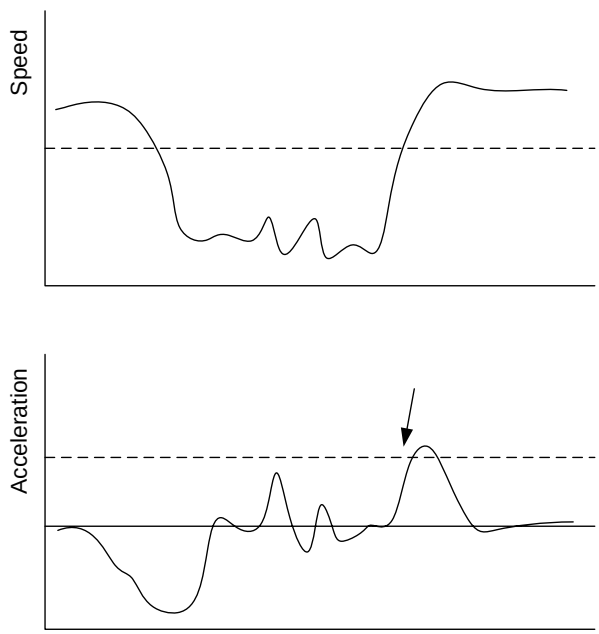


Figure 1-1 Illustration of the basic principle of the UCB probe-based algorithm (Source: Petty *et al.*, 1997)

1.4.5 TRANSMIT Algorithm

Mouskos *et al.* (1999) and Niver *et al.* (2000) discuss the performance of a probe-based incident detection algorithm using statistical travel time comparison between probe reports and continuously updated historical archives in TRANSCOM's (New York and New Jersey) system for managing incidents and traffic (TRANSMIT). In the TRANSMIT operational test, probe vehicles were equipped with E-ZPass electronic toll tags for traffic surveillance and incident detection. This system was initially installed along a 22-mile section of the

Garden State Parkway in New Jersey and the New York State Thruway in New York and served more than 1.5 million vehicles equipped with E-ZPass tags.

When an E-ZPass tag-equipped vehicle passes a roadside terminal or reader, the reader antenna radiates a signal to interrogate the tag and collects the tag identification number, location, lane position, and time information. These roadside readers are distributed along the route at distance intervals of 0.5 to 2.1 mi. The real-time information from each individual probe vehicles is then forwarded to the operations information center (OIC) located in Jersey City. The vehicle travel times between successive readers are computed every 15 min and then are used for traffic monitoring and incident detection.

The TRANSMIT algorithm is similar to the TTI algorithm discussed above in that it assumes that vehicle travel times tend to be normally distributed under incident-free traffic conditions and that an incident alarm is triggered when multiple successive vehicles arrive later than the expected value at a downstream reader a specific link of the system. For each detection zone during a certain time of day, the following travel time threshold *THi* is set,

$$TH_i = HT_i + MSD \times HSD_i \tag{1.2}$$

where *HTi* represents historical average travel time for the time interval *i*, *HSDi* denotes the standard deviation of historical travel time, and *MSD* is a multiplier for *HSDi* that was set to 3 in TRANSMIT algorithm. In this algorithm, the probability of a false alarm ($P(FA_{i,j})$) from a vehicle *j* during the time interval *i* is defined as,

$$\mathrm{P}(FA_{i,j}) = \mathrm{P}(E_i) + \mathrm{P}(NE_i) \times \mathrm{P}(LT_i) \tag{1.3}$$

where P(*Ei*) is the probability that a probe vehicle exits the route before reaching the downstream reader and is missed by the reader, P(*NEi*) is the probability that a vehicle does not exit, and P(*LTi*) is the probability that a vehicle arriving later than the expected time is not delayed by an incident. Once a probe vehicle's travel time exceeds the threshold *THi*, the probability P(LT_i) that this vehicle was not delayed by an incident is decreased from 1 to 0. Finally, the probability of an incident occurrence (P(*INi*)) during a time interval *i* is determined by all of the *n* probe vehicles reporting their travel times in the same time interval, which is expressed as,

$$\mathrm{P}(IN_i) = 1 - \prod_{j=1}^{n} \mathrm{P}(FA_{i,j}) \tag{1.4}$$

The evaluation results indicated that the TRANSMIT algorithm has a comparable performance to the common representative loop-based algorithms. However, its performance varied in that detection rates decrease significantly at a few specific locations.

1.4.6 Waterloo Algorithms

Three automatic vehicle identification (AVI) or electronic toll transponder-based incident detection algorithms characterizing mean and variance of travel times, named the

confidence limit algorithm, speed and confidence limit algorithm, and dual confidence limit algorithm, were proposed and examined by Hellinga and Knapp (2000). They employed the Integration simulator to model a 7.5-mi freeway section of Highway 401 in Toronto, Canada. On this route both eastbound and westbound directions were divided into 10 segments with AVI roadside antennas installed at both ends of each segment. For all three algorithms, the individual AVI-based travel time data were aggregated over 20-sec time intervals so as to reflect the polling frequency of most loop-based surveillance systems.

The basic idea behind the three incident detection algorithms using probe travel time data is that "the travel time experienced by vehicles over a section of roadway increases more rapidly as a result of a change in capacity (i.e., the reduction in capacity caused by an incident) than as a result of a change in demand" (Hellinga and Knapp, 2000). When an incident occurs on a segment, the traffic situation and the resulted travel time on this segment change. It is believed that travel times resulting from traffic conditions before and after an incident belong to two different populations. Therefore, the proposed algorithms are designed to distinguish travel times on either side of the confidence limit or threshold associated with the current population, i.e., under incident or incident-free conditions. There are two apparent features of the Waterloo algorithm that are different from the TTI and TRANSMIT algorithms (which also make use of travel time means and variances to distinguish traffic conditions): 1) the individual travel times in each time interval are assumed to be log-normally distributed, rather than normally distributed; and 2) the confidence limit or threshold is established based on the travel times from the previous N intervals, or the so-called "comparison window", not the historical travel times at the same interval of day. The log-normal mean (μ_i) and variance (σ_i^2) during the time interval i can be expressed as the following in *Equations 1.5* and *1.6*,

$$\mu_i = \ln\left(\bar{t}_i\right) - 0.5\sigma_i^2 \tag{1.5}$$

$$\sigma_i^2 = \ln\left(1 + \frac{var_i}{\bar{t}_i^2}\right) \tag{1.6}$$

where $\bar{t}_i$ and var_i represent travel time mean and variance from the comparison window. The upper confidence limit or threshold (UL_i) for the time interval i following the comparison window is defined as,

$$UL_i = e^{(\mu_i + z\sigma_i)} \tag{1.7}$$

where z denotes a specified level of confidence.

In the confidence limit algorithm, the mean travel time in each time interval is calculated and compared with the upper confidence limit of the corresponding comparison window. If it exceeds the upper confidence limit, an incident can be stated with a specified confidence level (z).

The speed and confidence limit algorithm is similar to the confidence limit algorithm, but requires an additional speed test. It is based on the premise that the decreased capacity caused by an incident is likely to create congestion upstream of the incident and reduce the flow downstream of the incident. The downstream flow reduction may increase the speed of the downstream vehicle stream. Thus, a downstream speed test is conducted using the same process as the travel time confidence limit test. An incident alarm is initiated when the speed and confidence limit tests both exceed respective thresholds.

The dual confidence limit algorithm is similar. In order to reduce the false alarm rate, however, it attempts to exclude the travel times in the current time interval from the comparison window for the test in the next time interval when the mean time is greater than the confidence limit threshold. Dual confidence limits, i.e., window limit and alarm limit, are established using different confidence level values (z), e.g., 1.5 and 3.5 respectively. When a calculated travel time mean in the current interval exceeds the window limit, the comparison window is not moved forward one interval when the test in the next interval is conducted. An incident alarm is triggered only when travel time exceeds the alarm limit.

Comparisons based on detection rate and false alarm rate showed that all three algorithms perform equally to or better than the loop-based McMaster algorithm under the assumed range of probe penetration rates.

1.4.7 Summary

Table 1-1 summarizes the operational features of all of the discussed probe-based algorithms. Most of them make use of travel time to detect traffic variations in order to judge whether or not an incident has occurred.

Most of the above probe-based incident detection algorithms are designed for freeway applications, although they may hold promise for detecting incidents on arterial streets, especially non-instrumented roadway segments. Most proposed probe-based incident detection systems making use of existing AVI/ETC systems may only have been applied to freeways because of technical and institutional barriers. However, there are some barriers to the implementation of probe-based incident detection systems for arterial streets. Probe-based algorithms need to have upstream and downstream data for individual vehicles; however, large numbers of probe vehicles may exit from an AVI-equipped route between the upstream and downstream readers due to the "open" geometric characteristic on arterials. GPS-based incident detection scheme, may suffer from weakening or even blockage of the GPS satellite signals caused by high buildings in CBD areas.

1.5 Driver-Based Algorithms

Driver-based algorithms are designed to screen and identify drivers' phone calls or other witness reports of incidents. Unlike automatic incident detection algorithms (i.e., roadway-based and vehicle-based algorithms), driver-based techniques deal with people's responses to incidents, not to traffic measures converted from sensor signals. Due to the complexity and inconsistency of report contents, the automatic process of witness reports and further incident detection and identification presents a great challenge to information processing

technology. Driver-based data sources used for incident detection present inevitable problems, including incorrect or incomplete information from witness reports about an incident location and severity, and false or prank reports.

Because of the characteristic of direct report and description in driver-based incident detection techniques, the focus (or the difficulty) of designing and implementing this type procedure is how to identify the location and characteristics of an incident. The current methods of locating reported incidents include fixed phone position identification and mobile geolocation determination techniques, and roadside reference location signs. To improve accuracy of driver-based incident detection (i.e., reduce false alarm rates), a general method is employed to trigger an incident alarm when more than a certain number of incident reports are received in a specified time interval. These thresholds are pre-determined based on local archival incident reports.

Several pilot studies to evaluate the effectiveness of driver-based incident detection techniques were carried on in simulation environments (Mussa and Upchurch, 1999, 2000; Tavana *et al.*, 1999) and on real roadways (Skabardonis *et al.*, 1998; Walters *et al.*, 1999). Improved performance of driver-based incident detection techniques are expected to be realized with the growing ownership of cellular phones and other personal communication devices and improved geolocationing technologies (refer to *Chapter 4*).

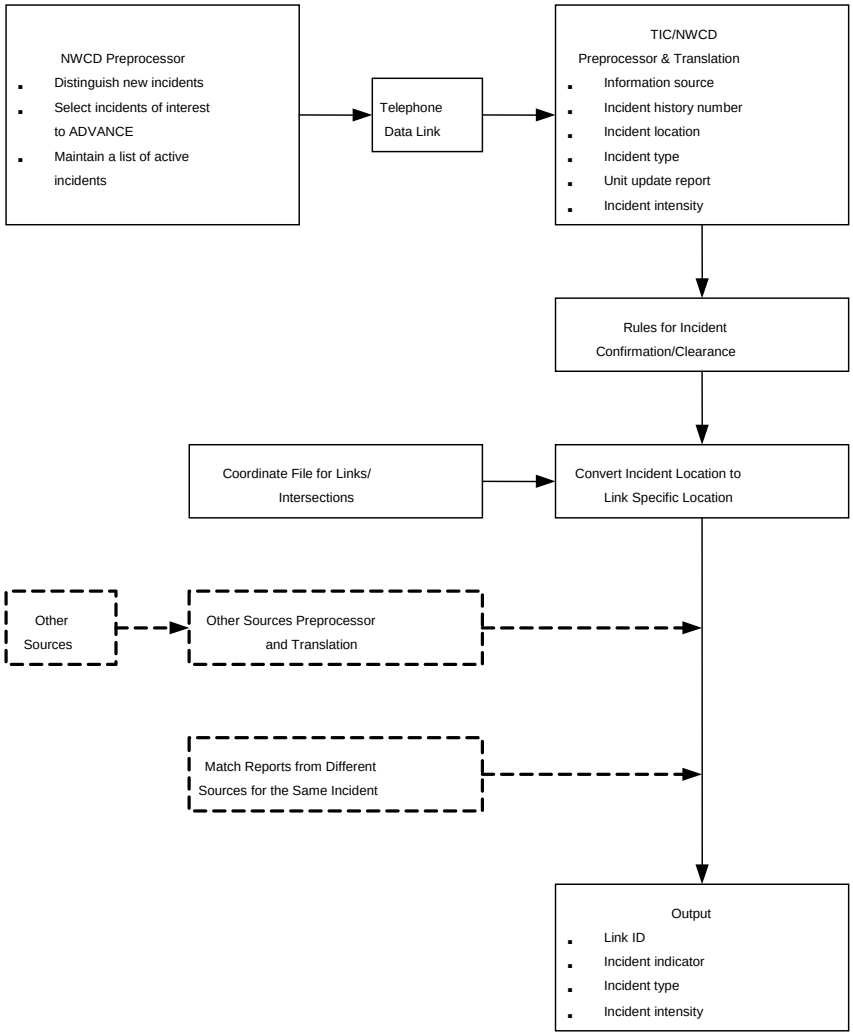


Figure 1-2 Example anecdotal incident detection algorithm configuration (Source: Bhandari *et al.*, 1995)

Driver-based incident detection procedures are still in the early development stage. However, as an example, the following driver-based incident detection algorithm (see *Figure 1-2*), which was developed for and integrated in the ADVANCE incident detection system (Bhandari *et al.*, 1995), may provide some initial ideas of how to construct an incident detection system to process anecdotal incident information. In this system, two primary sources of incident witness reports are collected: 1) the Northwest Central Dispatch System (NWCD), a computer-aided emergency service dispatch agency; and 2) the *999 Center, which receives toll-free phone calls from cellular phone users voluntarily reporting roadway incidents and other problems. This system was operated by the ADVANCE traffic information center (TIC).

In this procedure, the initial anecdotal data source is obtained by the NWCD, which is then preprocessed at NWCD and transferred to TIC. The NWCD preprocessor is used to distinguish new incidents from update reports, separate incidents of interest to ADVANCE,

maintain a list of active messages, and format messages for further processing. Data from other anecdotal sources have an independent preprocessor and translation module. Moreover, a procedure for matching witness reports from different sources for the same incidents is required in this system. The witness reports are received by the TIC/NWCD preprocessor and translation module that extract the characteristics from the reported information, e.g., information source, incident history number, location, type, severity and so on. The following criteria are used to confirm incidents and determine clearance: 1) incidents will be confirmed 3 minutes after the first emergency responder arrives on the scene unless that unit reports clear; and 2) incidents will be reported clear 5 minutes after the last emergency unit leaves the scene. Each incident is assigned with its characteristics with the conversion of link specific location. The link-specific witness reports on confirmed and cleared incidents are then saved in the TIC. The incident severity data may be used for estimating incident duration and traffic impacts. The TIC operator is also able to enter anecdotal reports of incidents from phone calls into the TIC or other communication sources and match or bypass them with the results from the anecdotal algorithm.

1.6 Sensor Fusion-Based Algorithms

The performance of incident detection algorithms is highly dependent on the quality of collected traffic data. It is reasonable to expect that using multiple data sources, e.g., fixed detectors (collecting point data) and probe vehicles (collecting spatial data), could enhance the input data reliability and completeness and hence improve the performance of an incident detection system.

Several researchers, including Westman *et al.* (1996); Ivan *et al.* (1995), Ivan and Chen (1997), Ivan and Sethi (1998); Bhandari *et al.* (1995); and Thomas (1998), applied the data fusion concept to integrate multiple data sources for incident detection. Within these, Westman *et al.* (1996) attempted to improve incident detection performance on freeways while the others applied a variety of data fusion techniques to address problems relevant to incident detection on surface streets/arterials.

Westerman *et al.* (1996) attempted to integrate probe vehicle and loop detector data for travel time estimation and incident detection. A parallel structure in the fusion process is employed, in which probe vehicle and loop detector algorithms perform independently but receive support from each other. A two-step structure (see *Figure 1-3*) characterizes this compound algorithm: a trigger mechanism that indicates a suspicion of occurrence of an incident, and a verification mechanism in which this suspicion is automatically verified. The probabilities of an incident occurrence from each algorithm (i.e., hybrid loop detector algorithm, probe vehicle algorithm, and local-related and section-related comparison algorithm) are combined to make a final decision in the verification mechanism, where a weight averaging fusion method is applied. The number of performed verification steps determines the weight factor for each component.

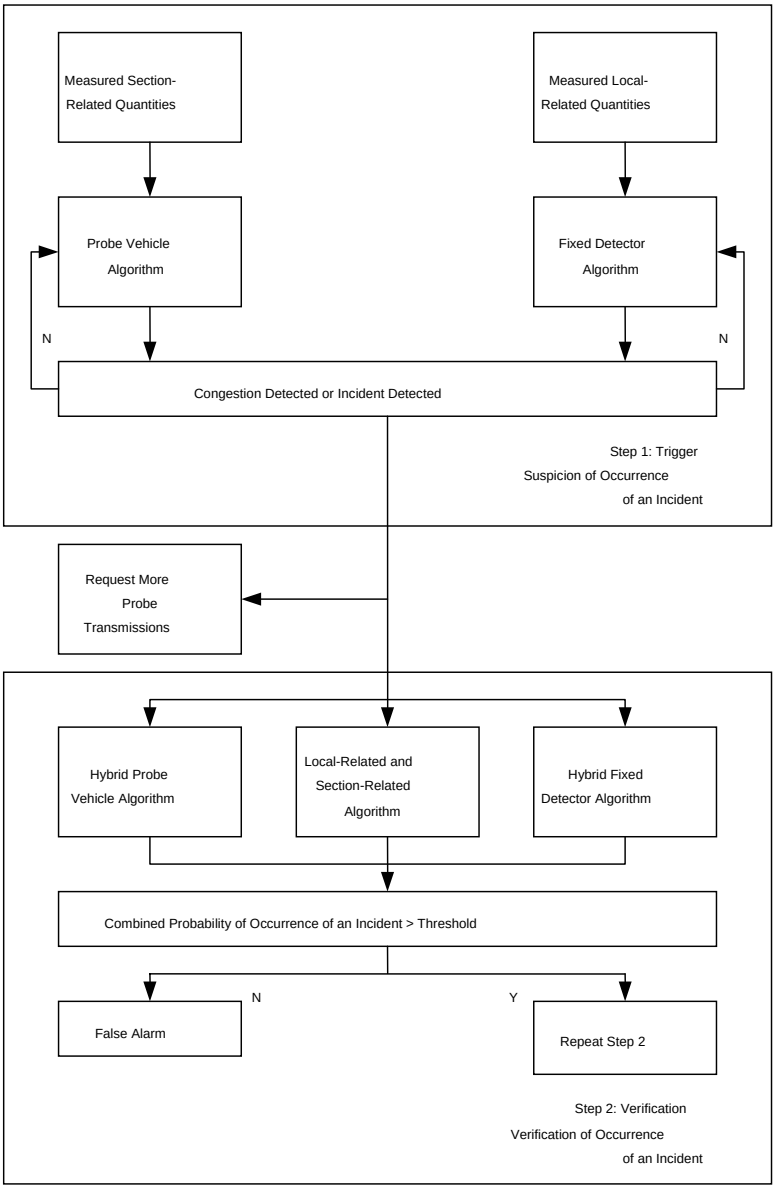


Figure 1-3 A compound loop detector and probe vehicle incident detection system (Source: Westman *et al.*, 1996)

In the ADVANCE demonstration project, Ivan and his colleagues (1995, 1997, 1998) developed two data fusion methods, i.e., *algorithm output fusion* and *integrated fusion*, combining fixed detector and probe vehicle data for urban arterial incident detection. The *algorithm output fusion* algorithm combines the incident likelihood scores estimated by two parallel and independent algorithms, i.e., a fixed detector algorithm and a probe vehicle algorithm, and then makes the final decision regarding the presence of an incident. The fusion process combining the incident likelihood scores is realized using an MLF-type neural network. In the *integrated fusion* algorithm, the single source processing algorithms and the fusion process are integrated in a neural network. Volume and occupancy (from fixed detectors) and travel

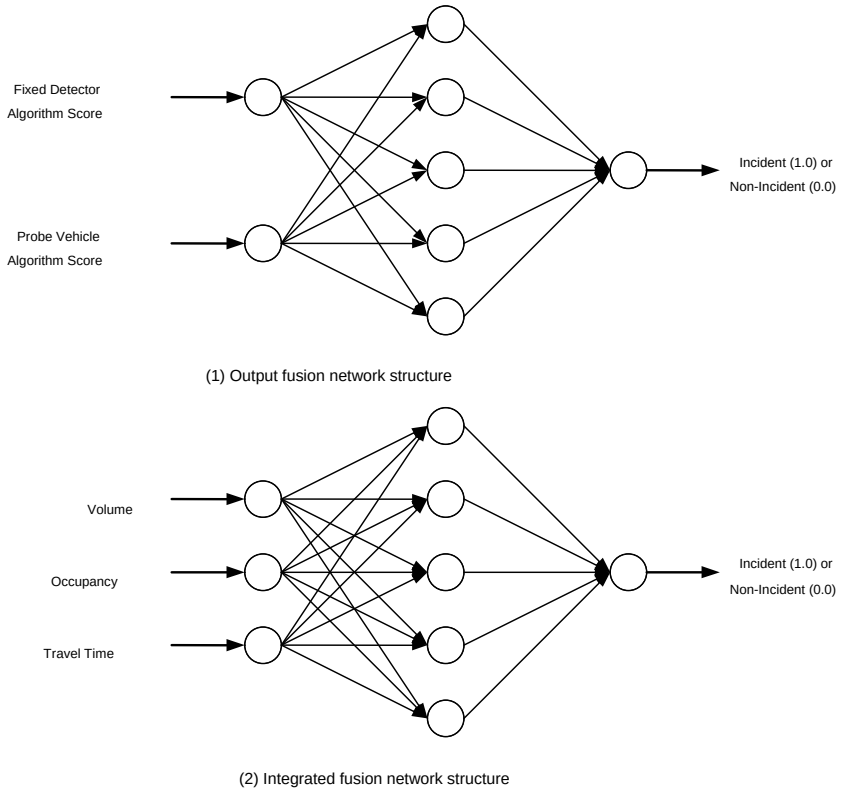


Figure 1-4 Two neural network structures fusing fixed detector and probe vehicle data (Source: Ivan *et al.*, 1995)

time (from probe vehicles) are directly read by the fusion process. The two data fusion algorithms are illustrated using neural network topology in *Figure 1-4*.

A comparison of the performance results in the studies listed above, suggests that neither fusion architecture outperforms the other; one fusion process did not always perform better when different data sets were applied.

Bhandari *et al.* (1995) also proposed an integrated arterial incident detection method in the ADVANCE project. They employed three distinct data sources: fixed detector data, probe vehicle data, and anecdotal reports. In their data fusion system, three independent modules pre-process the three data sources respectively: 1) the fixed detector algorithm uses the real-time and historical occupancy and the ratio of volume to occupancy provided by fixed detectors to classify traffic conditions on the detectorized streets; 2) the probe vehicle algorithm uses travel time reports by probe vehicles and historical travel times on these links to interpret traffic conditions as incident or non-incident; and 3) the anecdotal processing algorithm, as operated by the ADVANCE traffic information center (TIC), uses the information provided by emergency personnel and other motorists in the network to identify incidents, which includes the information collected by the Northwest Central Dispatch System (NWCD) and the *999 center. The data fusion process operates in two steps: (1) to

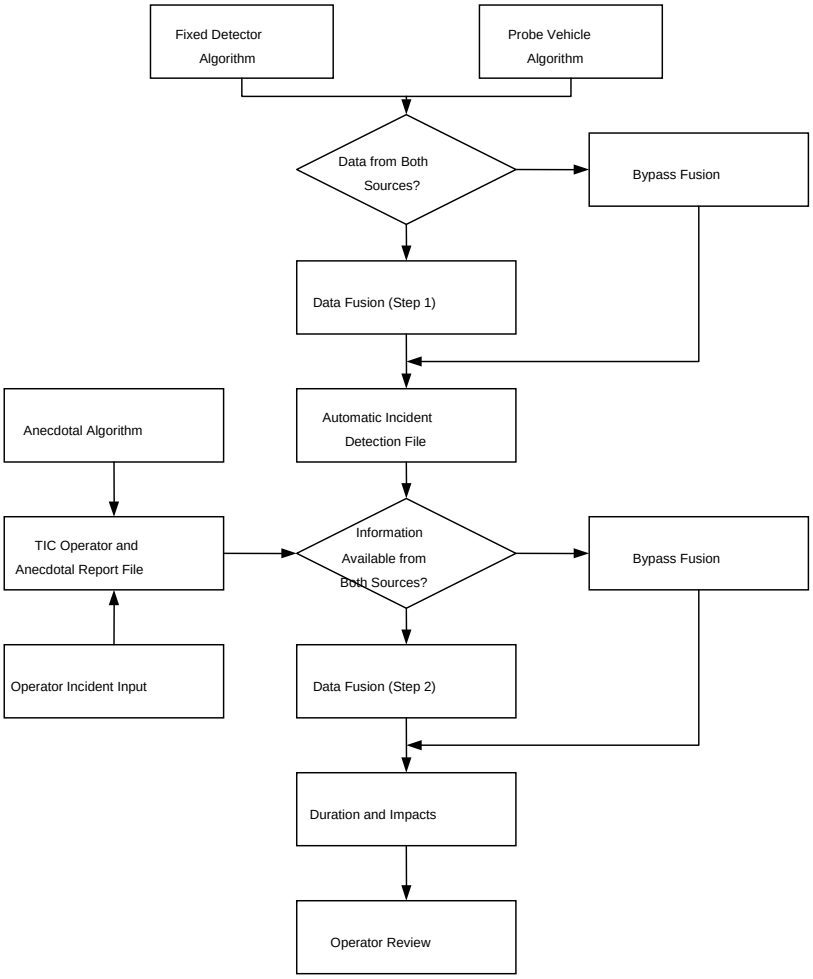


Figure 1-5 Data fusion system integrating three distinct data sources (Source: Bhandari *et al.*, 1995)

fuse the fixed detector and probe vehicle-based results from the two automated data sources using discriminant analysis; and (2) to fuse the output from the automatic data fusion algorithm (i.e., step 1) and anecdotal algorithm, as shown in *Figure 1-5*.

Thomas (1998) developed a multi-state and multi-sensor incident detection system for arterial streets. The algorithm input generated from a modified INTRAS simulation includes probe travel times, number of probe reports, lane specific detector occupancies, and vehicle counts. The starting point of her methodology has two aspects: 1) arterial traffic can be classified into multiple states depending on sensor type (fixed detectors and probe vehicles); and 2) the discrimination criterion of an incident is a multi-variable vector, not a scalar. Thus, the underlying principle of this approach is to utilize multivariate classifiers to differentiate between multiple traffic states on arterials. The combination of Bayesian discrimination and multiple attribute decision-making techniques was used to formulate and power the system. Two system configurations, *Systems A* and *B*, were proposed, as shown in *Figure 1-6*. *System A* processes spot detector data and spatial travel times (on link the level)

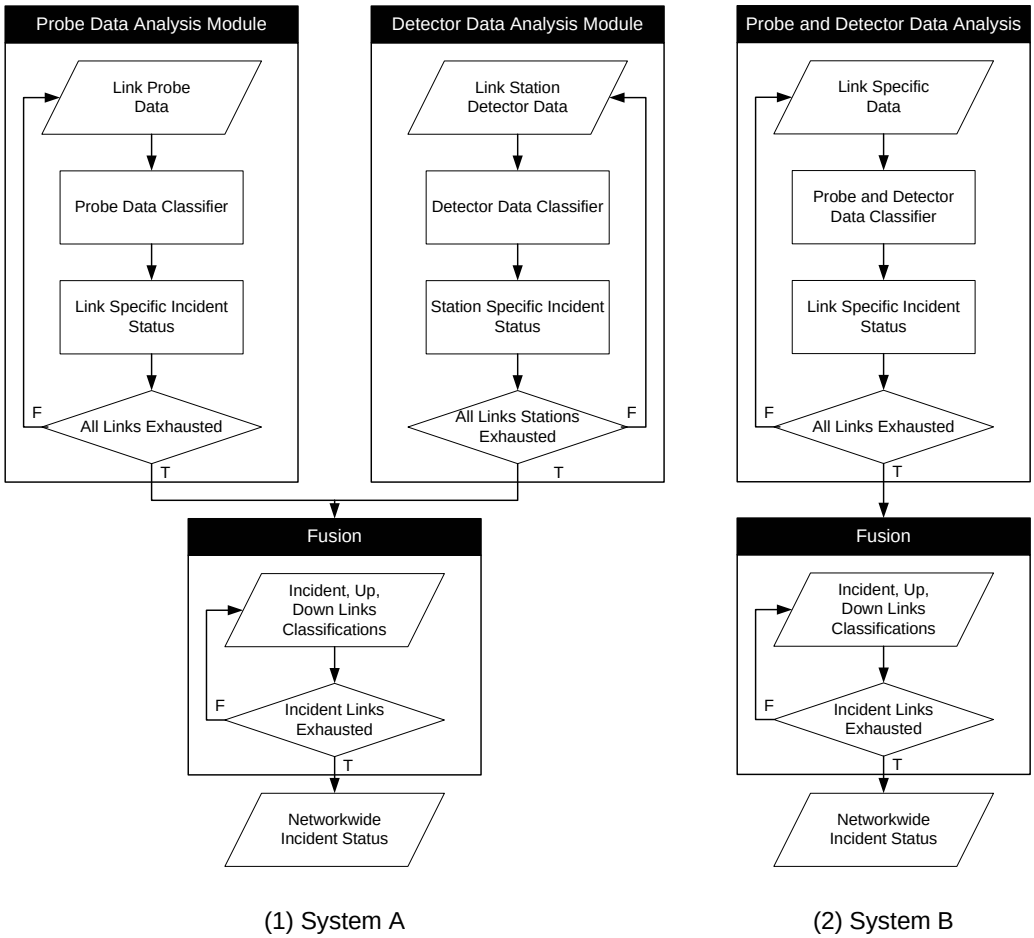


Figure 1-6 Multi-state and multi-sensor arterial incident detection systems (Source: Thomas, 1998)

while *System B* makes use of spatial data and probe data (on the link level). Here, the spatial detector data is achieved by preprocessing spot detector data. The evaluation results suggest that performance is enhanced compared to detector-based models with the incorporation of probe information.

1.7 Arterial-Applicable Algorithms

Due to disruptions from signal/sign control and other disturbances (e.g., pedestrian crossings, parking maneuvers, transit stops) on arterial streets, traffic varies more frequently and sharply with much greater complexity on arterials compared to freeways. In addition to commonly defined incidents, there are arterial-specific events that result in non-recurrent congestion on urban arterial streets, e.g., traffic signal malfunction, illegal stopping and parking, blockage of intersection, sports events and concerts, or VIP visits and parades. Traffic measures derived from roadway-based traffic detectors do not readily distinguish incidents from all other traffic variations, sometimes because the recurrent congestion caused by traffic control and bus stopping may often conceal a real incident. Moreover, traffic entering and leaving from side streets introduces discontinuities in the flow of traffic.

Since different traffic phenomena exist in freeway and arterial environments, most incident detection principles and algorithms applicable to freeways are not readily transferred to arterial cases.

Compared to the freeway incident detection studies conducted for nearly three decades, incident detection for arterial streets has received significant attention from traffic operations and control personnel only in recent years. Reviews of incident detection algorithms including ones described above are concerned with freeway algorithms not the arterial algorithms reviewed here. Having realized the importance of reducing non-recurring delay and enhancing safety related to incidents occurring on principal arterial streets, and having received fruitful outcomes from development of ATIS and ATMS research and technologies, the Federal Highway Administration (FHWA) and the Oak Ridge National Laboratory (ORNL) sponsored and hosted the first international workshop on arterial incident detection in 1996 (FHWA and ORNL, 1996). The objective of this workshop was to evaluate the state of research and development of arterial incident detection techniques and identify key research needs that lead to further development, testing, and evaluation of deployable arterial incident detection systems. The concept and requirements of arterial incident detection were considered and it was concluded that arterial incident detection is one of the major functions/elements under integrated urban traffic management systems (Khan and Franzese, 1998).

The following section provides a summary of a variety of incident detection algorithms developed for and applicable to arterial streets. In this report, each of them is named with its corresponding employed technique/algorithm to signify its underlying principle and operational features.

1.7.1 Pattern Matching Algorithms

Pattern matching/pattern recognition/comparative algorithms for arterial incident detection are designed to track variations of traffic measures and identify corresponding traffic patterns in order to distinguish incident from non-incident traffic conditions.

Thancanamootoo and Bell (1988) are credited with some of the earliest efforts to develop a pattern recognition algorithm in which a time-series technique was used to detect an incident through monitoring variations of detector volume and occupancy. Their principle is based on the hypothesis that an incident may reduce traffic flow at detectors upstream and downstream of the incident while increasing occupancy at the upstream detector and reducing occupancy at the downstream detector. If the measured flows and occupancies are much different from estimated values, an incident alarm should be triggered. The algorithm is formulated as the following three inequalities:

$$F_m(t) < F_e(t) - \alpha_1 S_F(t) \tag{1.8}$$

$$O_m(t) > O_e(t) - \alpha_2 S_O(t) \tag{1.9}$$

$$O_m(t) < O_e(t) - \alpha_3 S_O(t) \tag{1.10}$$

where $F_m(t)$, $F_e(t)$, and $S_F(t)$ denote measured volume, estimated volume, and estimated standard deviation of volume, similarly, $O_m(t)$, $O_e(t)$, and $S_O(t)$ represent measured occupancy, estimated occupancy, and estimated standard deviation of occupancy; and, α_1, α_2, and α_3 are three pre-specified or calibrated constants. The estimated values of these traffic variables and their standard deviations in a cycle t are calculated from their measured and estimated values in the last cycle $(t-1)$ by exponential smoothing. *Equation 1.8* is used for monitoring both upstream and downstream volume, while *Equations 1.9* and *1.10* are respectively applied for upstream and downstream occupancy. If all four inequalities are satisfied in a cycle t, an incident is declared.

This algorithm has a feature that enables it to maintain the continuity of a triggered alarm during an incident and detect the end of the incident. It is achieved by stopping the calculation of the new "smoothed average and dispersion terms" (i.e., estimated traffic measures and their standard deviations) of volume and occupancy as soon as an incident is detected. This is based on a simple assumption that traffic flow status before and after an incident should be comparable (i.e., *Equations 1.8*, *1.9* and *1.10* unsatisfied). According to simulation and field results, some problems with this algorithm were identified: 1) the performance of this algorithm is partly dependent on the position of an incident with respect to the detectors; and 2) the performance of this algorithm is adversely affected by chronic congestion in that incidents and recurrent congestion were not easily distinguished.

Han and May (1989) utilized another pattern recognition approach to identify unusual traffic operation problems on arterial streets, which includes system problems (e.g., detector malfunctions, signal malfunctions, and data communication problems), recurring congestion, and non-recurring congestion or incidents. The volume and occupancy data were smoothed and first passed through a module to identify problems from detector malfunctions. They built a detection algorithm based on traffic flow theory to detect operational problems. The type of operational problems (e.g., lane blockage, approach blockage, or arterial blockage) was classified based on the operating condition of detectors in adjacent lanes. The following simplified decision tree (see *Figure 1-7*) briefly shows the operation procedures of their algorithms. Their study concluded that the thresholds to distinguish incident and non-incident traffic status are highly location and time-dependent.

Both of the above studies concluded that arterial incident detection techniques were more effective for those incidents occurring in close proximity to a detector.

Rau and Tarko (2000) explored the use of the metering effect of arterial bottlenecks to estimate link capacities and detection of incidents on specific links. The estimation process generally uses historical and real-time data such as detector traffic measures, probe travel times, and signal parameters. They studied the relationship between (dynamic) link capacity and congestion considering the turning volumes at intersections (i.e., entering and exiting volumes) to then determine the congestion pattern. In their congestion-oriented model, surveillance data, road geometry, and signal timings were considered for capacity estimation

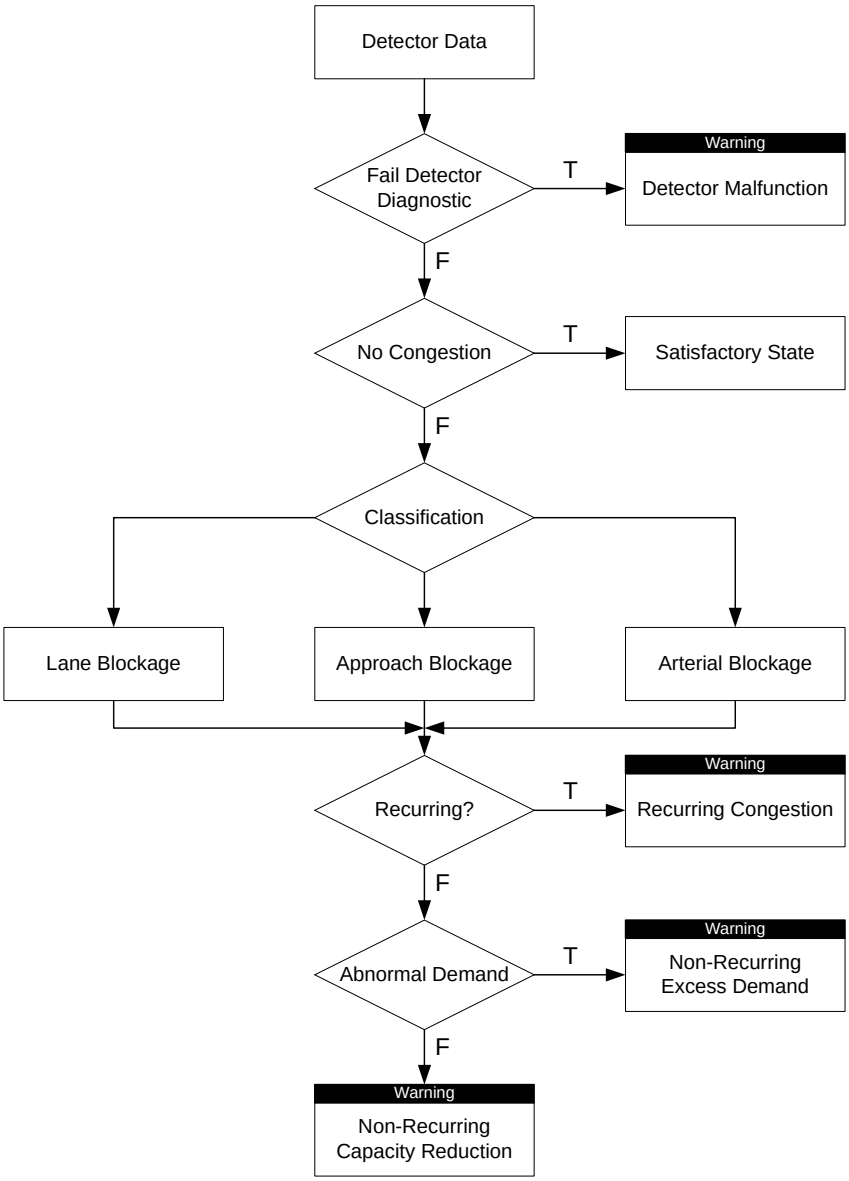


Figure 1-7 Simplified decision tree prototype for arterial operational problem detection (Source: Han and May, 1989)

and incident detection. The complete model structure is shown as *Figure 1-8*, including three primary modules: congestion detection module, capacity estimation module, and incident detection module.

A demonstration test using travel probe time reports from 20% of the vehicles generated by a NETSIM-based simulation was conducted. The preliminary results indicated that this model does not successfully detect incidents when the congestion pattern does not significantly change, and that a change in the pattern of congestion may take considerable time, thus adding to the time required to detect an incident.

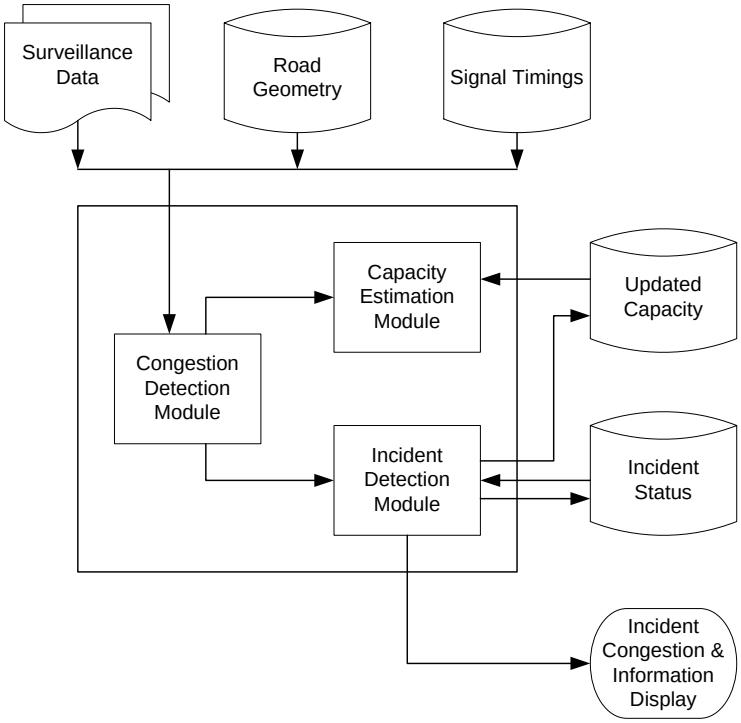


Figure 1-8 Congestion-oriented incident detection system (Source: Rau and Tarko, 2000)

1.7.2 Kalman Filtering Algorithms

Kalman filtering is a self-learning variable estimation/prediction mechanism that was derived from a solution to the Wiener problems (including prediction of random variables, separation of random signals from random noise, and detection of variables of known form in the presence of random noise), using the state-space model for dynamic and random processes. This technique estimates the state variables iteratively as they vary over time, so that there is a recursive relationship between the states of the system in consecutive time periods. At each time interval, the projected state of the system is adjusted to account for the observed values of various system parameters.

Bell and Thancanamootoo (1986) proposed using Kalman filtering to test for significant deviations between the stop line profiles estimated from measures of upstream and downstream sensors and to determine traffic status with or without an incident. More recently, Lee and Taylor (1999) applied Kalman filtering to arterial incident detection in another way. They used a modified discrete linear Kalman filtering algorithm to recursively filter and update aggregate traffic flow and speed to estimate true values. A comparison of measured traffic parameters with estimated values is used to trigger an incident alarm when a distinct difference is identified.

Chen and Chang (1993) proposed a dynamic arterial incident detection algorithm integrating Kalman filtering and discriminant analysis techniques. In their model, three major components are included: 1) a traffic prediction model based on Kalman filtering; 2) an incident identification model based on discriminant analysis; and 3) an incident

monitoring process to integrate the above two models. In their proposed traffic prediction model, the time-space traffic dynamics using time-series upstream and downstream information are taken into account. The disturbance of traffic is captured by incorporating the effects due to lane changes, spillback queues, bus stops, roadside/shoulder parking, illegal pedestrian crossings, signal control, and uncontrolled side-accesses. The data aggregation time-step in their model is not pre-specified, but is a dynamic parameter determined by the upstream and downstream detector speed. The traffic variables estimated by Kalman filtering include upstream and downstream speed, volume, and occupancy. At the next step, a set of multivariable discriminant functions are established to detect and classify incidents and assess their severity. The discriminant analysis algorithm is described in the following section.

The Kalman filtering based algorithm provides good estimations of traffic state and hence performs well on incident capture in dynamic arterial environments. However, the calibration procedure of this technique for incident detection is a relatively complex process.

1.7.3 Discriminant Analysis Algorithms

Linear discriminant analysis is a classification technique in which a linear combination of predictor variables describing traffic flow characteristics on links is used to classify cases into two or more mutually exclusive groups, such as incident and incident-free conditions in the incident detection application. Classification using discriminant analysis depends on a discriminant score, which is a function of the measured variables and the so-called prior probability. The prior probability of incidents is an incident sensitivity indicator that affects the trade-off between detection rate and false alarm rate.

Sethi *et al.* (1995) applied discriminant analysis to detect arterial incidents using fixed detector and probe vehicle data independently. Their algorithms work on two of the traffic flow perturbations an incident on a link is likely to cause: 1) an increase in occupancy, a reduction in speed (or an increase in travel time), and 2) a reduction in volume, upstream on the same link and on the adjacent link. Both the fixed detector and probe vehicle algorithms take into account impacts on both the incident link and the adjacent upstream link.

For the fixed detector algorithm, upstream and downstream volume, occupancy, and ratio of volume to occupancy from a single detector were taken into account to develop the discriminant analysis model. The model using occupancy and ratio of volume to occupancy showed the most promise. For the probe vehicle algorithm, link traverse time ratio, average speed ratio[1], and speed deviation were included in the model. In their experiments, approximately 30 probe reports on each link during a 7-minute aggregation period were generated. The results suggested that using speed variables (either speed ratio or speed deviation) rather than travel time are preferable for better incident detection performance. For both of the applications, the prior probability was selected as 0.01, subject to pre-judgment, to obtain a high detection rate with a false alarm rate close to 0.0%.

Based on the above attempt to model arterial incident detection, Sermons and Koppelman (1996) also studied the use of probe vehicle positioning data with discriminant

[1] These two ratio variables are the ratios of measured values during the current period to historic averages.

analysis algorithms. Unlike the above probe vehicle algorithm only using macroscopic traffic measures, they incorporated both macroscopic traffic measures (e.g., traverse time, running time, average speed, and running speed) and microscopic traffic data (e.g., individual vehicle position) in their discriminant analysis algorithm. A detailed review of their work can be found in *Section 1.4.2* regarding the ADVANCE algorithms.

Discriminant analysis models need to be calibrated using cases whose group membership are known (i.e., incident or incident-free conditions); the success of such algorithms is dependent on calibration from a data set consisting of a large number of membership-known cases with all traffic disturbance factors. The results from the above studies showed that the mean time-to-detect of incidents using discriminant analysis is relatively slow, typically up to 10 minutes.

1.7.4 Modular Neural Algorithm

As noted in *Section 1.3.6*, several researchers have applied pattern recognition and classification using artificial neural networks to incident detection. In contrast to the foregoing singular neural network models, Khan and Ritchie (1998) proposed using multiple neural networks in a modular architecture to detect arterial operational problems, including lane-blocking incidents, special on-street events, and detector malfunctioning. A modular neural network architecture allows decomposition and assignment of complex tasks to several modules that are single neural networks, e.g., the commonly used multi-layer feed forward (MLF) neural networks. The multiple modules decompose the problem into two or more subsystems, with each module solving a separate sub-task. Neural networks comprising the modular architecture compete with each other and learn training patterns by partitioning the function into independent tasks and allocating a distinct network to learn each task. Therefore, a modular architecture performs local generalization by learning the patterns of a particular region. Moreover, the interaction between modules would cause some of the modules to be used for a subtask. Khan and Ritchie applied an error function to encourage competition between modules using a gating network. The gating network can make a stochastic decision about which single module to use on each occasion. In their modular architecture, each module works as a MLF neural network and all modules receive the same input and have the same number of outputs. The gating network is also a MLF network and typically shares the same input as the other modules (see *Figure 1-9*). In this modular architecture, Y is the overall output, that is the linear combination of the output y_i from the ith module and g_i is the weight assigned for the module output y_i by the gating network.

In the training of this architecture model, one module may come closer to producing the desired output than the others for one training pattern. If the performance of the model is improved significantly for a given training pattern (displaying the smallest error), the weights of the gating network are adjusted to make the output of the "winner" increase towards 1, and the outputs of the "losers" decrease towards 0.

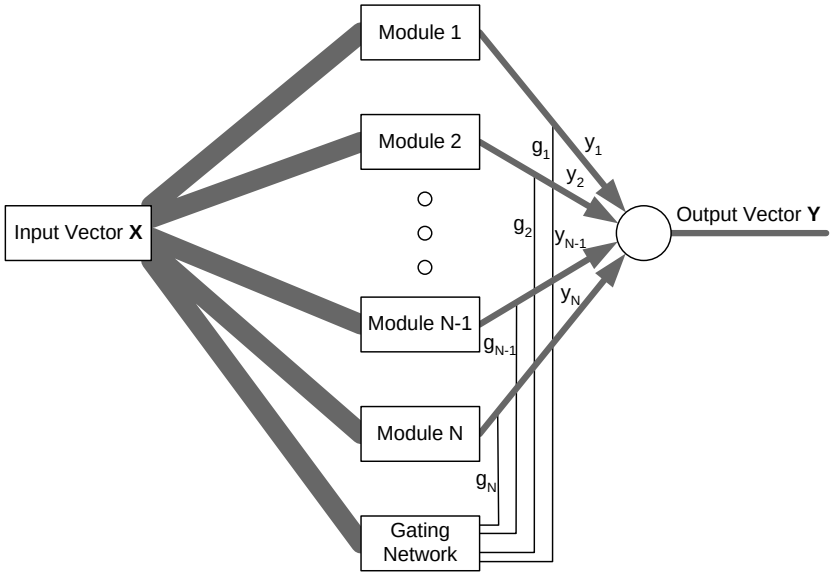


Figure 1-9 Modular neural network-based arterial incident detection architecture (Source: Khan and Ritchie, 1998)

Khan and Ritchie (1998) applied both field and simulated data to test the modular neural network-based algorithm, and compared it to several alternatives, including a single MLF model, discriminant analysis algorithm, and Bayesian algorithm. They concluded that the modular neural classifiers outperformed the other classifiers.

1.7.5 Fuzzy Logic Algorithm

Lee *et al.* (1998) developed a fuzzy logic-based algorithm to detect incidents on a signalized diamond interchange, which was controlled by a real-time traffic adaptive control system. Fuzzy logic is an effective solution technique for models that need to operate in real-time, require approximate reasoning, and exhibit uncertainty. The algorithm was designed for the operation in sequence of four components: 1) normality inference module; 2) incident location inference module; 3) incident severity assessment module; and 4) incident termination inference module. The input for this algorithm included lane-by-lane volumes, queue length, occupancy, and speed derived from the video monitoring system. The algorithm evaluates these traffic measures as indications of abnormal traffic conditions by comparing the current (or most recent minute) measure values to the past 5-minute values.

In this model, the normality inference module is designed to check queue length on each approach for abrupt changes that reflect the possibility of an incident. Fuzzy logic acts as the inference engine in this module. If the normality inference module detects an incident, the algorithm start up the incident location inference module to conduct an extended test on three traffic measures, i.e., queue length, occupancy, and speed, on all approaches of the

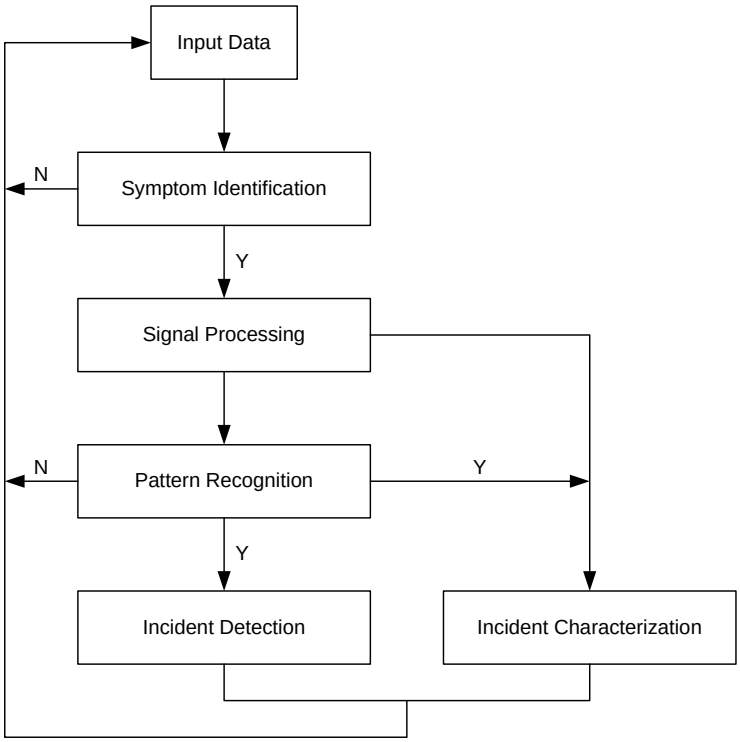


Figure 1-10 MSRPT-based arterial incident detection system architecture (Source: Sheu and Ritchie, 1998)

interchange and to confirm the occurrence of this reported incident (by the normality inference module) and infer its location. The location inference based on fuzzy logic works through comparing the resulting traffic measures against expected impact pattern and identifying the location associated with the best-matching pattern. Then, the incident severity assessment module determines the severity of an occurred incident through a more detailed examination of selected traffic parameters. The incident severity assessment module and the incident termination inference module are also operated based upon fuzzy logic.

1.7.6 MSRPT Algorithm

Sheu and Ritchie (1998) applied modified sequential probability ratio tests (MSRPT) for arterial incident detection. In their incident detection system, three sequential procedures were developed: 1) *symptom identification* is a logical knowledge-based rule for identification of incident symptoms; 2) *signal processing* is used for raw traffic data (i.e., volume and occupancy) pre-processing and real-time prediction of incident-related lane traffic characteristics; and 3) *pattern recognition* conducts a decision-making process for incident recognition. The system architecture can be referred to in *Figure 1-10*. The pattern recognition-based MSRPT concept is the key logic in the *pattern recognition* procedure, in which the estimated lane-changing fractions and queue lengths are utilized as inputs. An important feature of this algorithm is that it allows the probabilities of either a false alarm or a miss in decision making to be predetermined. The lane-changing fractions and queue length are generated in

the *signal processing* procedure through pre-processing raw traffic data. The MSRPT algorithm consists of the following procedures: 1) first, initiate the system status, pre-specify the probabilities of a false alarm, a miss and a detection and specify the thresholds for sampling; 2) estimate the current-time step lane-changing probability and the queue lengths in the lane which is identified as potential blocked lane by the *signal processing* procedure; 3) make a decision for both intersection and approach incident detection; and 4) enter the next data aggregation cycle and go to the *symptom identification* procedure.

Test results based on simulated and real data revealed several important factors affecting the performance of the current arterial incident detection algorithms: 1) abnormal lane-changing behavior, which occurs during upstream link incidents; 2) the influence of turning movements on intersection incident detection; and 3) signal timing plans are an important factor influencing the time to detect intersection incidents.

1.7.8 CUSUM Algorithm

The cumulative sum (CUSUM) chart is a form of process control that has been developed by industrial engineers to monitor and detect any abrupt change that may contaminate the quality of a product. This chart can detect small to moderate persistent shifts of statistical parameter by memorizing and accumulating past samples to determine the status of the process. Sattayhatewa and Ran (1999) applied the CUSUM method to capture disruptive traffic changes or shifts that have a tendency to persist over time under non-incident conditions. Occupancy and volume data were selected as algorithm inputs and the data aggregation time interval were set as one signal cycle to minimize the impact of traffic signals on detection performance. The CUSUM-based algorithms consists of three subsystems: *Algorithm A*, this test scans for differences between adjacent lanes; *Algorithm B*, this algorithm searches for a significant imbalance between adjacent lanes; *Algorithm C* is developed to supplement the two former tests, in order to address the problem that when an incident is too close to detectors, the variable imbalance caused by that incident may be too faint to be captured. *Algorithm C* is designed to detect an incident through the impact on the occupancies that have been reported over time. The three models can work independently for arterial incident detection. The preliminary tests in the NETSIM simulation indicated that the three sub-models have the comparable performance while the combination of them can greatly improve the detection rate with only a slight increase of false alarm rate.

1.7.9 Logit Algorithm

Incident detection can be regarded as a discrete choice problem where incident and incident-free conditions are two definable choices. Lee and Hwang (2001) attempted to apply a multinomial logit (MNL) model, which was originally developed in the econometrics area and widely used for discrete choice modeling and analysis, to model arterial incident detection problems. An incident index, representing the probability of an incident occurrence, was expressed as the utility of the MNL model. They incorporated detector occupancy and volume as the independent variables and assumed the error term followed a Gumbel distribution in the logit-based incident detection algorithm. The proposed algorithm was evaluated by applying simulated data generated from the NETSIM model and compared with a modified California algorithm (applicable to surface streets) and a neural

network-based algorithm. The test results indicated this logit-based arterial incident detection algorithm has a high efficiency and accuracy.

1.7.10 Other Algorithms

In addition, incident detection efforts for arterial streets also include models built on the data fusion concept. In *Section 1.6*, arterial incident detection methodologies using neural networks (Ivan *et al.*, 1995; Ivan and Chen, 1997; Ivan and Sethi, 1998) and Bayesian discrimination and multiple attribute decision-making (Thomas, 1998) are introduced. Also, Bhandari *et al.* (1995) proposed integrating fixed detector, probe vehicle, and anecdotal report data to detect incidents in a suburban arterial network.

1.7.11 Summary (Arterial Algorithms)

It is worth noting here that the arterial incident detection algorithms reviewed above were proposed and designed in terms of the detector configurations or layouts in their respective street networks. Some of them are appropriate only for their own sensor arrangements and geometric characteristics. Readers are encouraged to refer to the original documents for more details to understand the inherent relationships between the algorithms and the corresponding detector configurations.

Researchers have realized that traffic signals in either fixed or actuated mode have non-negligible impact on the traffic prediction and incident detection performance. One of ways to minimize this adverse effect is to select data aggregation time intervals with care or incorporate traffic signal control parameters, like cycle, red and green times, offset and so on, into incident detection algorithms, so that the algorithms may be able to distinguish recurring congestion caused by the signal from real incidents and hence reduce false alarm rates.

Incidents occurring in a signalized arterial network can be divided two types, link incidents and intersection incidents, in terms of the geometric characteristics. Arterial links and intersections, display varying traffic behavior and hence different incident detection mechanisms should be considered. Incidents occurring in an intersection may have more intense adverse influence on the arterial network efficiency and safety. Most arterial algorithms were designed for detecting incidents on arterial links; few of them are applicable to detect incidents in a signalized or non-signalized intersection.

CHAPTER 2: USE OF INCIDENT DETECTION ALGORITHMS AT A TMC OR TOC

A nationwide Web-based survey was conducted at 29 transportation management centers (TMCs) and transportation operations centers (TOCs) in the summer of 2001. This survey was designed to obtain information about applications of incident detection technologies and algorithms. The survey consisted of five parts: 1) responder's information; 2) TMC/TOC-related information; 3) implemented equipment and techniques; 4) algorithm application and evaluation; and 5) future plans and suggestions. Please refer to Appendix *A* for details of the survey questionnaire.

In the following, *Section 2.1* describes the methodology used in designing and conducting this survey; *Section 2.2* focuses on the qualitative and quantitative analysis of the survey data and the preliminary results, and *Section 2.3* presents conclusions and recommendations.

2.1 Methodology

The online survey is built on and conducted through the ECS (Engineering Computing Service) server at University of Massachusetts, Amherst (accessible at http://www.ecs.umass.edu/cee/chixie/). Most of the technical questions in the survey are presented in the form of single or multiple choices, check-off and short reply; some questions are descriptive and ask for comments/opinions/suggestions at the end of survey, in hopes of obtaining additional information about the responders' specific knowledge and experience.

The first step of this survey was to collect contact information for TMCs/TOCs for the survey throughout the country. Through a Web search and assistance provided by the I-95 Coalition and various State DOTs (Departments of Transportation), 34 TMCs/TOCs in 21 states were initially located. Then, a contact e-mail was sent to each TMC/TOC to determine who would be interested in and capable of responding to the survey and to alert them to the survey goals. Potential responders who confirmed that they would like to receive the survey were provided with a hyperlink to the online survey form. Responses could be provided in three ways: 1) fill in the Web-based form and submit it online; 2) fill in the electronic form in the downloadable "*.doc" or "*.pdf" format file and send it back by e-mail; and 3) fill in the downloadable "*.doc" or "*.pdf" format file and fax it back. Of 29 survey responses received, 22 responders choose the first method while 5 used e-mail and 2 used fax for submission.

There are 24 effective responses among the 29 received samples. Five responses were discarded because of serious incompleteness and deficiency of data feedback. The reasons are various: it was claimed that there is virtually no requirement for incident detection at their TMC/TOC due to the very low traffic volumes; the incident management function is now in the design progress or under construction; no traffic management is conducted except for simple traffic operations and safety inspection; or the survey is believed to be too technical to complete.

2.2 Data Analysis and Preliminary Results

2.2.1 Overview of TMCs or TOCs

Part 2 of the survey investigates TMC/TOC-related information. A list of the 24 TMCs/TOCs that responded with usable information is given in *Table 2-1*; their geographic location is indicated in *Figure 2-1*. These TMCs/TOCs have been in operation from approximately 1 year to more than 30 years; most of them (19 out of 24) have an operating history of 1-10 years.

Hours of Operation. As may be seen in *Figure 2-2*, all of the centers operate for at least 8 hours per day. Nine centers operate between 12 and 16 hours per day and 8 operate on a 24-hour per day basis.

Operation by Roadway Class. *Figure 2-3* shows the distribution of operation by roadway class. As would be expected, almost all (22 of the 24) of the surveyed centers operate on Freeways. Perhaps less expected, 4 of the centers operate at the Collector level and 3 at the level of local streets. The percentages in *Figure 2-3* add up to more than 100% as many of the centers operate on several classes of roadways.

Type of Operations. *Figure 2-4* shows the distribution of operations by type of operation. Not surprisingly, almost all of the centers reported that they carry out Traffic Management, Incident Management, and Traffic Information functions. Two centers report conducting Transit and/or HOV Lane functions.

Table 2-1 Overview of the surveyed TMCs/TOCs

Operating Agency	Name of TMC/TOC	Operating History (Years)	Responder's Title
Arizona State DOT	TOC of Arizona DOT	5-10	Transportation Engineering Specialist
California State DOT	Signal Central TMC of San Jose	5-10	Traffic Engineer
Delaware State DOT	TMC of Delaware DOT	1-5	TMC Manager
Florida State DOT	Sunguide Control Center of District 6	5-10	ITS Systems Engineer
Illinois State Dot	Traffic Systems Center of Illinois District 1	>30	Traffic Systems Center Manager
TRW under Kentucky Cabinet and Ohio DOT	ARTMIS Operations Control Center	5-10	Program Manager
TRW under Kentucky Cabinet and Ohio DOT	TRIMARC Interim TOC	5-10	TRW Project Manager
Michigan State DOT	MITSC	15-20	TMC Administrator
Minnesota State DOT	TMC of Minnesota DOT	20-30	Freeway Studies Engineer
Missouri State DOT	Discovery Center of Missouri District 8	5-10	Traffic Engineer
New York State DOT	Capital Region TMC	1-5	Operations Engineer
North Carolina State DOT	TOC of North Carolina DOT	1-5	Division Operations Engineer
North Carolina State DOT	Metrolina Regional TMC	1-5	Incident Management Engineer
North Carolina State DOT	Triangle TMC	1-5	Regional ITS Engineer
Rhode Island State DOT	TMC of Rhode Island DOT	1-5	TMC Manager
Texas State DOT	TOC of Austin District	1-5	Operations Engineer
Texas State DOT	DalTrans of Dallas District	1-5	Assistant Operations Director
Texas State DOT	DalTrans ITS Center	1-5	Freeway Management Engineer
Texas State DOT	TranStar	5-10	Operations Director
Texas State DOT	TransGuide	5-10	Traffic Management Engineer
Texas State DOT	TransVision	1-5	Incident Manager
Virginia State DOT	Smart Traffic Center	5-10	Operations Engineer
Virginia State DOT	STC of Virginia DOT	15-20	Transportation Engineer
Washington State DOT	Northwest Region TSMC	20-30	Transportation Engineer

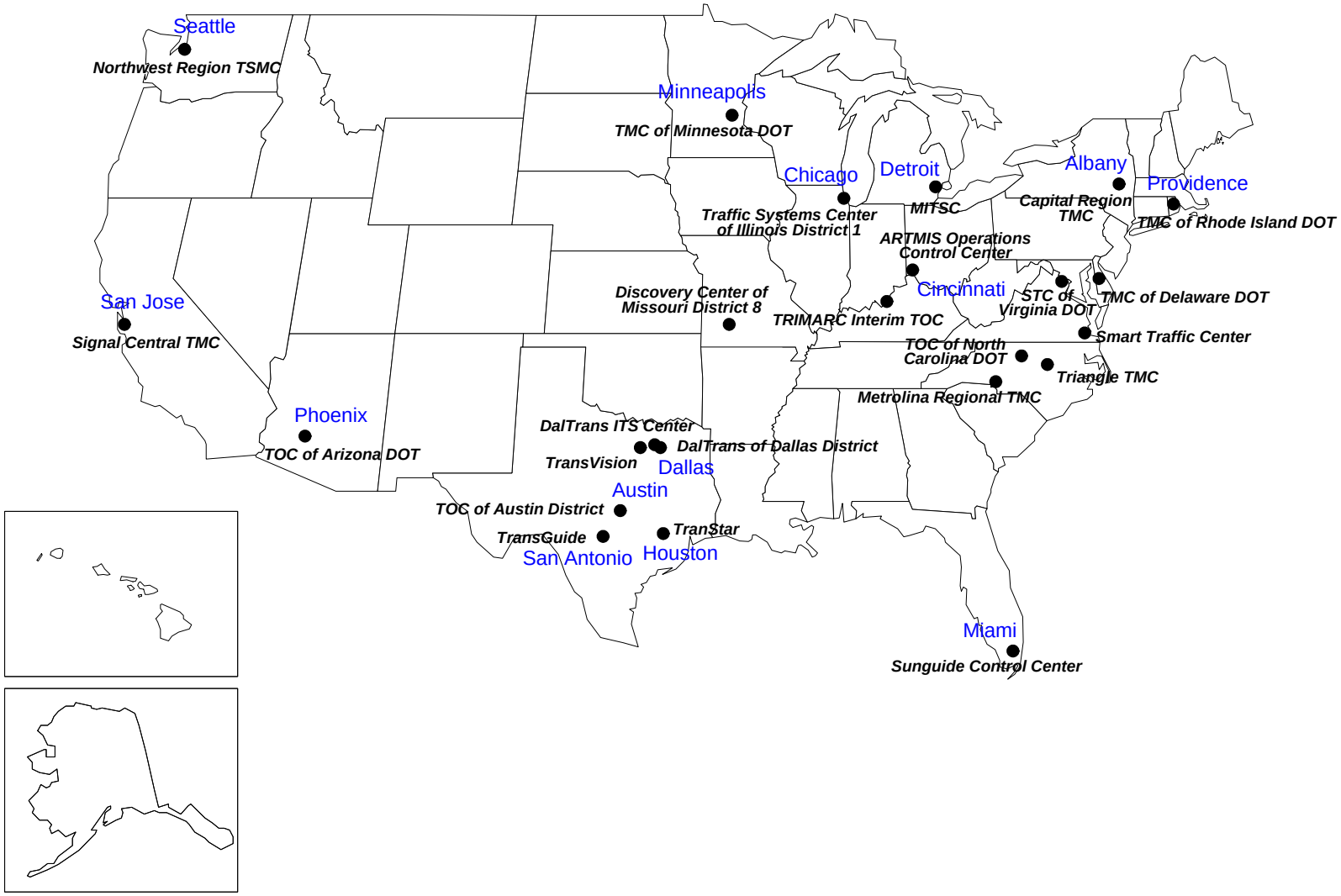


Figure 2-1 Geographical locations of the surveyed TMCs/TOCs throughout the country

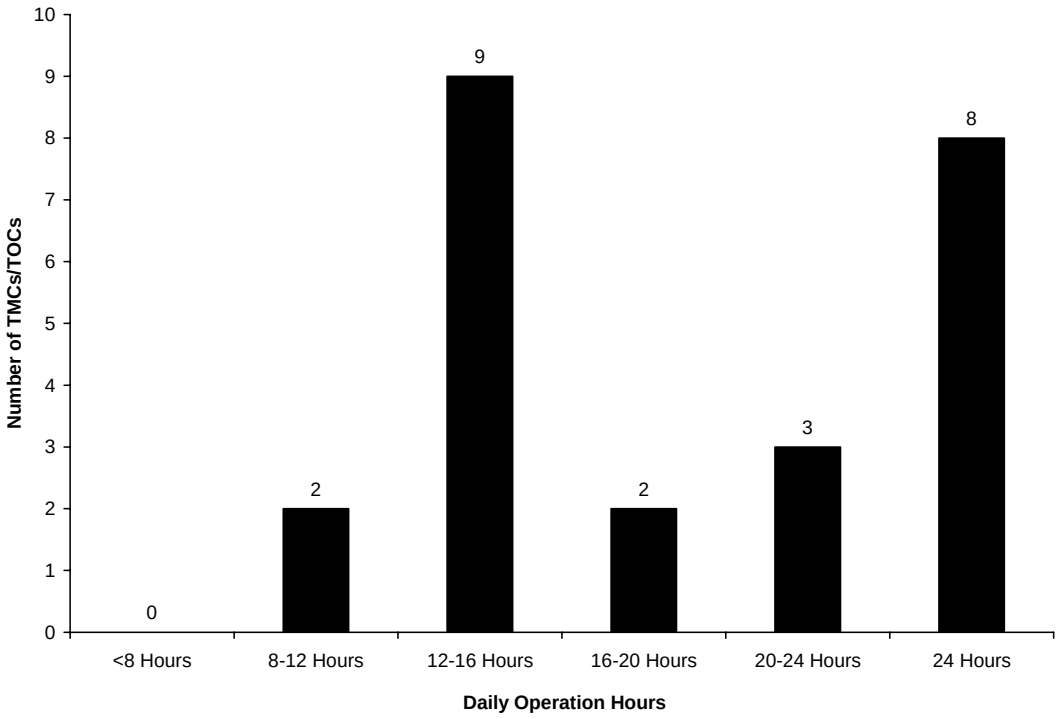


Figure 2-2 Daily operation hours of the surveyed TMCs/TOCs

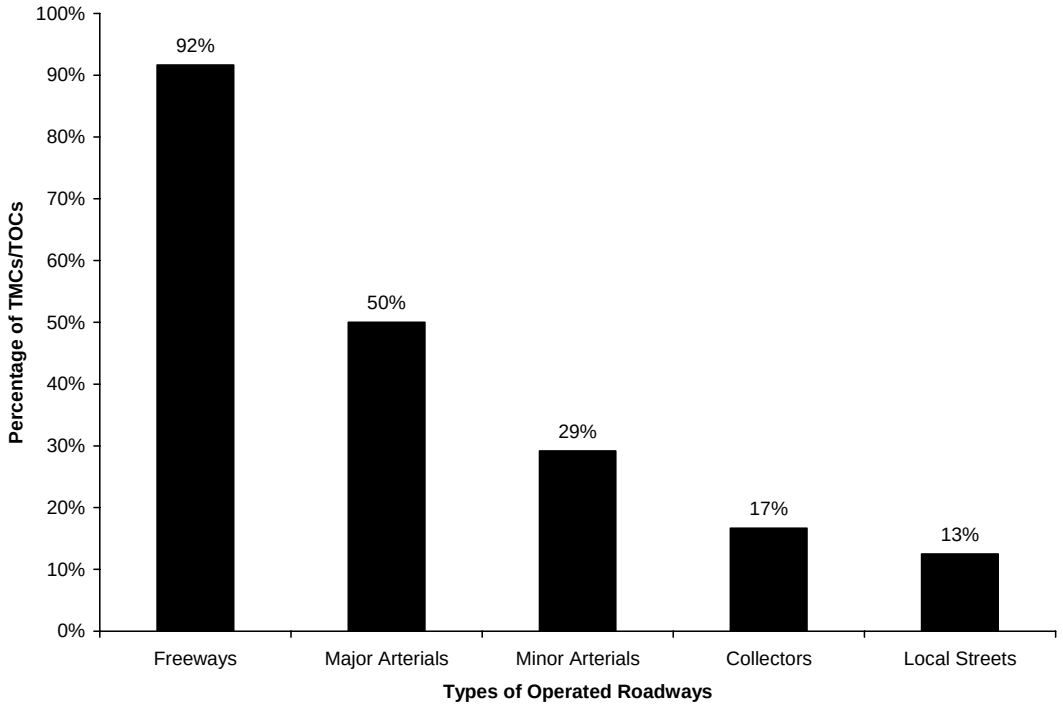


Figure 2-3 Proportions of TMCs/TOCs operating different roadway types

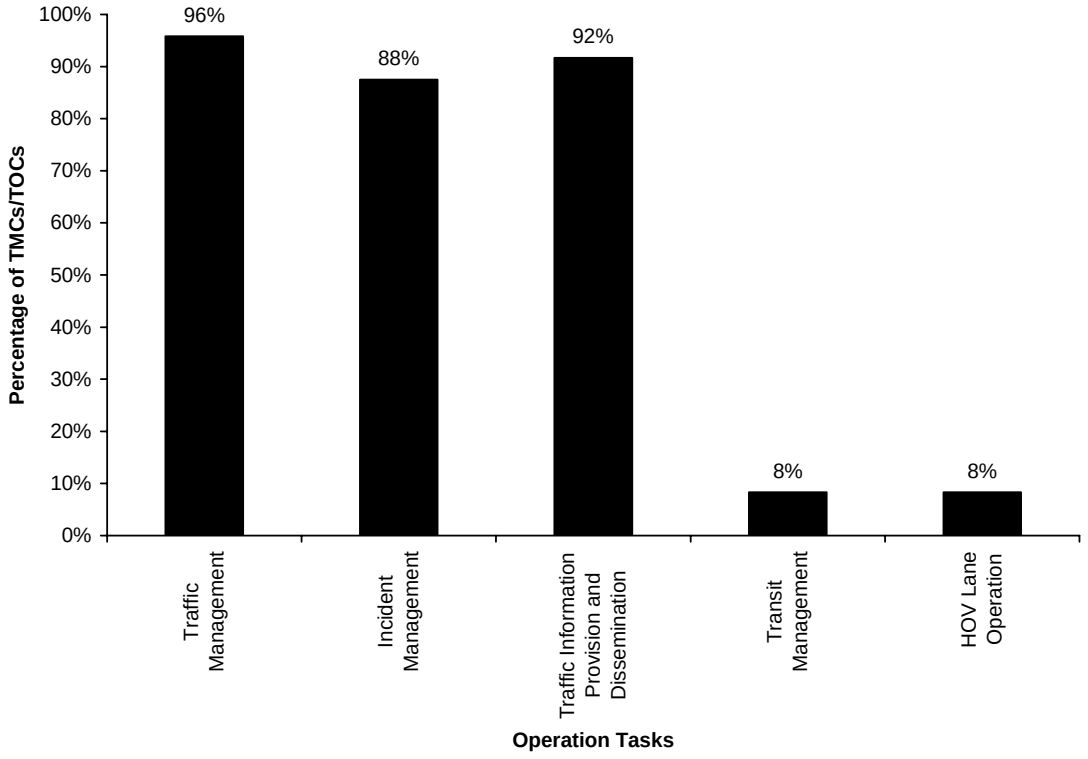


Figure 2-4 Proportions of TMCs/TOCs performing operation tasks

2.2.2 Summary of Incident Management Technologies

The four principal categories of incident detection/verification methodologies identified as being used by survey respondents were: 1) AID (Automatic Incident Detection) system alert; 2) CCTV (Closed-Circuit Television) monitoring; 3) highway patrol/maintenance crew patrol; and 4) witness report/police report/cellular phone call. AID, as the name suggests employs automated detection techniques; the remaining three approaches involve operator intervention to a lesser or greater degree. Most of the surveyed centers employ a combination of two or more approaches for both detection and verification, as illustrated in *Figure 2-5*.

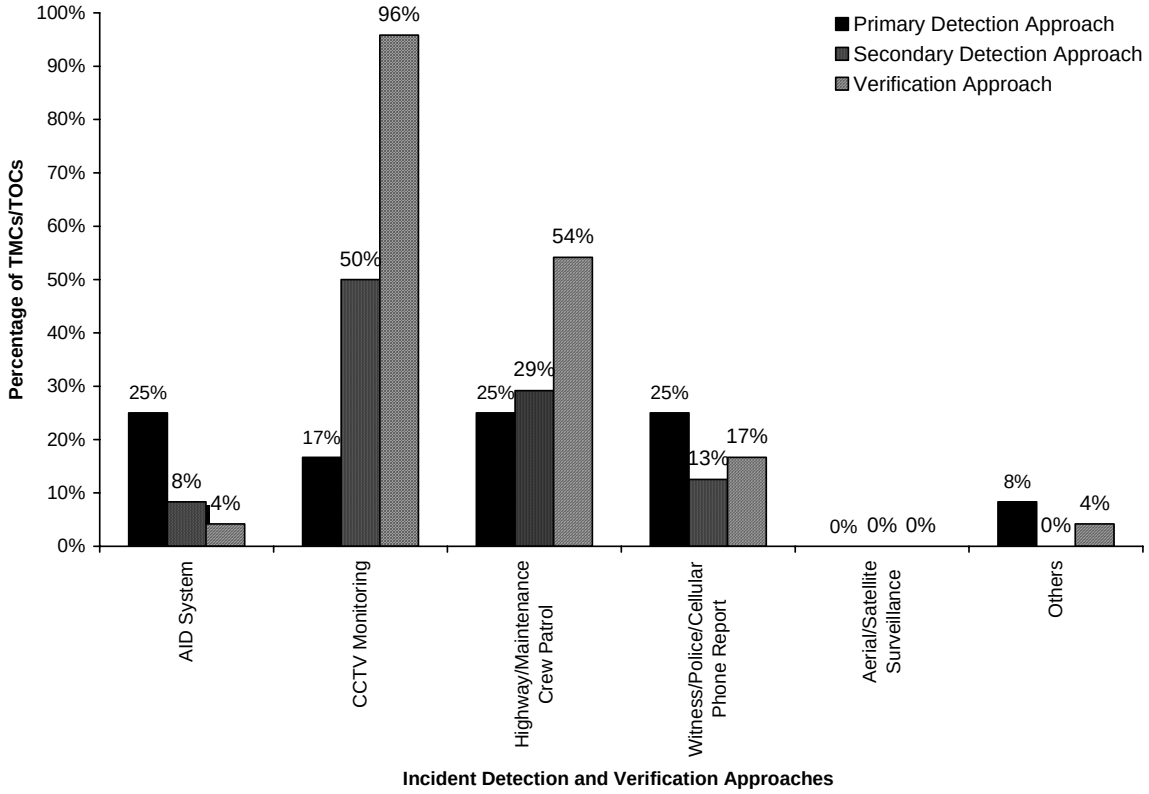


Figure 2-5 Proportions of incident detection and verification techniques

Two general categories of sensors/detectors were identified in the survey: fixed detectors (i.e., roadside-installed) and mobile detectors (i.e., probe-based). The fixed detectors primarily include traditional single ILD (inductive loop detector), double ILD, and VIP (video image processor). ILD has been widely implemented for traffic monitoring and management for more than three decades; VIP has been increasingly applied in recent years. With the exception of side-fired radar detectors, the use of other new-type roadside sensors/detectors (as reviewed in *Chapter 4*) is not reported in this survey. *Figure 2-6* shows the proportion of TMCs/TOCs employing the three main types of sensors/detectors. Side-fire radar is applied in three TMCs/TOCs: Metrolina Regional TMC (North Carolina), ARTMIS Operations Control Center (Kentucky and Ohio) and TRIMARC Interim TOC (Kentucky and Ohio).

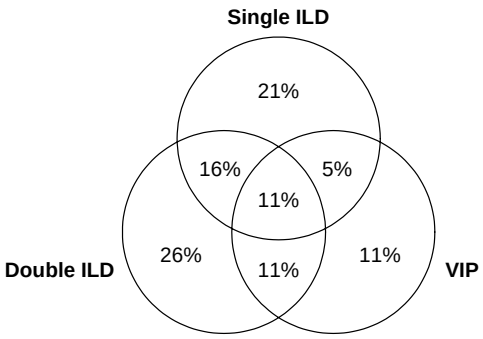


Figure 2-6 Single and combined usage of three primary types of detectors

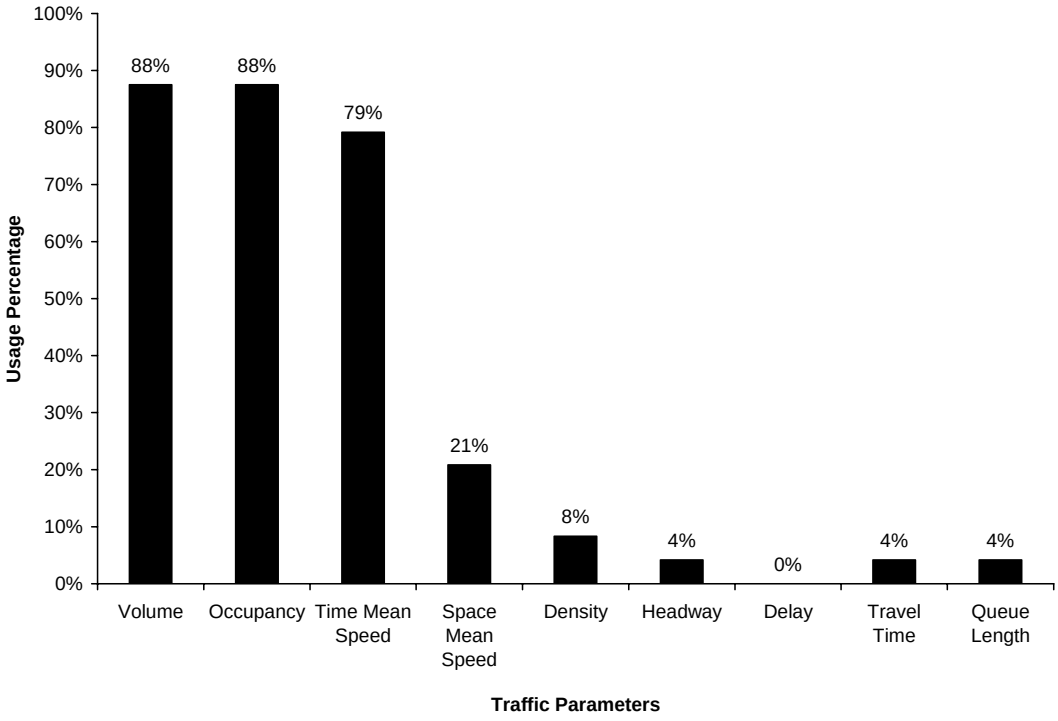


Figure 2-7 Usage of traffic parameters for incident detection and traffic management

The use of various types of traffic data obtained from fixed sensors/detectors is shown in *Figure 2-7*. Volume, occupancy and time mean speed play major roles. Other traffic parameters used for incident detection or traffic management reported in this survey include space mean speed, density, headway, queue length, delay and travel time. It is noted that a large number of TMCs/TOCs (19 out of 24) employ a combination of volume, occupancy and time mean speed as data sources while 5 TMCs/TOCs suggest that they use space mean speed or travel time instead of time mean speed in the above combination of data. However, it is not clear how they get true (non-point or very short section-based) space

mean speed or density with inductive loop detectors and video image processing. Other traffic parameters are less used.

Data communication media between detectors on site and TMCs/TOCs is another important technological concern. As may be seen in *Figure 2-8*, fiber optic cable and phone lines are most widely applied for data transmission, with coaxial cable and wireless communication also used to some degree. Fiber optic cable is increasingly used and has become the primary transmission media in the transportation industry due to its large capacity and high reliability. In contrast, the most popular type of communication link several years ago was commercial phone lines, and most of the TMCs/TOCs were experimenting with or upgrading to fiber optic cable (Parkany and Shiffer, 1996). In the survey, it was found that 9 TMCs/TOCs are using fiber optic cable for nearly 100% of their communications. Moreover, more than half of TMCs/TOCs make use of hybrid or integrated communication approaches, such as fiber optic cable/phone line, or fiber optic cable/wireless.

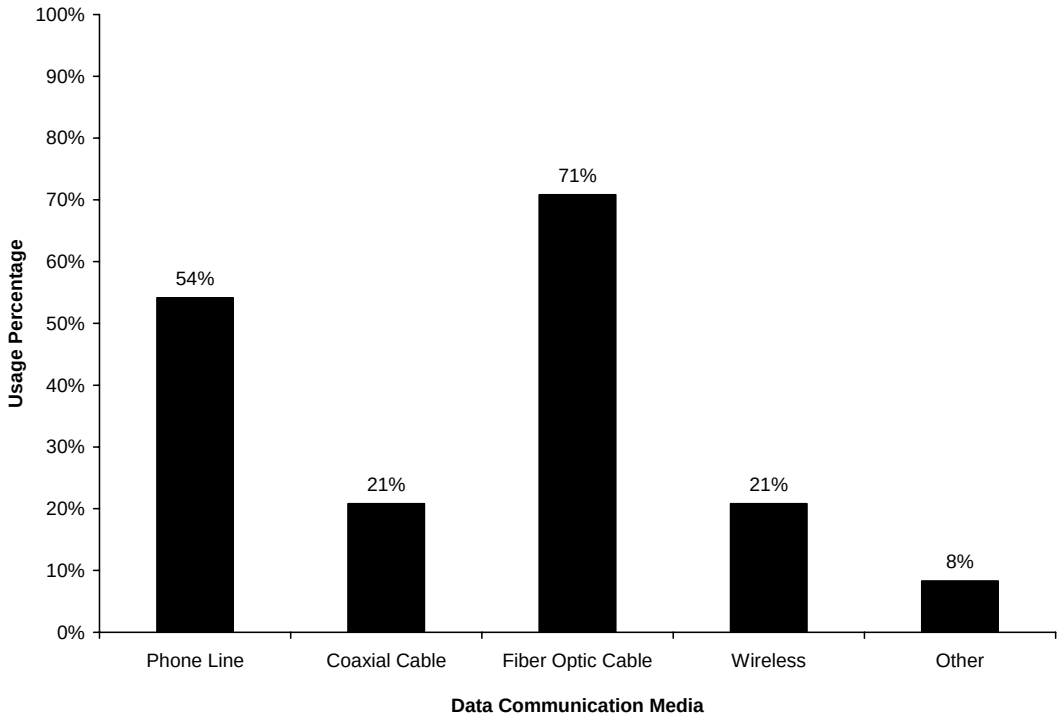


Figure 2-8 Usage of data communication media among the surveyed TMCs/TOCs

Probe-based sensor/detector systems are little used compared to fixed-type detectors. In this survey, only three TMCs/TOCs (Houston Transtar and Dallas DalTrans in Texas, and the STC Center in Virginia) reported that they employ or plan to employ AVL or AVI systems for incident detection, toll collection and/or traffic management. The reported

percentage of transponder-equipped vehicles ranges from 5% to 10% in these three areas, somewhat lower than the percentage (10-30%) reported in other metropolitan areas in North America and some cities in California. All three TMCs/TOCs reported that traffic data can be extracted from 100% of the transponders in their area.

Half of the responders are satisfied with implemented sensors or systems for incident detection and half of them not. Various reasons are reported for this dissatisfaction, including frequent malfunction, low accuracy, troublesome installation, inconvenient maintenance, performance instability, and long detection/verification time.

Other reported problems included: 1) installation and maintenance of pavement-imbedded detectors disturb or interrupt traffic, which may increase the potential for accidents/incidents; 2) currently, most incident detection/verification work relies on CCTV monitoring, highway patrol and maintenance crew patrols, and witness reports (including cellular phone calls and police reports) because automatic incident detection still suffers from low accuracy, reliability and stability; 3) the existing equipment cannot satisfy the demands of an increasingly large amount of data processing and transmission work.

2.2.3 Evaluation of Incident Detection Algorithms

In this section, some representative on-shelf or in-practice incident detection algorithms are listed. These include algorithms widely implemented in existing incident management facilities (e.g., California algorithm series) or under active investigation by transportation researchers (e.g., neural network algorithms), as well as others developed for specific demands of individual TMCs/TOCs. (see *Appendix A* for details). These algorithms refer to analytical or statistical models for AID alerts. *Table 2-2* lists the algorithms as well as their advantages and disadvantages reported by TMCs/TOCs. Surveyed TMCs/TOCs, other than those listed here, do not apply an AID algorithm for incident detection and hence are not included in this table.

2.3 Findings

● CCTV and witness reports are the principal means of incident detection/verification--Generalized algorithms do not appear to work very well because of poor transferability—some of TMCs/TOCs prefer to develop and use their own algorithms for local traffic conditions. There is little connection between algorithms found described in the literature and those algorithms actually implemented and used.

● Some TMCs/TOCs claimed that they had to discard a previously used AID algorithm due to high false alarm rates and long detection delays and resort to CCTV monitoring and witness reports.

● AID systems are effective principally for major incidents or for incidents that occur in the immediate vicinity of a sensor. Generally, the incident is reported from other (non-automatic) sources first.

Table 2-2 Advantages and disadvantages of the algorithms reported by TMCs/TOCs

Algorithm	Operator	Advantage	Disadvantage	Overall Reliability
California Algorithm Series	TOC of Arizona DOT; ARTMIS Operations Control Center; STC of Virginia DOT; Metrolina Regional TMC	High detection rate; Ease in implementation	Difficulty in calibration and implementation; low detection rate of <50%; high false alarm rate; too long time to detection	Sometimes reliable, sometimes unreliable
APID Algorithm	Smart Traffic Center; TRIMARC Interim TOC	Ease in implementation; high detection rate of 95-98%; short time to detection of 2-3 minutes	-	Fairly reliable
McMaster Algorithm	ARTMIS Operations Control Center	-	Difficulty in implementation; too costly	-
HIOCC Algorithm	Traffic Systems Center of Illinois District 1	Ease in implementation; high detection rate of 85-90%	Difficulty in calibration (continuous calibration needed); high false alarm rate of 20-30%; long time to detection of 5-10 minutes	-
Exponential Smoothing Algorithm	Capital Region TMC	-	Long time to detection	Less reliable
Comparison Algorithm[1]	MITSC	-	Time-consuming work in calibration	Fairly reliable

[1] The name of "Comparison Algorithm" is given by the authors to the incident detection algorithm comparing current and historical traffic conditions used in MITSC of the Michigan State Department of Transportation.

Sunguide Algorithm[1]	Sunguide Control Center	High detection rate of 90-95%; short detection time of <0.5 minutes	Difficulty in calibration and implementation	Fairly reliable
TxDOT LCU/SCU Algorithm	TOC of Austin District	-	Difficulty in calibration and implementation in that it may not apply well in all areas	Fairly reliable
Data Fusion Algorithm[2]	ARTMIS Operations Control Center	Ease in implementation and calibration; high detection rate of 95-98%; short time to detection of 2-3 minutes	-	Fairly reliable
TransGuide Specific Algorithm	TransGuide Operations Center	Ease in implementation and calibration; high detection rate of 95-98%; short time to detection of 2-3 minutes	High false alarm rate	
Single Station/Time of Day Algorithm	TRIMARC Interim TOC	Ease in implementation and calibration; high detection rate of 95-98%; short time to detection of 2-3 minutes	-	Fairly reliable
AVL or AVI Algorithm	Houston TranStar	-	-	-

[1] The name of "Sunguide Algorithm" is given by the authors to the algorithm developed by Kimley-Horn & Associates.

[2] The name of "Data Fusion Algorithm" is given by the authors to an incident detection algorithm employing multiple data fusion used in ARTMIS Operations Control Center, TRW under contract to Kentucky Transportation Cabinet and Ohio State DOT.

CHAPTER 3: PERFORMANCE OF ALGORITHMS

This chapter discusses common measures used to evaluate incident detection performance. The performance of the principal algorithms as applied in both the laboratory and in the field is also reported.

3.1 Performance Measures

The following measures are used in this study for evaluating the performance of several common types of algorithms: detection rate (DR), false alarm rate (FAR), time to detect (TTD), and information details and adequacy (IDA). An ideal algorithm would maximize DR and minimize FAR and TTD and provide correct and comprehensive IDA information. In practice, however, this ideal is never attained due to limitations in incident detection techniques and the complexity of the traffic and roadway environment all existing algorithms seek to stake a balance among the several objectives. The relationships among these performance measures are discussed in below.

3.1.1 Definitions of Performance Measures

Detection rate (DR) is defined as a ratio or percentage of the number of detected incidents to the total number of actual incidents during a given time period. It has the simple form shown below.

$$\text{DR} = \frac{\text{No. of detected incidents}}{\text{Total No. of actual incidents}} \times 100\% \tag{3.1}$$

False alarms are counted when an algorithm triggers an incident alarm but no actual incident has occurred. False alarm rate (FAR) has different definitions for different applications. The commonly used FAR is defined as the ratio of the number of false alarms to the total number of algorithm applications, as shown by FAR1, below. Alternatively, FAR may be defined as a fraction of the number of false alarms to the total number of declared incident alarms, including all correct and false alarms, as shown FAR2, below. A third FAR, FAR3 may be defined as the number of false alarms per day or per hour. This measure is used to reflect traffic operators' workload. In this chapter, the first definition is applied.

$$\text{FAR1} = \frac{\text{No. of false alarms}}{\text{Total No. of algorithm applications}} \times 100\% \tag{3.2}$$

$$\text{FAR2} = \frac{\text{No. of false alarms}}{\text{Total No. of declared incident alarms}} \times 100\% \tag{3.3}$$

$$\text{FAR3} = \frac{\text{No. of false alarms}}{\text{Time period}} \tag{3.4}$$

Time to detect (TTD) is used to evaluate the ability of an incident detection algorithm to identify an incident in a timely fashion. It is defined as the time spent from the moment an incident occurs until the time that the algorithm declares this incident. It is often expressed in units of minutes. Generally, the average time to detect (ATTD) is employed to give an average score of the reaction speed of an algorithm, as expressed below.

$$\text{ATTD} = \frac{1}{n}\sum_{i=1}^{n}\left(t^{i}_{\text{detection}} - t^{i}_{\text{occurrence}}\right) \tag{3.5}$$

Information details and adequacy (IDA) is not a numeric performance measure, but an indicator reflecting the reporting capability of an algorithm when it reports an unusual congestion problem. It incorporates incident-related information, such as incident location, type, severity, number of vehicles involved, etc. High IDA reporting capability can greatly facilitate incident confirmation and response. In a large-scale roadway network, when multiple incidents are identified, IDA information can be especially helpful in prioritizing these incidents for assigning action teams and other sources. The first three quantitative parameters have been used widely by traffic researchers and engineers. The IDA, as a qualitative measure, is increasingly being paid attention to and becoming an important consideration when transportation professionals assess the effectiveness of an incident detection and management system.

3.1.2 Relationships of Performance Measures

Weil *et al.* (1998) summarized a variety of factors affecting the performance of automatic incident detection algorithms. These factors include, but are not limited to: 1) operating traffic conditions (e.g., heavy, medium, light, at capacity, and well below capacity); 2) geometric factors (e.g., grade, lane drops, and ramps); 3) environmental factors (e.g., dry, wet, snow, ice, and fog); 4) incident duration; 5) incident severity; 6) detector spacing; 7) incident location (relative to detector station); and 8) heterogeneity of vehicle fleet. These factors are so complex that they cannot all be readily accounted for in a single algorithm, especially in an arterial environment. None of the existing algorithms has been tailored to consider all of these factors. Thus, they cannot be expected to succeed in all traffic environments. Al-Deek *et al.* (1996) studied the impacts and effectiveness of incident detection algorithms related to two of the above factors: geometry and incident characteristics. The result shows that the detection rate (DR) and mean time to detect (MTTD) are affected significantly when testing selected California algorithms (i.e., No. 7, No. 8 and No. 10) and negative impacts cannot be readily avoided.

3.2 Performance of Incident Detection Algorithms

A comparative performance analysis of several standard algorithms by Peterman (1999) resulted in different rankings at the model calibration and testing stages. In the calibration stage, the California No. 8 algorithm was superior for all incident detection while the Minnesota algorithm gave the best detection results for accident and stall detection. In testing, the McMaster algorithm performed best in detecting all incidents while the California No. 8 outperformed the others when detecting only accidents and stalls. From these

experiments, it was concluded that the three algorithms showed a similar incident detection performance and that each performed better than the Texas algorithm.

3.2.1 Subramaniam's Investigation

Subramaniam (1991) categorized incident detection algorithms developed prior to 1991 into 5 types: pattern recognition, statistical processing, catastrophe theory, neural networks, and video image processing. Their performances are compared, in terms of their own reported measures of effectiveness (MOEs), in *Table 3-1*. The data required to support these algorithms are derived from either inductive loop detectors (ILDs) or video image processors (VIPs). These numbers clearly illustrate the tradeoffs between the three performance parameters: detection rate, false alarm rate, and time-to-detect.

3.2.2 Stephanedes *et al.*'s Investigation

Stephanedes *et al.* (1992) evaluated the performance using sensitivity analysis of the most widely accepted conventional freeway automatic incident detection (AID) algorithms as well as the proposed Minnesota algorithm. Three types of AID algorithms were compared qualitatively and quantitatively: comparative logic (i.e., California algorithm series), statistical forecasting (i.e., standard normal deviation algorithm, double exponential algorithm, ARIMA algorithm, and HIOCC algorithm), and macroscopic traffic analysis (i.e., McMaster algorithm, dynamic algorithm, and fictitious volume algorithm[1]). They found that these algorithms suffered from certain limitations stemming from: 1) the unsatisfactory quality of raw data (i.e., ILD data) and the use of raw data with only limited filtering; and 2) the inability to distinguish incidents from bottleneck congestion or other incident-like traffic situations. The best algorithms in the types of comparative logic and time series were selected in terms of DR-FAR curves and compared to the Minnesota algorithm using a data set collected on Interstate 35 in Minneapolis, Minnesota. The performance comparison figures, the DR-FAR curve and TTD histogram respectively, are shown in *Figure 3-1* and *Figure 3-2*. As explained in the footnote to *Figure 3-2*, the negative TTD values are due to "0" being the time that the operator determines that an incident has occurred. However, if the operator has determined this, then an automatic detection algorithm which takes longer is not needed.

[1] The algorithm name of "fictitious volume" is given by the authors, which was proposed by Cremer (1981) to improve the detection performance by modeling the attenuation of the road capacity with an additional (fictitious) volume input at the location of the incident.

Table 3-1 Performance comparison of incident detection algorithms based on ILD and VIP sensors (Source: Subramaniam, 1991)

Type	Algorithm	Detection Rate	False Alarm Rate	Mean Time to Detect
Pattern Recognition	California Algorithm #7	67%	0.13%	2.91 min
	APID Algorithm	86%	0.05%	2.55 min
Time Series or Statistical Processing	SND Model	92%	1.3%	1.10 min
	Bayesian Algorithm	100%	0%	3.90 min
	ARIMA Model	100%	1.4%-2.6%	0.39 min
	Smoothing Model	92%	1.87%	0.74 min
	DES Model	82%	0.28%	5.05 min
	HIOCC Algorithm	96%		
	Filtering Model	95%	1.5%	0.67 min
	Dynamic Model		Prob. < 0.02%	Short
Catastrophe Theory	McMaster Algorithm	100%	0.04%	1.5 min
Artificial Intelligence	ANN Model	97%	0.21%	2.83 min
Video Image Processing	INVAID-TRISTAR System	90%	1 every 3 hours	0.33 min

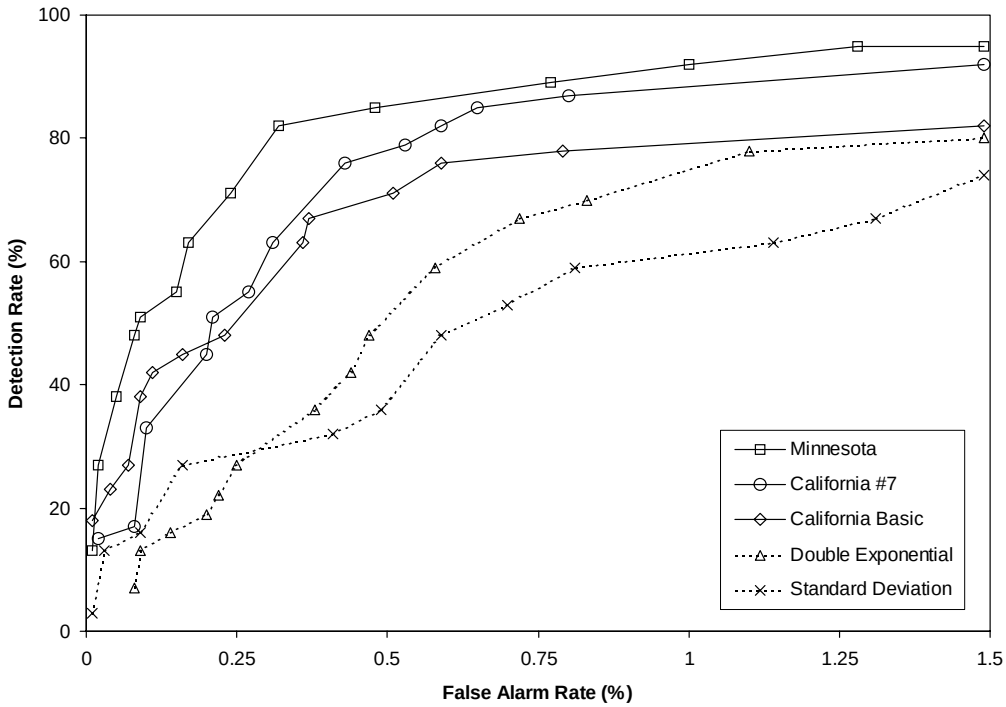


Figure 3-1 DR-FAR performance comparison of the representative algorithms (Source: Stephanedes *et al.*, 1992)

Based upon these evaluations, Stephanedes *et al.* concluded that raw detector (i.e., ILD) data are often inappropriate for incident detection if traffic noise cannot be filtered out before use. In particular, this is a weakness characterizing comparative algorithms—when corrupted by noise, incident patterns in the traffic data may not be detected easily by a comparative algorithm. Similarly, fluctuations produced by noise sources can be mistaken for incidents. As a result, the only traffic patterns easily identified are those occurring under severe incident conditions and satisfying every test of an algorithm. As for statistical forecasting algorithms, they employ filtering as dictated by their design specifications, so that their transferability is greatly limited. The major weakness of these algorithms lies in their inability to distinguish incidents from similar traffic patterns.

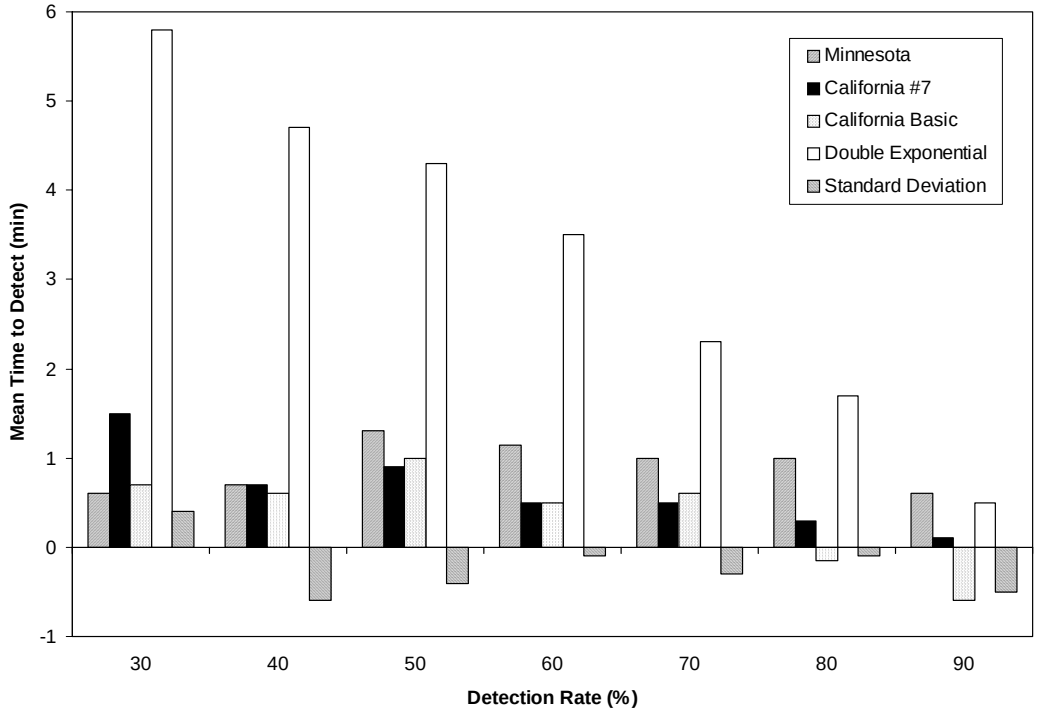


Figure 3-2 TTD performance comparison of the representative algorithms[1] (Source: Stephanedes *et al.*, 1992)

3.2.3 Balke's Investigation

Balke (1993) evaluated a variety of common incident detection algorithms on the basis of both theory and practice. The algorithms were evaluated in terms of their reported performance, data requirements, ease of implementation, ease of calibration, and operational experience. The algorithms were placed into one of five groups: comparative algorithms, statistical algorithms, time-series algorithms, smoothing or filtering algorithms, and modeling algorithms. The results of the theoretical evaluations and on-site investigations indicated that [repeated from Section 1.2.3]: 1) most freeway management centers were using a modified version of the California algorithm, except for Toronto, where the McMaster algorithm was employed [This contrasts a bit with our 2001 results shown in *Table 2-2*.]; 2) generally, operators did not depend heavily on automatic algorithms to alert them to the presence of incidents; 3) for the most part, the operators relied on other mechanisms, such as radio reports or closed-circuit television (CCTV) monitoring, to alert them to incidents on freeways; and 4) of those systems that have discontinued algorithm use, improper calibration appears to the most prevalent reason why the algorithms generated a high number of false alarms. Furthermore, it was believed that the algorithms could not be properly calibrated unless an incident affects every detection zone.

[1] Note that the negative time-to-detect values in the figure result from the fact that time of incident is the instant when the operator identifies that incident, usually a few minutes after its occurrence.

According to the theoretical and empirical evaluation described above, the following three tables respectively summarize the reported best performance, data requirements, and difficulty of implementation.

Among the three primary performance measures, i.e., DR, FAR and MTTD, MTTD is influenced significantly by the structure or procedure of a particular algorithm. Some algorithms (e.g., California No. 7, California No. 8 and low-pass filter algorithms) use special tests (e.g., persistence test or compression wave test) to extend the detection confidence and, hence, to reduce FAR. This feature, however, adds to the overall detection time. In cases where algorithms include persistence test and comprehensive wave test, it is logical for these algorithms to have higher detection times (Balke, 1993).

Table 3-2 The reported best performance of existing ILD data-based incident detection algorithms (Source: Balke, 1993)

Type	Algorithm	Detection Rate	False Alarm Rate	Mean Time to Detect
Comparative	California Basic	82%	1.73%	0.85 min
	California No. 7	67%	0.134%	2.91 min
	California No. 8	68%	0.177%	3.04 min
	APID	86%	0.05%	2.5 min
Statistical	SND	92%	1.3%	1.1 min
	Bayesian	100%	0%	3.9 min
Time Series	ARIMA	100%	1.5%	0.4 min
Smoothing or Filtering	DES	92%	1.87%	0.7 min
	LPF	80%	0.3%	4.0 min
Traffic Modeling	McMaster	68%	0.0018%	2.2 min

The comparison of data requirements in *Table 3-3* shows that occupancy (or a derivative of occupancy) is the most commonly used control measure to detect incidents.

Table 3-3 Traffic parameters used as control variables of existing ILD data-based incident detection algorithms (Source: Balke, 1993)

Type	Algorithm	Occupancy	Volume	Speed	Other
Comparative	California Basic	√			
	California No. 7	√			
	California No. 8	√			
	APID	√	√	√[1]	
	PATREG	√			
Statistical	SND	√	√		Energy[2]
	Bayesian	√			
Time Series	ARIMA	√	√		
	HIOCC	√			
Smoothing or Filtering	DES	√			Station[3] Discontinuity
	LPF	√			
Traffic Modeling	Dynamic	√	√		
	McMaster	√	√	√[4]	

Balke (1993) provided a rough qualitative assessment of the ease with which each algorithm could be implemented in the proposed design of the TxDOT surveillance and control system. The assessment is based on judgments relating to the complexity of the design and structure of the algorithm and the amount of processing required by each algorithm, as shown in *Table 3-4*.

[1] Derived from occupancy and volume
[2] Derived as the square of volume divided by occupancy
[3] Comparison of kinetic energy of individual lanes
[4] Optional parameter

Table 3-4 Time interval and update cycle of traffic parameters used in existing ILD data-based incident detection algorithms (Source: Balke, 1993)

Type	Algorithm	Degree of Complexity	Ease of Integration
Comparative	California Basic	Low	Easy
	California No. 7	Moderate	Easy
	California No. 8	Moderate	Easy
	APID	Moderate	Easy
	PATREG	Low	Difficult
Statistical	SND	Low	Easy
	Bayesian	High	Moderate
Time Series	ARIMA	High	Difficult
	HIOCC	Low	Difficult
Smoothing or Filtering	DES	Moderate	Moderate
	LPF	Moderate	Easy
Traffic Modeling	Dynamic	Extremely High	Extremely Difficult
	McMaster	Moderate	Moderate

3.2.7 Conclusion

It must be recognized that the design of each algorithm determines its own application environment, as the performance of the same algorithm can differ considerably in different environments. Environmental factors include geometric characteristics, sensor type, sensor configuration, data type, data aggregation period, as well as traffic disturbance factors. Although it is desirable to evaluate all types of algorithms in consistent environments, that is usually infeasible.

The presented results are taken from the literature that is comprised of comparison studies of freeway incident detection algorithms using inductive loop data. However, the performance measures can be applied to probe or section-based algorithms as well as arterial algorithms. We imagine that driver-based reports have the highest IDA: information details and adequacy.

CHAPTER 4: REVIEW OF DETECTION/SENSOR TECHNOLOGIES

Incident detection involves both data collection and data processing. The collection of useful data, in turn, depends on the reliability and accuracy of the detection/sensor technology employed. Improvements in sensor technologies can yield significant improvements in traffic operations and incident detection. In this chapter, we focus on classifying, reviewing, and comparing the capabilities and characteristics of different types of sensors used for incident detection. A distinction is made here between point-based sensors, which measure traffic characteristics at a single point on the roadway, and section-type sensors, which provide information regarding the characteristics of traffic over a section of roadway. The strengths and limitations of these technologies are compared.

A variety of detection/sensor technologies are used in detecting and providing real-time traffic information for incident detection. These technologies can be divided into three categories: roadway-based, probe-based, and driver-based.

Roadway-based sensors can be regarded as part of the roadway infrastructure system. Roadway-based sensors commonly involve the use of inductive loop detectors (ILD) and loop emulators. According to Underwood (1990), these sensors fall into three types in terms of their detection means: magnetic sensing (i.e., ILDs and magnetic sensors), range sensing (i.e., microwave sensors, infrared sensors, ultrasonic sensors, and acoustic sensors), and image sensing (i.e., video image processors (VIPs)). Roadway-based sensors are embedded in the pavement, installed roadside or mounted on a gantry over the road. They actively or passively "scan" the traffic where they are located (i.e., the detection zone) and provide fixed-point or short-section traffic information extracted from vehicles passing the detection zone.

Probe-based sensors are mobile in use. This type of technology makes use of sensors carried by vehicles operating in the traffic stream to obtain traffic information. They commonly feature in Automatic Vehicle Identification (AVI) applications associated with Electronic Toll and Traffic Management (ETTM) and Automatic Vehicle Location (AVL) systems used in vehicle positioning and navigation. Compared to roadway-based sensors, they are able to probe traffic flow variation over space. They report point-to-point or section measurements of traffic information. However, due to the limitation of current market penetration rate, traffic flow information is only derived from a portion of vehicles running on roads.

Driver-based technology involves reports of incidents from drivers and/or service patrol crews. Unlike the two former technologies, it provides manual, rather than automatic detection of incidents. Driver-based technology includes wireless phone reports (to 9-1-1 emergency centers or to a dedicated call-in number at a TMC), in-vehicle personal communication systems (PCS), police on-road cruisers, freeway service patrol (FSP), roadside call boxes, and others. Closed-circuit television (CCTV) monitoring, while not a probe vehicle form of sensing, also involves manual, as contrasted with automatic, incident detection.

The point needs to be made that the term *sensor* used here refers to the hardware and incorporated processing software that detects vehicles and converts the information into traffic flow characteristic data. The processing software can be located in the sensor hardware module, roadside cabinet, or at the traffic management center (TMC) or traffic operations center (TOC). This software exacts raw data from the detected electronic signals, typically as vehicle passage, vehicle presence, or successive traffic images. These processing algorithms may also provide processed data such as headway, individual vehicle speed and time-averaged values of various traffic parameters (Nelson, 2000). However, such algorithms are part of sensors and are distinct from the incident detection algorithms.

4.1 Roadway-Based Sensors

Roadway-based sensors refer to inductive loop detectors and loop emulators. The inductive loop detector (ILD), which was the earliest large-scale application of sensor technology for traffic surveillance and monitoring, remains the primary component of traffic management and incident detection systems. However, the information supplied by loops is usually limited to one or two short sections along a road, so that they generally do not represent comprehensive roadway conditions. Especially, on urban arterial roads, the spatial variation of traffic flow is complex, so it is difficult for such fixed-point or short-section sensors to measure traffic information for a whole link or a long segment of roadway. This type of sensor traditionally measures spot time-average traffic parameters, such as volume, occupancy, spot speed, as well as vehicle passage and presence and vehicle classification. Recently, vehicle identification techniques based on a pair of ILDs (Sun *et al.*, 1998; Coifman, 1998, 2000), VIPs (Washburn and Nihan, 1999; Shuldiner and Upchurch, 2001) or laser sensors (Abramson and Chenoweth, 2000) to measure section-related traffic information, i.e., travel time, have been developed, which may generate promising new approaches to using fixed-point sensor technology to detect incidents.

4.1.1 Inductive Loop Detectors

ILDs are the most commonly used sensors in traffic surveillance and management applications. Currently, most incident detection systems and algorithms use traffic data derived from ILDs.

The standard ILD is a length of insulated wire bent into a closed shape, traditionally a square or a rectangle, and connected to a power source/sensor on both sides of the wire. The wire loops are embedded in a shallow cutout in the pavement. A lead-in cable runs from a roadside pull box to the controller cabinet to an electronics unit located in the controller cabinet. When a vehicle stops on or passes over the loop, the inductance of the loop decreases, which in turn, increases the oscillation frequency and causes the electronics unit to send a pulse to the controller, indicating the passage of a vehicle and registering its presence in its detection zone. New versions of ILDs use higher frequencies to identify specific metal components of vehicles, which can be used to classify vehicles (Nelson, 2000).

The sensitivity of an ILD is adjustable and can be tuned for a variety of different locations and environments. In operation, ILDs tends to go out of "tune" over time and

requires readjustment (Berka and Lall, 1998). The received presence information can be used to calculate volume and occupancy. Occupancy is computed by taking the ratio of time the detector registers the presence of vehicles in its detection zone to the total sample time. However, ILDs have a tendency to double-count trucks (Labell and May, 1990). Due to the vehicle's structure, trucks as well as other long vehicles often are regarded as two passenger cars by an ILD. Tractor-trailer units often have concentrations of metal far enough above the loop so that the detector electronics cannot detect them, resulting in detection gaps.

ILD systems still suffer from poor reliability, related to causes such as inclement weather, improper connections made in pull boxes, and in the application of sealants over the cutout. These problems are accentuated when ILDs are installed in poor pavement or in areas where utilities frequently disturb the roadbed. Most cities with mature systems report that 25 to 30 percent of their detectors are not operating properly at any given time (Underwood, 1990). Moreover, the installation and maintenance of ILDs require lane closures to dig grooves in the road, causing traffic disturbances. In addition, the precise nature of an incident detected by ILDs cannot be ascertained, and ILDs perform less effectively for incident detection in low volume conditions.

4.1.2 Magnetic Sensors

Magnetic sensors work on the principle that the presence of a vehicle distorts the magnetic field which shrouds the earth. Although different in appearance and specific technology, they operate on a similar principle to ILDs. Magnetic sensors are often installed in place of loops on bridge decks, and in heavily reinforced pavement, where steel adversely affects loop performance (Nelson, 2000). ILDs and magnetic sensors each have their respective applications and tend to complement one another.

There are two types of magnetic sensors for traffic flow parameter measurement: active devices, such as magnetometers; and passive devices. The first type, two-axis fluxgate magnetometers, are active devices, excited by an electrical current in windings around a magnetic core material. They detect changes in the vertical and horizontal components of the earth's magnetic field. They can measure the passage of a vehicle when operated in the pulse output mode, yielding count data, and provide a continuous output as long as a vehicle occupies the detection zone when operated in the presence output mode. The Self-Powered Vehicle Detector (SPVD), a type of magnetometer developed with FHWA support, is powered by a self-contained battery, with a limited expected life, say 1 to 2 years. It is connected to a remotely located controller cabinet via a radio link. Thus, no direct connection is required.

A magnetometer presents installation and maintenance problems similar to ILDs. To install and repair a magnetometer, traffic needs to be disrupted for a sufficiently long period for removing the sensor and reinserting it in a borehole. Compared to an ILD, this device, though road-embedded, shortens lane closure time for each repair, but increases the frequency of lane closures for such repairs, especially in the case of SPVD (Labell and May, 1990).

The second type, passive magnetic detectors, sense perturbations in the earth's magnetic flux produced when a moving vehicle passes over the detection zone. These magnetic sensors are induction magnetometers. Most require some minimum vehicle speed for producing an output signal, usually 3 to 5 mph; hence, they cannot detect stopped vehicles nor provide presence measurements (Klein and Kelley, 1996; Klein, 2001).

Magnetic detectors are easier to install and more maintainable than ILDs for a similar price (Coutellier, 2000). They can come pre-installed in tubing. Compared to ILDs, magnetic detectors can sustain greater stresses and break down less often. Alternative installation procedures may further improve their reliability. The biggest disadvantage of magnetic detectors is that they cannot measure occupancy. Speed may be calculated by installing two magnetic detectors in a close succession, and from speed and flow measurements, occupancy can be calculated. However, if two magnetic detectors are placed too closely together, they may interfere with each other (Labell and May, 1990).

4.1.3 Microwave Sensors

Microwave sensors currently used in traffic surveillance fall into two types in terms of their working waveforms: constant-frequency waveform (CW) and frequency-modulated waveform (FMCW), as illustrated in *Figure 4-1*.

The first type, which is termed the continuous microwave detector, makes use of the Doppler principle to compute vehicle speed from CW microwave radar that transmits electromagnetic energy at a constant frequency. Because only moving vehicles are detected by CW Doppler radar, vehicle presence cannot be measured with this waveform and hence this type of microwave sensor is not suitable for incident detection.

The second type is termed the pulse microwave detector. These detectors transmit electromagnetic energy in frequency bands between 2.5 to 24.0 GHz. They are capable of counting vehicles, measuring speeds and detecting vehicle presence. Pulse microwave detectors can also classify vehicles by measuring the vertical profile of a vehicle (Black and Loukakos, 2000).

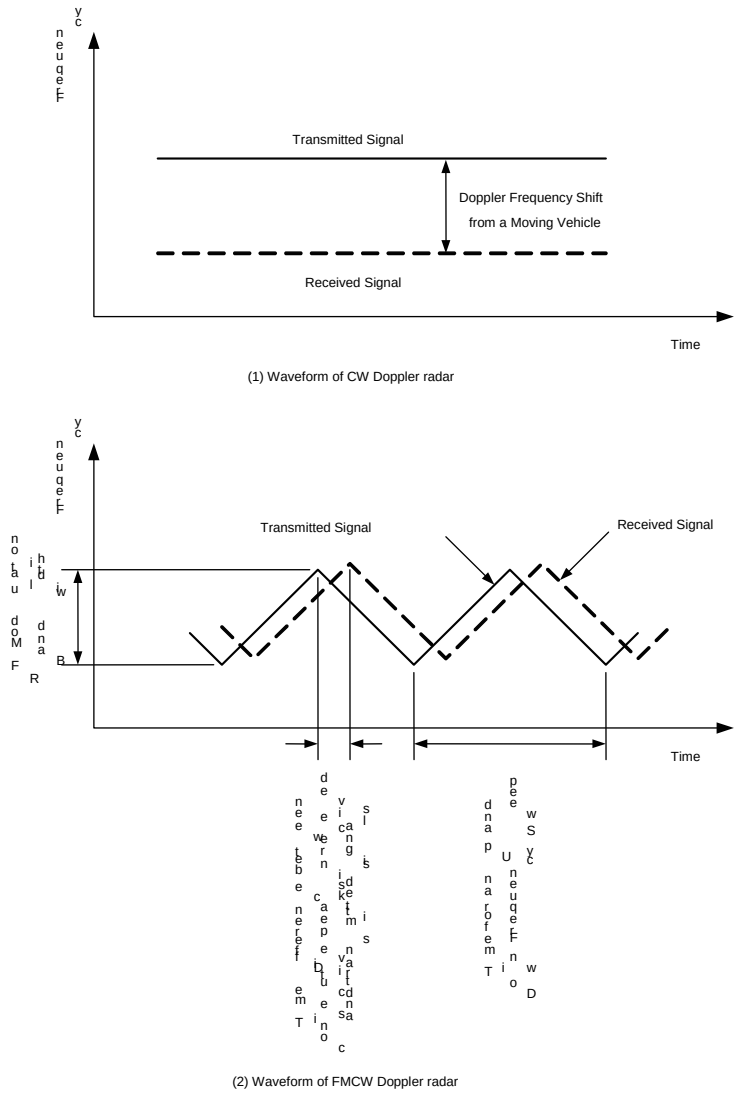


Figure 4-1 Two kinds of waveforms used with microwave traffic sensors (Source: Klein, 2001)

Microwave sensors provide a cost-effective alternative to ILDs for vehicle presence detection and hence for incident detection. They are relatively smaller, lighter in weight and easier to install than ILDs and magnetic sensors, and they can detect multilane traffic and cover a longer range (say 100 meters to 1000 meters), as shown in *Figure 4-2*. Their small size, low cost and low power consumption makes them suitable for traffic surveillance both at intersections and on highways. However, it needs to be noted that that a newly installed microwave sensor may interfere with other similar microwave-based devices in its vicinity.

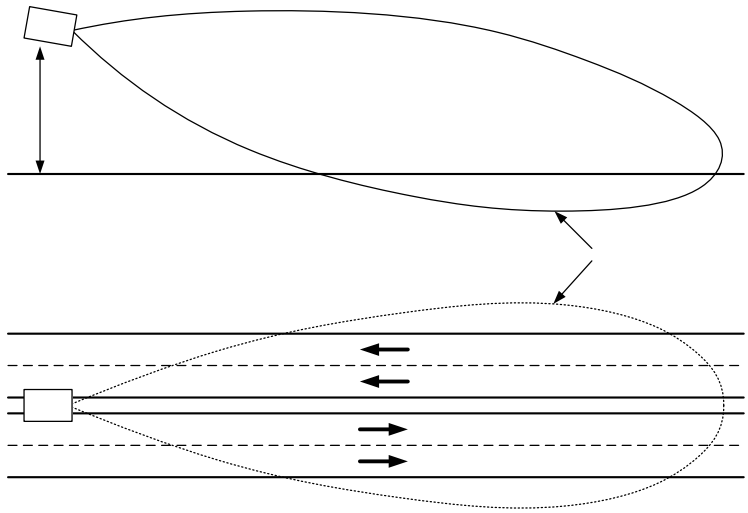


Figure 4-2 Illustration of the typical coverage of a microwave sensor for incident detection (Source: Lion and Roussel, 1995)

Radar

4.1.4 Infrared Sensors

The infrared sensors referred to here are non-image infrared devices. Infrared sensors can operate in active or passive modes. Similar to microwave sensors, infrared sensors are mounted overhead or in a side-looking configuration.

In the active mode, a detection zone is illuminated with infrared energy transmitted from laser diodes operating in the near infrared spectrum. A portion of the transmitted energy is reflected back to the sensor by vehicles traveling through the detection zone. An infrared-sensitive element converts the reflected energy into electrical signals that are analyzed in real time. Infrared sensors can measure presence, speed, volume, occupancy, and vehicle classification. Active infrared detectors are vulnerable to weather conditions such as fog, clouds, shadows, mist, rain, and snow, which scatter and attenuate wave energy. High cost is cited as one of the reasons that they are not more widely used in traffic surveillance. Active sensors are more expensive than passive ones.

Passive infrared detectors measure the same traffic parameters as active detectors except for speed. They do not transmit their own energy but use an energy-sensitive element to measure the thermal energy (i.e., temperature) emitted by vehicles (which differs from the energy emitted from the road) in the field of view of the detector. When a vehicle enters the field of view, the change in emitted energy from the scene is sensed. Passive infrared sensors have difficulty measuring speed because the extended nature of the vehicle distorts the infrared signature, making velocity less clear. On the other hand, multi-zone passive infrared sensors can measure speed and vehicle length as well as the more conventional vehicle count and lane occupancy (Klein, 2001). Inclement weather,

Radar

such as fog, snow, and precipitation that scatter energy, and changes in light, may have adverse effects on performance.

4.1.5 Ultrasonic Sensors

Ultrasonic sensors transmit pressure waves of sound energy at frequencies between 25 and 50 KHz (Labell and May, 1990; Nelson, 2000). They fall into two types: pulse-waveform ultrasonic sensors and constant-frequency ultrasonic sensors. Most ultrasonic sensors operate with pulse waveforms; only this type is discussed here. Pulse waveforms are used to measure distances to the road surface and the vehicle surface by detecting the portion of the transmitted energy that is reflected back towards the sensor. When a distance other than that to the background road surface is measured, the sensor interprets that measurement as the presence of a vehicle. The received ultrasonic signal is converted into electrical energy that is analyzed by signal processing electronics. This technique is similar to that used by pulse microwave sensors.

Ultrasonic sensors can measure speed, occupancy, presence, and in some configurations, queue length. Moreover, vehicle profiling can be achieved by installing a pulse ultrasonic detector above the roadway; excellent classification performance can be achieved for most vehicle types (Black and Loukakos, 2000). Ultrasonic sensors have no moving parts so they tend to be reliable, durable and require little maintenance. They are also small and can be sited permanently or used as a portable unit. However, air turbulence and temperature adversely affect operational performance.

4.1.6 Acoustic Sensors

Acoustic sensors are operated in a passive mode, and are usually configured as a two-dimensional dipole array of microphones that are sensitive to the acoustic energy (i.e., audible sounds) produced by approaching vehicles. The time delay between the arrival of sound at the upper and lower microphones changes with time as the vehicle emitting the sound passes under it. When a vehicle passes through the detection zone, an increase in sound energy is detected by the signal processing algorithm and a vehicle presence signal is generated. When the vehicle leaves the detection zone, the sound energy level drops below the detection threshold and the vehicle presence signal is terminated. Vehicles are tracked using cross-correlation between microphones. Best results are achieved when the data is filtered to a bandwidth of 50-2000 Hz (Black and Loukakos, 2000). For this type of acoustic sensor, the preferred mounting is at a 10- to 30-degree angle from the vertical. This sensor can count vehicles and measure presence, speed, volume and occupancy. Interference between the noises of multiple vehicles is a limitation to acoustic technology. Its performance is also affected by low temperature and by snow, and dense fog that may muffle sound and lead to undercounting.

A second type of acoustic sensor uses a fully populated microphone array and adaptive spatial processing to form multiple detection zones. This sensor can monitor as many as six to seven lanes when mounted over the center of the roadway. Mounting heights range from 20 and 40 feet.

4.1.7 Laser Sensors

Laser sensors have been used for traffic surveillance and management for only a few years. They operate in the active mode and work on the same principle as microwave radar sensors, using light frequencies. Laser sensors can offer high-speed measurement accuracy and measure all the vehicle characteristics needed for traffic surveillance and incident detection (Abramson and Chenoweth, 2000). A vehicle detection and classification system utilizing laser sensors has been deployed on I-4 in Orlando, Florida, for obtaining data needed for incident detection.

Generally, laser sensors are mounted on a gantry over the highway; each unit can provide coverage for two adjacent lanes. A wireless modem connected with the sensor transmits the information between the sensor and a control and processing computer. Almost all traffic parameters, such as presence, classification, speed, volume, occupancy and so on can be measured by laser sensors. Moreover, they provide the detailed vehicle shape characteristics needed to uniquely identify vehicles. This capability can be used to measure travel times between two locations on highways, which offers the possibility to develop incident detection schemes based on variations in travel time like the ones that utilize probe-based data.

4.1.8 Video Image Processors

Video Image Processors (VIP) employ machine vision techniques to automatically analyze traffic data collected with Closed Circuit Television (CCTV) systems or other video cameras. A VIP system consists of one or more video cameras, a microprocessor-based computer for digitizing and processing the video imagery, and software for interpreting the images and converting them into traffic flow data. The image processing algorithms in the computer analyze the variation of groups of pixels contained in the video image frames. By analyzing successive video frames, the VIP is capable of calculating traffic flow information.

VIP systems fall into one of three classes: tripline, closed-loop tracking, and data association tracking (Nelson, 2000). Tripline systems operate by allowing the user to define a limited number of detection zones in the field of view of video cameras. These systems are the most common and are essentially expensive loop emulators. Closed-loop tracking systems permit vehicle detection along larger roadway sections, which provide additional traffic flow information such as lane-to-lane vehicle movements. Data association tracking systems can identify and track a specific vehicle or group of vehicles as they pass through the field of view of the camera, in which the unique connected areas of pixels are searched, identified and tracked from frame-to-frame to produce tracking data for a selected vehicle or vehicle group. This technique has the potential to provide link travel time and origin-destination pair information (Washburn and Nihan, 1999).

One of the primary advantages of using VIP for incident detection is that incidents are not blocked by the resultant traffic queues if the surveillance video camera is installed so as to provide upstream viewing (Nelson, 2000). Some VIP systems are able to exact a wide range of traffic parameters, including density, queuing length and speed profiles. Other

advantages of using VIP for incident detection also include possibly short detection time, quick identification, as well as recognition of the incident type (using human operators), multilane surveillance by one sensor and easy installation. The performance of VIP systems, however, is affected by variations of light and climate, so the installation position and the calibration of image processing algorithms need to be adjusted accurately. In addition, the transmission of video images requires more bandwidth than transmission of voice and data, which increases the cost of transmission. There appear to be no technological barriers, given the technical maturity of VIPs, to the implementation of incident detection systems; the main challenge lies in refining its corresponding automatic incident detection algorithms (Loukakos, 2000).

4.2 Probe-Based Sensors

Probe-based sensors refer to vehicle-mounted sensors that have positioning or identification functions and have the capability of transmitting real-time individual probe data to roadside readers or to a remote base station through wireless communication. The sensors move in the traffic stream and report an individual vehicle's movement parameters, i.e., position and velocity with time tag, with a pre-selected frequency or as they pass reader locations. The information, which includes point data, point-to-point data and/or section data, is then transmitted to the traffic management center (TMC) or traffic operations center (TOC), and aggregated and processed for traffic surveillance and incident detection. Compared to roadway-based sensors, this type of sensor is mobile and hence can sense the spatial variation of traffic flow over a wide area. With the increase in the penetration rate of vehicles equipped with sensors in a traffic network, the collected traffic information from probe-based sensors can better reflect actual traffic conditions. Ideally, if each vehicle acts as probe vehicle, we could measure traffic stream conditions temporally and spatially on the finest level.

Emerging probe-based sensor technologies that have potential for incident detection include automatic vehicle location/global positioning systems (AVL/GPS), signpost/beacon systems, cellular locationing systems, and automatic vehicle identification (AVI). The first three sensor technologies all belong to automatic positioning and navigation techniques, while AVI was initially designed for electronic toll collection (ETC) or electronic congestion pricing (ECP).

4.2.1 Automatic Vehicle Location/Global Positioning System

Automatic vehicle location (AVL) systems are designed to determine the location of a particular vehicle (typically using long-range communications) at a particular point in time. The most widely used AVL technology is the global positioning system (GPS), which is operated and maintained by the U.S. Department of Defense (DOD). GPS is a satellite-based radio positioning and time transfer system, which is used in every mode of transportation. Other satellite-based positioning systems used for AVL include Global Navigation Satellite System (GNSS), Geo-stationary Earth Orbit (GEO), Low Earth Orbit (LEO), and Medium Earth Orbit (MEO) (Krakiwsky, 1996).

A horizontal positioning accuracy of 5 meters 95% of time can be realized by GPS techniques in traffic measurement. This accuracy greatly enhances the reliability of using GPS to collect real-time congestion information and detect incidents. Using geographic information system (GIS) and map matching techniques, an in-vehicle unit can possibly locate an individual vehicle's position on a road accurately along with speed and time parameters. Sermons and Koppelman (1996) applied traffic dynamic measures using GPS positioning data to detect incidents in an arterial environment. More recent efforts (Du and Aultman-Hall, 2004) describe the difficulties in map matching GPS signals to specific roadways.

Another disadvantage of GPS technology is its inability to handle obstructions. Because GPS signals are transmitted via high-frequency microwave (i.e., short wavelength of 19-24 cm), they are incapable of passing through most objects. Therefore, GPS may suffer from signal blockage in the central business district (CBD) of a city, and in tunnels or under bridges. Other positioning techniques, such as dead reckoning (DR), have been incorporated into GPS systems or combined with GPS receivers in order to improve operating reliability. (Sweeney and Loughmiller, 1993; Levine and McCasland, 1994).

4.2.2 Signpost/Beacon System

Signposts/beacons are infrared, microwave, or radio frequency (RF) devices mounted on the sides of the roadway or existing cellular base stations (Nelson, 2000; Garg and Wilkes, 1996). These devices are capable of transmitting and receiving data from vehicles equipped with transceivers when these vehicles pass in close to proximity to the signpost/beacon. These systems can be either self-positioning or remote positioning. In the first case, a tag in the vehicle picks up a signal from the beacon. In the second case, the beacon senses a tag on the vehicle. The basic configuration includes antennas, transmitter electronics, and receiver electronics. Radio frequency beacon systems are becoming more common for applications in traffic surveillance and parking management. Petty *et al.* (1997) proposed a preliminary incident detection algorithm using probe vehicles equipped with radio transponders, in which the performance, infrastructure requirements, and feasibility of radio frequency beacon systems were discussed.

4.2.3 Cellular Geolocation System

ITS applications of cellular geolocation technology are currently being explored by researchers and practitioners. The Federal Communications Commission (FCC), as part of its requirements for the E911 system, has directed the cellular telephone industry to implement a system that is able to locate two-thirds of all mobile 911 callers within 125 meters of accuracy. This requirement enhances applications using cellular phone calls from and to motorists as mobile traffic sensors. Several tests of vehicle location and speed-estimation using telemetry data from cellular phone receivers have been conducted (Sakagami *et al.*, 1992; Transportation Studies Center, 1997; Lovell, 2001; Smith *et al.*, 2001; U.S. Wireless, 2001).

According to U.S. Wireless (2001), pattern recognition using radio frequency (RF) signals transmitted from a cellular phone is the fundamental means used by this system to

determine location. The system can identify a "signature" based on the RF pattern (i.e., multi-path phase amplitude characteristics) of an operating cellular phone. It then compares the RF pattern signature to a database of previously identified RF signatures and their corresponding geographic locations within the calibrated network. By matching the signature pattern of a caller's signal with the database containing known signature patterns, the caller's location can identified. The available raw data from the cellular location system include: 1) the mobile identification number (MIN) of a call—during a call, all other parameters may change, but the call's MIN is unique and unchanging; 2) the longitude and latitude of the call location; 3) instantaneous speed; 4) heading—the current compass heading of the call's mobile device; and 5) time stamp—the moment the location entry is received by the system. Other common techniques include signal strength, angle of arrival (AOA), and the difference of arrival (TDOA).

This sensor technology used for traffic surveillance has several advantages (Drane and Rizo, 1997). It makes use of an existing infrastructure, and requires no alteration to the base station or subscriber handsets and hence significantly reduces the cost of service establishment. Cellular phones already have a spectrum allocation and a large installed user base. They also can potentially be used as vehicle probes in much the same way toll tags in AVI are currently used. Moreover, cell phone systems have been proven to work especially well in complex environments such as dense urban zones and hilly or mountainous areas. In 1998, the national average market penetration rate of wireless phones was estimated at 17 percent (Sutton, 1998). Current increases are estimated to be 33,000 new subscribers per day, with industry analysts predicting more than 100 million users in 2001. This would mean approximately one-third of all drivers nationwide might be expected to be cellular phone subscribers (Walters *et al.*, 1999). Wireless technologies offer tremendous possibilities for cost savings with the potential to work with implemented hardwired systems in the ITS domain. However, the US Wireless efforts are now (2004) defunct and there are no known current efforts to track cell phone signatures for traffic purposes.

4.2.4 Automatic Vehicle Identification

Automatic Vehicle Identification (AVI) is designed to identify (typically using short-range communications) a vehicle that is situated at a specific location at a specific time. AVI systems have two primary components, the in-vehicle unit (i.e., tag or transponder) and the roadside unit (i.e., reader), and a wireless communications link between them (Bernstein and Kanaan, 1993). Most AVI systems transmit information through microwave, infrared or radio frequency (RF). Under good conditions, the reported accuracy of an AVI system is usually in the 99.5% to 99.9% range. However, their accuracy may be reduced by adverse weather conditions and interference from other radiation sources. AVI technology is applied principally for electronic toll collection (ETC), electronic congestion pricing (ECP), and fleet control.

The capability of multiple-purpose usage makes AVI a promising sensor technology for incident detection, as long as the percentage of the transponder-equipped vehicles in the market reaches a certain level. Hallenbeck (1992), Parkany and Bernstein (1995), and Hellinga and Knapp (2000) studied the capabilities and performance of AVI for incident

detection in simulation environments. An operational test conducted in Houston by TTI in conjunction with TxDOT assessed the feasibility of using probe-based travel time information to detect incidents on freeways and a major arterial by means of a manual cellular-phone-reporting form (Balke *et al.*, 1996). In the New York City metropolitan area, the feasibility of using the vehicles equipped with E-ZPass tags as traffic probes for incident detection was evaluated using TRANSCOM's system for managing incidents and traffic (TRANSMIT) (Mouskos *et al.*, 1998; Niver *et al.*, 2000).

4.3 Driver-Based Sensors

Driver-based "sensors" involve the reporting of incidents directly by road users or other human observers. The advantage of this type of incident detection is that the location, type, and severity of an incident can be described clearly. Generally, incidents are reported by means of cellular phones (to 911 or to a dedicated call-in number at a TMC), CCTV monitoring, service patrol vehicles, police cruisers, roadside call boxes, and calls by public entity personnel, i.e., roadway maintenance crews, transit operators, fire departments, etc.

4.3.1 Highway Service Patrol

Typically, service patrol vehicles, police in highway cruisers and CCTV monitoring by operators serve as the main sources of information for incident detection. Service patrol vehicles are intended to monitor and assist vehicles and they generally operate on freeways at a specified frequency. The advantage of this approach is that service patrols can detect and verify incidents at the same time and respond to accidents and other incidents quickly, which greatly reduces verification, response, and clearance time.

The cost of service patrols is not inconsequential. For example, the California Freeway Service Patrol (FSP) program is implemented along more than 900 mi of freeway in fifteen counties, with 250 tow trucks patrolling for almost 600 hours per day across the state. The estimated annual cost is approximately $22 million (Bertini *et al.*, 1997). With limited patrol vehicles and staff and hence limited dispatch frequency, the time to detect is relatively long; e.g., in the above limited service period it was reported that the average responding time to an incident is approximately 8 to 11 minutes. With the limited daily service duration (e.g., generally 8 hour patrol period per day), the temporal coverage cannot satisfy the demand of monitoring incidents for the whole day. Police patrols suffer from similar limitations.

4.3.2 Remote CCTV Monitoring

Video technology is widely used in most of TMCs/TOCs responding to our survey for traffic monitoring and surveillance. It provides direct and continuous on-site images in real-time. In comparison, other sensors/detectors only provide limited traffic parameters. Most of the current applications at TMCs/TOCs are for incident verification when an incident alarm is triggered or reported from other data sources. With advances in video image processor (VIP) technology, traffic movement in the video captured by a CCTV system could be converted into point-based traffic parameters. Integrating VIP with

CCTV monitoring might provide a promising method for more reliable incident detection in which automatic and non-automatic detection techniques work under a hybrid or fused mode sharing the same set of equipment.

4.3.3 Cellular Phone Reports

Due to ever expanding coverage of cellular phones and low investment and operating cost, the potential for using cellular phone reports for incident detection has been widely recognized by many transportation agencies. TxDOT plans to use cellular incident detection via information sharing with the local 911 Public Safety Answering Points (PSAPs) in the Dallas District. It is expected that this combination will result in faster and more cost-effective deployment (i.e., 2 years and $2 million) and more extensive coverage of the freeway system, compared to the previously planned loop detector system with conduit and fiber optic cables (10 years and $23 million) (Walters *et al.*, 1999). Cellular phone reports provide broader monitoring coverage and more mobility than other existing surveillance system. They have the potential to cover both major roads and minor roads. Current penetration rates are much higher than that of any existing probe AVL or AVI transponder system and are increasing rapidly.

Several operational experiments have been carried out by the Massachusetts State Police (Kennedy, 1991), and in Chicago, Illinois (McLean, 1991), Portland, Oregon (McCourt, 1993), Denver, Colorado (Hattan *et al.*, 1993), Houston, Texas (Levine, 1993), San Francisco Bay Area, California (Skabardonis *et al.*, 1998) and Dallas, Texas (Walters *et al.*, 1999). These studies indicate that wireless phone calls responding to emergency services, i.e., 911 or dedicated call-in number to a TMC, can provide valuable and timely information for incident detection, with detection times in the order of one minute. However, these studies also reveal low detection rates. Hence, previous recommendations were that cellular phone-based incident reporting systems must be operated in conjunction with traditional traffic surveillance systems. Nevertheless, given the rate of increase of the penetration rate of cellular phones in the driving population, the frequency and promptness of driver-reported incidents are expected to increase. With the same set of equipment, cellular phone calls can work together with the automatic geolocation function of the wireless network, as discussed in the last section, providing both quantitative and descriptive data for traffic monitoring and incident detection.

Several theoretical and applied studies have evaluated the effectiveness of using cellular phone reports for incident detection (Tavana *et al.*, 1999; Mussa and Upchurch, 2000; Skabardonis *et al.*, 1998; Walters *et al.*, 1999). These studies suggest that overall accuracy is based on the prevailing traffic flow, penetration of wireless phone ownership across the driving population, drivers' willingness to report an incident, and the number of erroneous calls. The fraction of motorists with wireless phones onboard is closely related to the market penetration of wireless phones in an area. Given that the cost of purchasing and using wireless phones need not be included in the cost of deploying such systems, broad coverage may be attained without much public investment. The cost for the "sensors" does not need to be considered. However, other factors—drivers' willingness to report and their capability to provide an accurate report—heavily affects the report's utility. Thus, it is reasonable to include the educational and promotional costs of increasing the

driving public's awareness and sense of responsibility as a part of the investment for an incident detection and management system. Moreover, it is suggested that reference location signs should be installed on roadsides at frequent intervals to provide drivers with more accurate location information (Walters *et al.*, 1999). On the other hand, no algorithm or parameter calibration work is involved. According to the nationwide survey of TMCs/TOCs, it is known that they face time-consuming, difficult calibration and validation efforts when implementing an algorithm. Since calibration is not an issue with cell phone systems, procedures developed in one area may be more readily transferable.

CHAPTER 5: EVALUATE COSTS OF DATA COLLECTION AND PROCESSING VERSUS DATA ACCURACY

The appropriate selection of incident detection and analysis systems depends on a variety of factors including the anticipated effectiveness of alternative systems and their cost, both initial and continuing. Decisions are almost invariably site specific and constrained by the availability of funds. This chapter is intended to supplement the discussion of sensor/detector technologies provided in the previous chapter by providing information regarding data quality and costs associated with different types of incident detection and analysis systems.

5.1 Factors and Costs Related to Sensor Data Accuracy

Errors affecting the accuracy of traffic sensors derive from a combination of three sources: 1) sensor measurement; 2) deterministic or systematic error associated with computing the estimator for the control parameter; and 3) random variations that corrupt the estimate of the control parameter (Klein, 2001). A typical standard for a 5-minute collection interval and a 30-second monitoring interval assumes that data accuracy will satisfy the requirement that vehicle detection is realized within ±1 vehicle for 90% of all 5-minute intervals; occupancy should measured within ±1% at 25% occupancy, volume within ±1 veh/min at 2,000 veh/h and speed within ±2-4mph 95% of the time (Klein, 2001; Robertson *et al.*, 1994).

5.1.1 Accuracy Issues of Roadway-Based Sensors

Most roadway-based traffic sensors can provide traffic parameter measurements on a satisfactory level for the above requirements. For example, a typical accuracy of speed measurement provided by magnetic or radar sensors is 2 km/h (Coutellier, 2000; Lion and Roussel, 1995). However, due to the difficulty of proper installation and calibration and the external influence of vehicle-induced pavement vibration and inclement weather, the accuracy of a sensor may be much lower. Accuracy is heavily dependent on a sensor's stability and reliability within a specific environment.

Although the reliability of ILDs has improved over the years, their performance is often compromised by inappropriate installation and maintenance procedures. Contributing factors are poor connections in the pull boxes; failure to twist wire pairs properly, leading to crosstalk; and faulty sawcut sealant application procedures (Klein, 2001). These problems are exacerbated when ILDs are installed in poor pavement or in areas where utilities frequently dig up the roadbed. Maintenance and replacement are an important consideration. It is reported that loop replacement costs in an intersection varied from $107 to $628 (Middleton and Parker, 2000).

Along with unit installation costs, the number of sensors required in a given application needs to be taken into account in evaluating their cost-effectiveness. The required distance between adjacent stations is directly related to the time required to detect an incident (Payne and Thompson, 1997). Thomas' research (1999) regarding the relationship between detector

location and travel characteristics indicated that the traditional placement of detectors at a 0.5- or 1-mile interval is inadequate to detect incidents quickly. In certain applications, wide-area detection sensors, e.g., VIP, which may be more expensive per unit, may be a better choice. For example, a typical urban intersection may require as many as 12 to 16 ILDs, the cost of which becomes comparable to that of a VIP (Klein, 2001). Furthermore, the installation and maintenance cost of the traditional ILD system may turn out to be much higher than that of a VIP system; and, the additional traffic data and visual information from the VIP system may yield greater benefits in terms of traffic monitoring and management.

Table 5-1 summarizes the findings of an evaluation of several detector technologies in a typical detection application (i.e., signalized intersection) conducted by the Texas Transportation Institute. The cost and accuracy of each technology is summarized. Traffic disruption costs should be included along with installation and maintenance costs when evaluating ILDs. The Texas Transportation Institute estimates that the total installation cost for placing three micro-loops under a typical two-lane state highway is $9,000 (Middleton, *et al.*, 1999). These costs include installation and the influence on the road traffic. As a potential alternative, multi-detection zone presence-detecting radar sensors have purchase costs significantly less than this amount with a lower installation cost.

Table 5-1 Quantitative evaluation of sensors at a typical detection zone (i.e., signalized intersection) (Source: Middleton *et al.*, 1999)

Sensor	Cost for a single detection zone[1]	Detection Accuracy	
		In-Pavement or Overhead	Roadside
ILD	$3,278	98%	-
Infrared (Active)	$14,520[2]	97%[3]	-
Infrared (Passive)	$8,051	97%	-
Microwave Radar	$3,590	95%	90%
Microwave Doppler	$6,496	-	-
Ultrasonic	$6,350	-	-
VIP	$3,370	95%	82%

[1] Four by four intersection with single left-turn lane.
[2] Assuming that four poles with mast arm are needed.
[3] Dropped to 77% in inclement weather.

5.1.2 Accuracy Issues of Probe-Based Sensors

Probe-based sensor systems are inherently less sensitive to individual sensor malfunction than are roadway systems in that the traffic variables are obtained through the aggregation of data from many probe sensors. The traffic measurement accuracy of a probe-based traffic surveillance system is mainly determined by two conditions: 1) the measurement accuracy of an individual probe sensor; and 2) the market penetration rate of probes in the traffic stream. Errors due to imprecision of individual probe sensors are unlikely to affect the accuracy of measured traffic variables (i.e., travel time) because relative differences in successive measurements tend to be consistent.

Figure 5-1 shows the relationship between the accuracy of average speed measurements and the percentage of GPS-equipped probes in the traffic stream in an arterial environment. The data were generated by means of an Integration-based simulation (Van Aerde, 1998). In this figure, the 2-RMSE (i.e., root mean square error) curve represents the speed accuracy at the 95% confidence level. It indicates that measurement errors of arterial link journey speed or travel time diminishes with an increase in the proportion of probe vehicles (i.e., the increase of investment) in the traffic stream and that the accuracy levels off at a probe proportion of approximately 15% to 18%. Measurement errors in travel time reflect the performance of incident detection algorithms based on travel time to some degree. This suggests that further investment in probe-equipped sensors and communication infrastructure would yield only marginal improvements in the performance of traffic surveillance and incident detections.

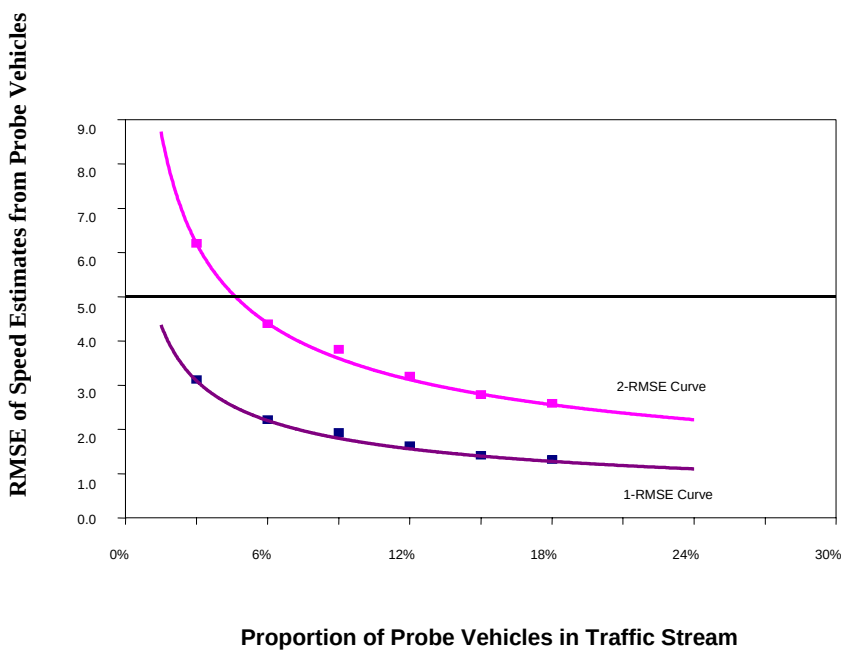
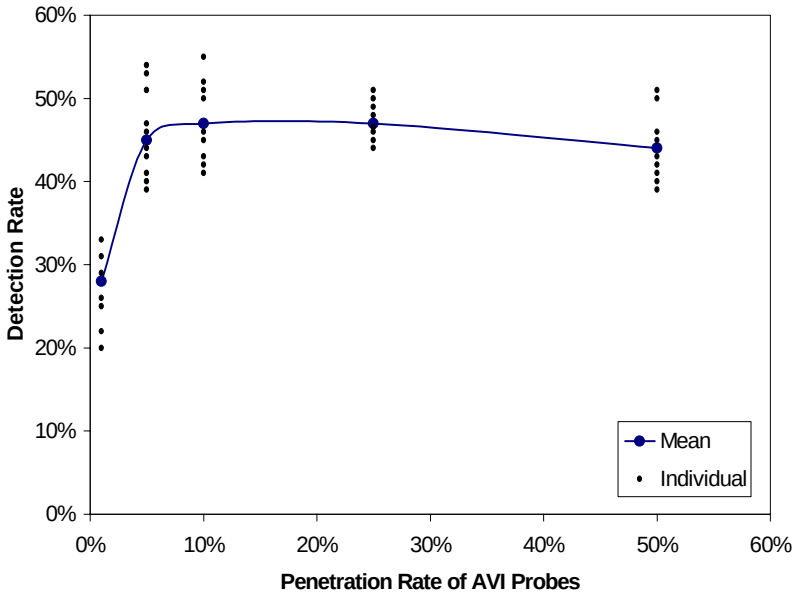
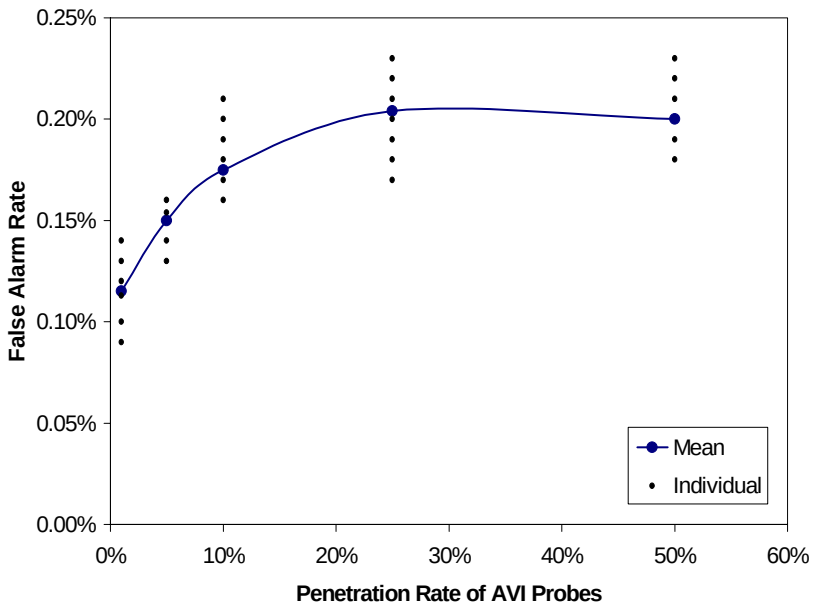


Figure 5-1 RMSE (Root Mean Square Error) of average link speed from probe vehicles versus proportion of probe vehicles (Source: Cheu *et al.*, 2000)

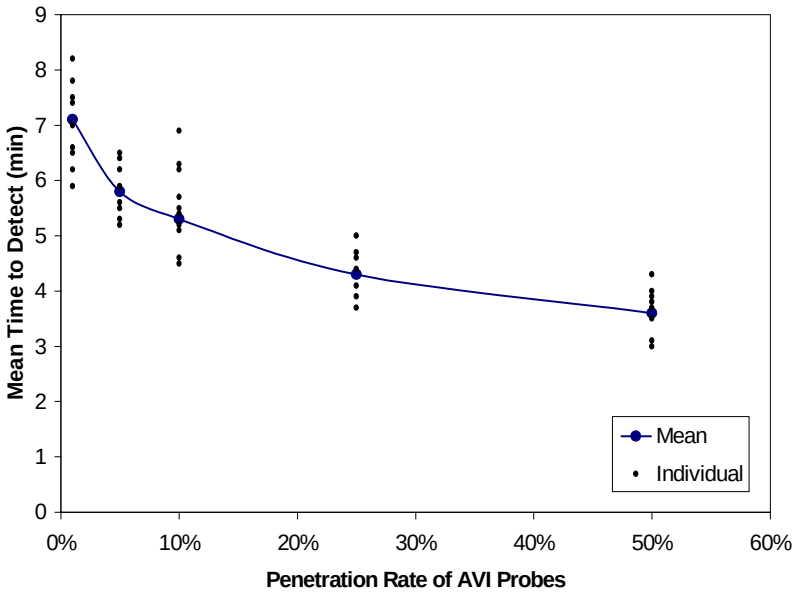
Hellinga and Knapp (2000) studied the relationship between AVI-based incident detection results and probe penetration rate on freeways. *Figure 5-2* illustrates the relationship between mean DR, FAR, and MTTD and probe penetration for a particular travel time-based incident detection algorithm (i.e., the so-called Speed and Confidence Limit algorithm, see *Chapter 1* for details). These performance measures indicate outcomes very similar to those shown in *Figure 5-1*. Incident detection performance can be improved by increasing the probe percentage when the penetration level is below approximately 20%; beyond that point, system performance increases only slightly, if at all.



(1) Detection rate versus probe penetration rate



(2) False alarm rate versus probe penetration rate



(3) Mean time to detect versus probe penetration rate

Figure 5.2 Relationship of incident detection performance and probe penetration rate

5.1.3 Accuracy of Driver-Based Sensors

As described in Section 4.3.3, the accuracy of driver-based incident detection techniques (e.g., wireless phone) depends on the prevailing traffic flow, penetration of wireless phone ownership across the driving population, drivers' willingness to report an incident, and the number of erroneous calls. The fraction of motorists with wireless phones onboard is closely related to the market penetration of wireless phones in the area. Since the cost of purchasing and using wireless phones does not fall upon the public agency and is essentially unrelated to the use of cell phones to report incidents, this cost need not be considered when evaluating this approach to incident detection. However, other factors— drivers' willingness to report and their ability to provide a correct report—heavily affect the timeliness and accuracy of those events that are reported. It may, therefore, prove to be cost-effective for public agencies to invest in educational and advertising programs designed to increase the driving public's awareness of the service that they can provide as a part of the investment in incident detection and management systems.

5.2 Sensor Unit and System Cost Evaluation and Comparison

A meaningful cost-effectiveness comparison between various sensor technologies can only be made in the context of a specific application.

Typical costs and other characteristics of sensor units and systems are reviewed below. *Table 5-2* summarizes the principal strengths and weaknesses of various roadway-based sensor technologies; *Tables 5-3* and *5-4* list the types of data provided by each type of sensor along with communication bandwidth requirements, unit costs, and other data.

Table 5-2: Strengths and weaknesses of commercially available sensor technologies (Klein, 2001)

Technology	Strengths	Weaknesses
Inductive Loop	Flexible design to satisfy large variety of applications. Mature, well-understood technology. Large experience base. Provides basic traffic parameters (e.g., volume, presence, occupancy, speed, headway, and gap). Insensitive to inclement weather such as rain, fog, and snow. Provides best accuracy for count data as compared with other commonly used techniques. Common standard for obtaining accurate occupancy measurements. High frequency excitation models provide classification data.	Installation requires pavement cut. Improper installation decreases pavement life. Installation and maintenance require lane closure. Wire loops subject to stresses of traffic and temperature. Multiple detectors usually required to monitor a location. Detection accuracy may decrease when design requires detection of a large variety of vehicle classes.
Magnetometer (Two-axis fluxgate magnetometer)	Less susceptible than loops to stresses of traffic. Insensitive to inclement weather such as snow, rain, and fog. Some models transmit data over wireless RF link.	Installation requires pavement cut. Improper installation decreases pavement life. Installation and maintenance require lane closure. Models with small detection zones require multiple units for full lane detection.
Magnetic (Induction or search coil magnetometer)	Can be used where loops are not feasible (e.g., bridge decks). Some models are installed under roadway without need for pavement cuts. However, boring under roadway is required. Insensitive to inclement weather such as snow, rain, and fog. Less susceptible than loops to stresses of traffic.	Installation requires pavement cut or tunneling under roadway. Cannot detect stopped vehicles unless special sensor layouts and signal processing software are used.
Microwave Radar	Typically insensitive to inclement weather at the relatively short ranges encountered in traffic management applications. Direct measurement of speed. Multiple lane operation available.	CW Doppler sensors cannot detect stopped vehicles.
Active Infrared (Laser radar)	Transmits multiple beams for accurate measurement of vehicle position, speed, and class. Multiple lane operation available.	Operation may be affected by fog when visibility is less than 20 ft (6 m) or blowing snow is present. Installation and maintenance, including periodic lens cleaning, require lane closure.

Technology	Strengths	Weaknesses
Passive Infrared	Multizone passive sensors measure speed.	Passive sensor may have reduced vehicle sensitivity in heavy rain, snow & dense fog. Some models not recommended for presence detection.
Ultrasonic	Multiple lane operation available. Capable of overheight vehicle detection. Large Japanese experience base.	Environmental conditions such as temperature change and extreme air turbulence can affect performance. Temperature compensation is built into some models. Large pulse repetition periods may degrade occupancy measurement on freeways with vehicles traveling at moderate to high speeds.
Acoustic	Passive detection. Insensitive to precipitation. Multiple lane operation available in some models.	Cold temperatures may affect vehicle count accuracy. Specific models are not recommended with slow moving vehicles in stop-and-go traffic.
Video Image Processor	Monitors multiple lanes and multiple detection zones/lane. Easy to add and modify detection zones. Rich array of data available. Provides wide-area detection when information gathered at one camera location can be linked to another.	Installation and maintenance, including periodic lens cleaning, require lane closure when camera is mounted over roadway (lane closure may not be required when camera is mounted at side of roadway) Performance affected by inclement weather such as fog, rain, and snow; vehicle shadows; vehicle projection into adjacent lanes; occlusion; day-to-night transition; vehicle/road contrast; and water, salt grime, icicles, and cobwebs on camera lens. Requires 50- to 70-ft (15- to 21-m) camera mounting height (in a side-mounting configuration) for optimum presence detection and speed measurement. Some models susceptible to camera motion caused by strong winds or vibration of camera mounting structure. Generally cost-effective when many detection zones within the camera field-of-view or specialized data are required.

Table 5-3 Types of data, needed bandwidth, and costs of roadway-based sensors (Klein, 2001)

Sensor Technology	Count	Presence	Speed	Output Data Occupancy	Classification	Multiple Lane, Multiple Detection zone data	Communication Bandwidth	Sensor Purchase Cost (each in 1999 US $)
Inductive Loop	✓	✓	✓	✓	✓		Low to Moderate	Low ($500-$800)
Magnetometer (two axis fluxgate)	✓	✓	✓	✓			Low	Moderate ($900-$6,300)
Magnetic Induction Coil	✓	✓	✓	✓			Low	Low to Moderate ($385-$2,000)
Microwave Radar	✓	✓	✓	✓	✓	✓	Moderate	Low to Moderate ($700-$2,000)
Active Infrared	✓	✓	✓	✓	✓	✓	Low to Moderate	Moderate to High ($6,500-$3,300)
Passive Infrared	✓	✓	✓	✓			Low to Moderate	Low to Moderate ($700-$1,200)

Ultrasonic	✓	✓		✓			Low	Low to Moderate (Pulse Model: $600)
Acoustic Array	✓	✓	✓	✓		✓	Low to Moderate	Moderate ($3,100-$8,100)
Video Image Processor	✓	✓	✓	✓	✓	✓	Low to High	Moderate to High ($5,000-$26,000)

Table 5-4 Unit cost overview of roadway-based sensors (Source: Middleton and Parker, 2000; Berka and Lall, 1998)

Sensor	Mode	Unit Cost	Coverage
ILD	Passive	$370	Single Lane
Magnetic	Passive	$875[1]	Single Lane
Microwave Radar	Active	$3,500[1]	Multiple Lanes
Microwave Doppler	Active	$1,000[1]	Multiple Lanes
Infrared	Active	$4,500[1]	Multiple Lanes
Infrared	Passive	$1,500	Multiple Lanes
Ultrasonic	Active	$560[1]	Single Lane
Acoustic	Passive	$485	Single Lane
Laser	Active	N/A	Double Lanes
VIP	Passive	$3480	Multiple Lanes

Typical data reflecting the unit costs and current penetration rate of probe-based sensors are listed in *Table 5-5*.

[1] Prices are up-to-date as of June 1996.

Table 5-5 Unit cost overview of probe-based sensors (Source: Sutton, 1998; Walters *et al.*, 1998; Klein, 2001)

Sensor	Functions	Unit Cost	Penetration Rate
GPS Receiver	Positioning, route guidance, fleet management	$200-500	1%-5%[1]
AVI Transponder	ETC/ETTM, ECP	$15, 100-250[2]	10%-30%[3]
Cellular Phone	Personal communication	$0	17%-36%

When viewing these tables, the following should be kept in mind: 1) the cost as well as the penetration rate indicated in the above tables are based on the corresponding cases and can be influenced by local conditions and particular configurations; 2) the data collected in the past five years may not reflect the latest information; and 3) many of these technologies are constantly being improved and hence their accuracy may increase and their price may decrease over time.

A more site-specific set of cost comparisons including capital (hardware and installation) and annual (maintenance and operations) costs is provided in *Table 5-6*. This table is abstracted from a report prepared for TRANSMIT (Transportation Operations Coordinating Committee's System for Managing Incidents and Traffic) by Mouskos *et al.* (1999) and Niver *et al.* (2000). It shows cost comparisons of 4 types of sensors for an incident and traffic management system along a 6-lane highway. The hardware capital costs include field components of a typical detection site installed along the system as well as the ancillary equipment. The system installation cost covers the field installation of hardware, cabinet and foundation, cables, and so forth. The maintenance costs for a detection site include on-site hardware and software support and personnel expenses. Operations costs involve costs for leased telephone lines and utilities expenses.

[1] Typical data currently reflected in some U.S. main metropolitan areas.
[2] Different types of transponders (i.e., IVR, toll, or beam) have dramatically different prices.
[3] Typical data currently reflected in Toronto, Dallas, Houston, Oklahoma, San Diego, San Antonio metropolitans and some counties in California

Table 5-6 Comparative costs of incident detection systems per detection site (Source: Mouskos *et al.*, 1998)

Cost Item		ILD	VIP	MRD[1]	AVI
Capital Cost	Hardware	$ 4,100	$ 24,500	$ 26,500	$ 14,700
	Installation	$ 50,560	$ 45,100	$ 25,200	$ 21,700
	Total	$ 54,660	$ 69,600	$ 51,700	$ 36,400
Annual Cost	Maintenance	$ 7,950	$ 3,300	$ 2,900	$ 2,900
	Operations	$ 2,040	$ 2,040	$ 2,040	$ 2,040
	Total	$ 9,990	$ 5,340	$ 4,940	$ 4,940
Year-One Total Cost		$ 64,650	$ 74,940	$ 56,640	$ 41,340

The results show that ILD and VIP systems have the highest installation and capital costs. The maintenance cost used for ILD system is much higher (i.e., 2-3 times) than other sensor systems.

[1] MRD stands for microwave radar detection system in the TRANSMIT project.

CHAPTER 6: REVIEW PROCEDURES FOR CALIBRATING INCIDENT DETECTION ALGORITHMS AND PARAMETERS

Incident detection algorithms and procedures need to be calibrated at at least three different levels: the sensors used to collect traffic data need to be calibrated or adjusted to obtain the most accurate information, the data need to be pre-processed before they are used in detection algorithms or procedures, and all three types of incident detection methods -- roadway-based, probe-based, and driver-based -- need algorithm- or procedure-specific calibration.

6.1 Sensor-Based Calibration

As described in Chapters 4 and 5, most of the sensors used to acquire data for incident detection require calibration or at least adjustment to obtain the most accurate data. In fact, poor performance of incident detection methods can generally be linked to poor initial data quality and lack of or poor calibration of installed sensors. This calibration affects the performance of different types of sensors whether they are used on freeways or arterials.

6.1.1 Calibration of Roadway-Based Sensors

The most widely used roadway-based sensors are Inductive Loop Detectors (ILD). The spotty performance of these sensors is well known. Installation of inductive loops, as described in Chapter 4, may result in data problems due to improper connections in pull boxes, sealants being applied poorly, sporadic communication with controller or central traffic management center, etc. Each individual sensor must be calibrated so that vehicle presence and occupancy may be standardized along a roadway. Pairs of loop detectors providing speed measures need further calibration for accurate speed measurements

Other types of roadway-based sensors such as magnetic, infrared, ultrasonic, etc. need as much or more site-specific calibration before data is acquired. Side and overhead-mounted detectors and video processing systems may also get "jilted" or moved in severe weather or in a crash requiring calibration before data can be again used from the sensor.

6.1.2 Calibration of Probe-Based Sensors

In contrast to the roadway-based sensors, most probe-based sensors are not likely to need calibration. However, modified point-based sensors that are used to re-identify vehicles at different points along the roadway (mentioned in Section 4.1) require a great deal of calibration.

6.1.3 Calibration of Driver-Based "Sensors"

The system recommended in the next chapter relies heavily on what we have referred to as driver-based "sensors" including individual cell phone reports of crashes and other incidents along the roadway. Professionals, including freeway service patrols and police patrols, are generally able to identify clearly to traffic management center (TMC) personnel the location, severity, and immediate impacts of an incident. However, incident

reports from citizens, no matter how well intentioned, may not provide desired information to TMC personnel. Thus, such reports need to be calibrated in order to best determine existing traffic conditions—and to filter out false alarms.

6.2 Data Pre-Processing

Before data is used in a detection algorithm or procedure, it should be pre-processed for false alarms and erroneous data. Pre-processing also includes aggregation of raw data into formats used in the algorithms and procedures. For example, the raw data of most roadway-based sensors are aggregated into 30-second or 1-minute intervals for use in algorithms. Longer aggregation periods are more likely to smooth anomalous or "noisy" data, but longer aggregation periods lead to a longer time-to-detect if an incident occurs. Similarly, largely due to the limited availability (small penetration rate) of probe-based sensors, aggregation periods tend to be longer—even up to 15 minutes, as described in Chapter 1. One recommendation is to use longer aggregation periods only on lower volume roadways (and possibly on roadways with lower percentages of vehicles with transponders and other probes). Shorter periods, such as five minutes or less, can be used on roadways with greater percentages of probe vehicles (over 20%, as indicated in the Figures in Chapter 5) and/or during peak periods.

6.2 Algorithm or Procedure-Specific Calibration

Much of the literature focused on algorithm-specific calibration of roadway-based sensor (inductive loop-based) algorithms. Algorithm performance depends in part on calibrating detection parameters for each roadway section. Using incident data, one needs to determine the best combination of parameters that maximizes detection rate and minimizes false alarm rate and time-to-detect, as described in Chapter 3. One study reports that algorithms cannot be properly calibrated unless an incident occurs in every detection zone (Balke, 1993). This is likely too extreme a requirement, but the few calibration efforts reported in the literature do describe calibration of algorithm parameters in every detection zone (between every set of detectors). Algorithms with more parameters, such as the McMaster algorithm (with ten parameters requiring calibration), make the process and accurate reporting of incidents difficult. One can argue that more parameters leads to better results, but smaller numbers of parameters are likely to aid in transferability of different algorithms and procedures and ease of implementation, as reported in Chapter 3.

Even "self-calibrating" algorithms or learning processes such as neural networks and genetic algorithms require extensive training with real incident data and subsequent testing with additional incident data. Difficulties with calibration and the general lack of success with automatic algorithms reported by traffic management centers, as well as the increasing availability of cell phone reports, leads us to the conclusion that interest in the exclusive use of automatic algorithms is waning in favor of some combination of roadway-based detection systems and driver-reported information.

PART 7: RECOMMEND AN INCIDENT DETECTION APPROACH

Much space in this report has been given to the traditional roadway-based automatic algorithms and their performance. But despite years of modifications by many researchers and individual traffic management centers adopting their own automatic incident detection algorithms, staying with a traditional roadway-based automatic incident detection system does not seem appropriate given the new types of sensors and even more glaringly, the preponderance of cellular phones and the ability to almost-instantaneously report crashes with high accuracy in terms of location. The system that we propose here is to use driver-based phone reports with some supplements.

7.1 Driver-Based Cell Phone Reports

Cell phone use is ubiquitous. Over two-thirds of Americans own a cell phone, many of which are used in vehicles (American Demographics, 2002). Americans cite "security and safety" as reasons to have a cell phone and thus they are likely to think of them to report a crash that they are involved in or that they are affected by. A major advantage to cell phone reports is that all roadway types, including minor roads (not just freeways or major arterials), are covered. As more and more cell phones are adopted and their use increases, the potential exists for a large percentage of crashes and incidents to be reported instantly. Compared to roadway-based and probe-based incident detection systems, cell-phone reports are "rich" in terms of specific incident location, number of vehicles directly affected, whether the incident is in a traffic lane and can be easily moved out of a traffic lane, etc. As described in Chapter 4, drawbacks to using cell phone reports for incident detection include drivers' willingness to report crashes and their ability to relate accurately crash location, severity, effect on traffic, etc. Here we suggest some ways to improve reporting and ease operator work in identifying appropriate callers, and discuss elements that can be used to supplement cell phone reports.

Chapter 4 provides a review of the literature concerning the use of cell phone reports for incident detection. A 1999 TxDOT study (Walters *et al.*, 1999) suggests that managing a cell phone incident detection system requires 10% of the costs of a loop detector system that employs a fiber-optic network. Both systems require operators at a traffic management center, but there are no field hardware requirements with a cell phone system, especially if E911 technology can be utilized to pinpoint callers' locations.

Using cell phone reports requires a trade-off between encouraging only affected vehicles to call in with a crash report (thus, it may take longer for crashes involving vehicles without a cell phone in them to be reported) and receiving many phone calls about "atypical congestion" from frustrated motorists. Too many phone calls places an undue burden on traffic operations center personnel, who need to quickly identify pertinent information about the incident and then manage the incident rather than field additional phone calls. But discouraging phone calls from motorists not directly affected in an incident may result in a longer time to detect an anomaly if directly affected motorists do not have a cell phone or do not quickly report the mishap.

Anecdotal reports suggest that some traffic management centers consider the occurrence of an incident to have been confirmed only after three phone reports are received. Multiple callers are likely to provide slightly different versions of the crash. Some callers may be better than others at quickly providing pertinent incident details. Without multiple-caller information, the traffic management center can use police or freeway service patrols or video camera systems to confirm that a crash has occurred and that traffic management is needed. While several hundred miles of freeways are monitored by freeway service patrols during peak hours, video surveillance systems only operate on limited freeway sections. Waiting for on-scene verification may add unduly to the incident detection time and delay appropriate traffic mitigation measures. Thus, we suggest a system using multiple cell phone reports to confirm that an incident worthy of further attention has occurred. Further, operators need to be trained to prompt callers for desired information and how to detect a possible erroneous phone call. Operators need to determine whether the current caller can provide necessary information or whether it is better to listen to another caller.

A basic cell phone reporting system should have two components: signage and driver education. A more sophisticated system may use a recording for heavy call times. All systems can be supplemented as described below.

The most effective systems include roadway signage providing a call-in number for incident reporting (*99, 911), etc. The signs should include text such as "Report observed crashes to *99", or "Dial *99 if you are involved in a crash." Many road users are likely to remember the appropriate number through subsequent use of the roadway, but new (non-local) users are likely to also pay attention to the signs.

If the Traffic Management Center is not able to utilized E911 technology that pinpoints the location of emergency callers, then mileage markers (every mile and 1/10 of a mile) are needed on major roadways to help identify the caller's location. Many callers are not able to describe clearly the distance they are from a freeway exit but this information is likely to be needed by TMC personnel. On arterial streets, mileage markers are less useful because callers are more likely to report the cross-streets of adjacent intersections. Currently, GPS chips are available in many cell phones. If the cell phone user subscribes to certain networks and services, the phones can be tracked (and location pinpointed) when the cell phone is on with free-domain software. Carriers are required to include GPS-chips as a standard feature on phones by the end of 2005. It is not clear that all phones will be "trackable" immediately, but the emphasis on locating E911 callers should have great benefit to traffic management and information centers.

Signage can educate drivers about an incident-reporting system, but billboards, public service announcements, messages with drivers license renewals and driver education training are likely to be as effective or more effective in encouraging drivers to accept their responsibility to report an incident from a given class of roadway, and what information to provide.

Many traffic management centers work with 911 operators, who speak to affected drivers and then pass appropriate information on to the TMC. Working in conjunction with 911 systems and operators has the advantage of available position location systems and using the 911 operators to talk with individuals while TMC personnel obtain only traffic-important information. Another advantage may be the reduction in false alarms as most of the public is unlikely to falsely call 911. A disadvantage may be a slight delay in obtaining necessary location and traffic information, but the advantages are likely to counteract this. Working with the 911 system is likely the best option for smaller traffic management facilities.

A recorded-message phone system may alleviate TMC/TOC operator workload during peak hours or during incidents. After multiple phone calls have been received about an incident, further calls within a specified time period (20 minutes, say, or until clearance of the incident) can be initially answered with a recording, ideally modified with the introduction "We are aware of the crash/incident/accident reported at _____ location and Center personnel are working to manage congestion related to this incident." Callers who are either directly involved in the incident or who want to report an additional incident are then instructed to push a specified number to provide new information. Ideally, all callers should get information during the phone call about who should be reporting incident information and, ideally, be directed to a 511 system that would provide traffic information that will help reduce their delays.

7.2 Supplements to the Driver-Based Phone System

As described above, existing driver-based surveillance elements such as police patrols, freeway service patrols, and video monitoring systems, can be used to verify that an incident has occurred and to call for appropriate actions by transportation management center personnel to alleviate congestion. As shown in Figure 2-5, the TMCs and TOCs that were surveyed utilize closed circuit TV monitoring, highway and maintenance patrols and phone reports to verify incidents.

Here we propose also to use new sensors including travel times of probe vehicles to confirm that an incident has occurred and to help with post-incident traffic management plans. With more and more drivers acquiring electronic transponders for electronic toll payments, determining travel times on all kinds of roadways requires a system of readers that recognize that the same vehicle has passed different reader locations. Readers may be placed on freeways and on arterials and other roadways. Similar information can be obtained with license plate reader systems, but toll tag reading technology and matching can be piggybacked on existing electronic toll systems and, thus, will likely prove to be more cost-effective. Chapter 1 described automatic algorithms that reported incident occurrence when travel times did not match historic times. These automatic algorithms seem to be imperfect as a primary detection system as described in Chapter 3, but as a supplemental and/or confirmation system, they should be valuable to a traffic management system.

Using non-driver based sensors require algorithms (matching algorithms, for example) and calibration (at least of appropriate aggregation periods). Some of the pitfalls described in Chapter 6 apply. But the goal of most traffic management systems should be to utilize available traffic information. Cell phone reports are available with a minimum of

signage and education. Some of the new sensors such as toll transponders with better section/travel time traffic information are becoming more commonly available. A combined system is likely to be most appropriate for current traffic management centers. A subset of these combinations can be used by smaller and new facilities.

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APPENDIX A: THE COVER LETTER AND QUESTIONNAIRE OF THE SURVEY – "INCIDENT DETECTION ALGORITHMS AND THEIR IMPLEMENTATIONS"

"INCIDENT DETECTION ALGORITHMS AND THEIR IMPLEMENTATIONS"

A Nationwide Survey on Transportation Management Centers and Transportation Operations Centers

Dear Fellow Transportation Engineer,

Traffic Management Centers (TMCs) and Traffic Operations Centers (TOCs) have spent millions of dollars implementing automatic incident detection (AID) algorithms. We question how worthwhile these expenditures have been. We intend to formulate criteria for successful implementation partly through sharing your experiences. Therefore, the University of Massachusetts Transportation Center has been carrying out a research project titled "A Complete Review of Incident Detection Algorithms and Their Deployment: What Works and What Doesn't" for the New England Transportation Consortium (NETC). In order to obtain technical information concerning the application and implementation of incident detection systems, we are conducting a nationwide survey on TMCs and TOCs.

It is our pleasure to know that you are interested in and capable of responding to us for this survey as a professional at your TMC. The online survey includes five parts: 1) Responder's information; 2) TMC-related information; 3) Implemented equipment and techniques; 4) Algorithm application and evaluation; and 5) Future plans and suggestions. This survey is designed so that it should take about 10 minutes for you to complete it. **Please fill out what you can as soon as possible and send it back to us. You may want to forward the survey or the link to colleagues that you think may be better prepared for some of the questions. Thank you for your time and effort!** Alternatively, you can print out the survey form in either "*.PDF" or "*.DOC" format and fax it back to us at (413) 545-9569. You also can fill out the "*.DOC" version of the survey and email it back to us at cxie@ecs.umass.edu, but there may be some formatting errors in using the earlier versions of Microsoft® Word™.

Should you have any questions or comments, please feel free to contact our project staff member Mr. Chi Xie at (413) 545-3852 or e-mail address cxie@ecs.umass.edu. If you are interested, please indicate at the end of the survey questionnaire that you would like to receive a technical report summarizing this survey. Thank you very much. We look forward to learning from your responses.

Sincerely,

Dr. A. Emily Parkany, Ph.D.
Assistant Professor
Department of Civil and Environmental Engineering
University of Massachusetts, Amherst

UMass® Transportation Center

[Part 1] Responder's Information

Please provide your agency name and facility name, at a minimum. If you provide us with a mailing address, we will send you a summary of our survey when our results are collected and analyzed. Herein, we guarantee that we do not intend to disclose any of your specific information to any other individuals or institutions without your prior written permission.

☐ Please check this box, if you would like to receive the final report of this survey in a few months after we receive a complete questionnaire from you.

Agency: [_____]

Facility: [_____]

State: [_____] **Zip Code:** [_____]

Mailing Address: [_____] (Office)

First Name / Middle Initial / Last Name: [_____ / _____ / _____]

Prefix: ☐ **Dr.** / ☐ **Mr.** / ☐ **Mrs.** / ☐ **Ms.**

Title: [_____]

Phone: [(_____) _____ - _____] **Fax:** [(_____) _____ - _____]

E-mail: [_____@_____]

[Part 2] TMC - Related Information

This part includes some descriptions of your Transportation Management Center, such as location, roadway types, operation functions and services.

TMC: [_____] (If TMC name is different from facility name above)

Operational History: [_____]

A. < 1 Year B. 5-10 Years C. 10-15 Years D. 15-20 Years E. 20-30 Years F. > 30 Years

Daily Operation Hours: [_____]

A. 24 Hours B. 20-24 hours C. 16-20 Hours D. 12-16 Hours E. 8-12 Hours F. 4-8 Hours G. < 4 Hours

Types of Operated Roadway: (Please check all that apply)

☐ Freeways ☐ Major Arterials ☐ Minor Arterials ☐ Collectors ☐ Local Streets

☐ Other: [_____] (Please indicate)

Operation Tasks: (Please check all that apply)

☐ Traffic Management ☐ Incident Management ☐ Commercial Vehicle Operations

☐ Transit Management ☐ Fleet and Freight Management ☐ Traffic Information Provision and Dissemination

☐ Toll / Revenue Collection ☐ Other: [_____] (Please indicate)

☐ Other: [_____] (Please indicate)

Degree of application of advanced technologies at your TMC, as compared to other TMCs throughout U.S.: [_____] (Based on your estimation)

A. Highly Advanced B. Fairly Advanced C. Intermediate D. Less Advanced E. Outmoded

[Part 3] Implemented Equipment and Techniques

Please describe the equipment and techniques applied for incident detection and incident response at your TMC.

Primary approach for Incident Detection: [_____]

A. AID (Automatic Incident Detection) System Alert B. CCTV (Closed-Circuit Television) Monitoring

C. Highway Patrol / Maintenance Crew Patrol D. Witness Report / Police Report / Cellular Phone Call

E. Aerial / Satellite Surveillance F. Other: [_____] (Please indicate)

Secondary approach for Incident Detection: [_____]

A. AID (Automatic Incident Detection) System Alert B. CCTV (Closed-Circuit Television) Monitoring

C. Highway Patrol / Maintenance Crew Patrol D. Witness Report / Police Report / Cellular Phone Call

E. Aerial / Satellite Surveillance F. Other: [_____] (Please indicate)

How to verify an incident reported by the incident detection system at Your TMC? [_____] (Check all that apply)

A. No Identification Method B. Consistent Test in AID System C. CCTV (Closed-Circuit Television) Monitoring

D. Patrol Report E. Other Witness Report F. Other: [_____] (Please indicate)

Fixed (i.e., roadside-installed) sensors and detectors applied for AID, number of sensors in one detection section (e.g., a freeway section, an on-ramp or off-ramp section, or a link of signalized streets) and approximate total number in the whole management region:

For example: ☑ Single Inductive Loop Detector | Number in One Section: [2] | Total Number: [1000]

☐ Single Inductive Loop Detector | Number in One Section: [_____] | Total Number: [_____]

☐ Double Inductive Loop Detector | Number in One Section: [_____] | Total Number: [_____]

☐ Video Image Processor | Number in One Section: [_____] | Total Number: [_____]

☐ Other: [_____] | Number in One Section: [_____] | Total Number: [_____]

Types of traffic data derived from fixed sensors or detectors for incident detection and output frequency:

For example: ☑ Volume | Frequency: [0 minute(s) 30 second(s)]

☐ Volume | Frequency: [_____ minute(s) _____ second(s)]

☐ Occupancy | Frequency: [_____ minute(s) _____ second(s)]

☐ Time Mean Speed | Frequency: [_____ minute(s) _____ second(s)]

☐ Space Mean Speed | Frequency: [_____ minute(s) _____ second(s)]

☐ Density | Frequency: [_____ minute(s) _____ second(s)]

☐ Headway | Frequency: [_____ minute(s) _____ second(s)]

☐ Delay | Frequency: [_____ minute(s) _____ second(s)]

☐ Queue Length | Frequency: [_____ minute(s) _____ second(s)]

☐ Other: [_____] | Frequency: [_____ minute(s) _____ second(s)]

☐ Other: [_____] | Frequency: [_____ minute(s) _____ second(s)]

Communication between the fixed field detectors or collectors and TMC: (Please check all that apply and give approximate percentage of data obtained via this kind of communication)

☐ Phone Lines | Estimated Percentage: [_____%]

☐ Coaxial Cable | Estimated Percentage: [_____%]

☐ Fiber Optic Cable | Estimated Percentage: [_____%]

☐ Wireless | Estimated Percentage: [_____%]

☐ Other: [_____] | Estimated Percentage: [_____%]

Mobile (i.e., vehicle-based) systems applied for Incident Detection and estimated percentage of vehicles equipped with the transponder in the traffic stream:

What percentage of your system has toll transponders? [_____%]

What percentage of these transponders can you get traffic data from? [_____%]

Please describe whether these transponders are used for automatic incident detection: [_____]

A. Current B. Will use C. Want to use D. No

Are you satisfied with the implemented sensors or systems for Incident Detection? ☐ Yes or ☐ No.

If you selected "No" in the last question, please select all applicable reasons and rank them: ("1" indicates most severe)

[_____] Frequent Malfunction [_____] Low Accuracy [_____] Troublesome Installation

[_____] Inconvenient Maintenance [_____] Instability [_____] Not Cost-Effective

[_____] Other: [_____] (Please indicate)

Please describe any problems or drawbacks existing in the hardware of your system:

[_____

_____

_____

_____

_____]

[Part 4] Algorithm Application and Evaluation

Please indicate your applied algorithm for incident detection and give advantages and disadvantages.

Which major AID (Automatic Incident Detection) algorithm is implemented at your TMC? (Check all that apply)

- ☐ **California Algorithm Series** (Developed by California State Department of Transportation)
- ☐ **APID (All Purpose Incident Detection) Algorithm** (Developed for the Toronto COMPASS advanced traffic system)
- ☐ **McMaster Algorithm (Catastrophe Theory)** (Developed at University of McMaster in Canada)
- ☐ **Minnesota Filtering Algorithm** (Developed at University of Minnesota)
- ☐ **Neural Network Algorithms**
- ☐ **Algorithms for AVL (Automatic Vehicle Location) or AVI (Automatic Vehicle Identification) Systems**
- ☐ **Algorithms Using Multiple Data Fusion or Integration**
- ☐ **SND (Standard Normal Deviate) Algorithm** (Developed in the Texas Transportation Institute)
- ☐ **Bayesian Algorithm**
- ☐ **Time Series ARIMA Algorithm**
- ☐ **HIOCC (High Occupancy) Algorithm**
- ☐ **Exponential Smoothing Algorithm**
- ☐ **Low Volume Incident Detection Algorithms**
- ☐ **Fuzzy Set Algorithms**
- ☐ **Other: [_____]** (Please indicate) | **Algorithm Developer: [_____]**
- ☐ **Other: [_____]** (Please indicate) | **Algorithm Developer: [_____]**

- ☐ **High Detection Rate: [_____]**

  A. 98-100% B. 95-98% C. 90-95% D. 85-90% E. 80-85%

- ☐ **Low False Alarm Rate: [_____]**

  A. 0-1% B. 1-2% C. 2-5% D. 5-10% E. 10-15% F. 15-20%

- ☐ **Short Time to Detection: [_____]**

  A. < 0.5 minute B. 0.5-1 minute C. 1-2 minutes D. 2-3 minutes E. 3-5 minutes F. > 5 minutes

Disadvantages of the implemented algorithm: (Check all that apply)

- ☐ **Difficulty in Implementation | What is the major difficulty? [_____]**
- ☐ **Difficulty in Calibration | What is the major difficulty? [_____]**
- ☐ **Low Detection Rate: [_____]**

  A. < 50% B. 50-60% C. 60-70% D. 70-80% E. 80-90%

- ☐ **High False Alarm Rate: [_____]**

  A. 10-20% B. 20-30% C. 30-40% D. 40-50% E. > 50%

- ☐ **Long Time to Detection: [_____]**

  A. 1-2 minutes B. 2-3 minutes C. 3-4 minutes D. 4-5 minutes E. 5-10 minutes F. > 10 minutes

Overall reliability of detection result of the implemented algorithm, compared to CCTV monitoring and other witness reports:

☐ **Mostly Reliable** ☐ **Fairly Reliable** ☐ **Sometimes Reliable, Sometimes Unreliable** ☐ **Less Reliable** ☐ **Unreliable**

Data requirements for the above implemented algorithms: (Check all that apply)

☐ **Volume** ☐ **Occupancy** ☐ **Speed** ☐ **Individual Vehicle Location and Speed**

☐ **Other: [_____]** (Please Indicate) ☐ **Other: [_____]** (Please Indicate)

Incident detection report content of the implemented algorithms:

☐ Incident Occurred or Incident Free ☐ Incident Location ☐ Incident Severity

☐ Other: [_____] (Please Describe) ☐ Other: [_____] (Please Describe)

What are possible improvements to the implemented algorithm?

[_____

_____

_____

_____]

How do you evaluate the implemented AID (Automatic Incident Detection) system at your TMC? [_____]

A. It is very necessary and can satisfy our needs very well

B. It is very necessary but can fit for our needs only if it works in combination with other incident detection approaches

C. It is necessary but functions as a supplementary system for incident detection

D. It is not necessary

Do you have any other comments related to Automatic Incident Detection algorithms?

[_____

_____

_____

_____]

[Part 5] Future Plans and Suggestions

In the last part of this survey, please describe future plans for the application of advanced technology at your TMC. Moreover, any suggestions or comments about this survey are welcome!

What operational changes or enhancements to your TMC do you have planned for the future?

[_____

_____

_____

_____]

What plan for incident detection do you have for the future? Please describe the plan (including approximate implementation year, type of new implemented technology, function of new technology at your TMC):

[_____

_____

_____

_____]

Please describe your TMC's plan to remove outmoded techniques or equipment:

[_____

_____

_____

_____]

Please feel free to give us any suggestions or comments about this survey:

[_____

_____

Thank You Very Much for Your Participation!

Please fax the completed questionnaire to the project staff member Mr. Chi Xie at (413) 545-9569 or email to cxie@ecs.umass.edu.