4

Incident Detection

4.1 Introduction

Incident detection and verification is the first step of an efficient incident management process. (It is a misnomer to call the first step of incident management process “incident detection” instead of the more complete term “incident detection and verification.” However, it is well understood that incident verification is an integral part of this first step.) Incident detection can be defined as the process of identifying the spatial and temporal coordinates of an incident. It is important to emphasize verification as part of a complete incident detection concept, because most of the subsequent incident management steps are undertaken only after the existence of the incident has been verified.

This chapter attempts to give a satisfactory description of the state of the practice in the area of incident detection and verification. Because of the large body of literature that exists in this area, it is impossible to cover all possible algorithms. Our aim is to introduce the concept of incident detection and verification by presenting some of the more prominent algorithms that are widely used today. More important, some of the new field operation tests involving the deployment and evaluation of incident detection techniques are presented. By doing so, we hope to give the reader a snapshot of recent and interesting incident detection projects across the United States.

Another important aspect of this chapter is its presentation of developments in the area of surface street incident detection rather than limiting the discussion to freeway incident detection. The latter usually receives more attention for many reasons, which are discussed later in this chapter.
4.2 What Is Incident Detection?

Incident detection is not a new concept in traffic management. It has been around since the mid-1960s and early 1970s as part of standard traffic/incident management practice. In the 1960s, loop detector occupancies greater than 40% were used in Chicago to identify high reduction in capacity and as an early warning of potential freeway incidents. Incident detection, which is the process of determining the presence and location of an incident, has two major steps:

1. Determine the existence of congestion using data obtained from a surveillance system.
2. Analyze the data to determine if the cause of the congestion is an incident.

4.2.1 Traffic Surveillance and Data

The first step requires some kind of traffic surveillance system, which is also an integral part of the traffic management process. In traffic engineering terminology, surveillance denotes the real-time observation of traffic flow conditions in time both and space. The first step of incident detection process, namely, surveillance of roads, has been around since the early 1960s. Detroit was the first U.S. city to implement a surveillance system that comprised CCTV cameras, loop detectors for traffic detection, and variable signs for control purposes. The system became operational in the spring of 1961. Since then, almost all the major cities in the United States implemented a form of traffic surveillance for traffic monitoring and control purposes. The traffic surveillance systems include a variety of traffic sensors on the road and highway safety or police patrols. In addition to those data sources, drivers report incidents using emergency call boxes, cellular phones, and citizens band (CB) radio. The TOC plays an important role by coordinating the incoming data regarding incidents and making decisions for managing the incidents. Thus, the surveillance systems coupled with other data sources and the TOC play an important role in incident detection.

4.2.2 Analysis of Traffic Data

The increasing number of incidents and the subsequent need for quick detection to reduce adverse effects of incidents resulted in the development of automated incident detection (AID) systems. The analysis of traffic data is done using AID algorithms developed over the last three decades. Courage and Levin
developed the earliest AID algorithm [1], which was implemented on the John C. Lodge Freeway in Detroit.

4.2.3 Importance of Incident Detection Time

Incident detection can be seen as a crucial component of the overall incident management process. It is clear that an incident has to be detected and verified before any other incident management actions can be taken. To guarantee the success of any incident management process, it is critical that incidents are detected as soon as they have occurred. Timely and accurate incident management becomes more important when we consider the negative effects of not clearing an incident as quickly as possible. A delay in detecting an incident can cause long queues and traffic congestion, which, in turn, are the primary cause of secondary accidents.

Another important advantage of quick incident detection is the possible reduction of fatalities. In that context, fatality is defined as a person involved in a motor vehicle crash dying within 30 days of the accident. In a recent report [2], Evanco states that the outcomes associated with injury trauma are time dependent. He reports that the initial results of ITS operational tests indicate that if more effective incident detection techniques are used the incident detection and verification time (accident notification time) can be reduced to 2–3 minutes, from an estimated average of 5.2 minutes in 1990.

In the same report, Evanco develops a Poisson regression that estimates the number of fatalities as a function of variables such as, vehicle miles traveled (VMT), mean vehicle speed (MVS), alcohol consumption per capita (ACC), young/aged driver (YAD) fraction, accident notification time (ANT), and personal income per capita (IPC). Evanco uses the 1990 data from individual states in the United States to calibrate the following relationship, which is expressed in logarithmic:

\[
\ln(NF_i) = a_0 + a_1 \cdot (VMT_i) + a_2 \cdot (MVS_i) + a_3 \cdot (ACC_i) + a_4 \cdot (YAD_i) + a_5 \cdot (ANT_i) + a_6 \cdot (IPC_i)
\] (4.1)

In (4.1), the subscript \(i\) represents the state \(i\) in the United States; \(\ln()\) is the natural logarithm; and \(a_0, a_1, a_2, a_3, a_4, a_5, \) and \(a_6\) are the model parameters that need to be estimated using actual incident data. It is important to note that Evanco’s study focuses on urban freeways. The data set he used contained a total of 2,331 fatalities on 11,500 miles of urban freeways. Thus, his numbers regarding the reduction of fatalities reflect the total number of fatalities on urban freeways rather than the total number of highway fatalities in the United States.
Equation (4.1) can be used to determine the effect of a change in the notification time, \(D(\text{ANT})\), on a change in the number of fatalities, \(D(\text{NF})\), as follows:

\[
\frac{\Delta \text{NF}}{\text{NF}} = 0.27 \cdot \frac{\Delta \text{ANT}}{\text{ANT}} \tag{4.2}
\]

Using the relationship shown in (4.2), Evanco concludes that if the 5.2-minute accident notification time is reduced to 3 minutes through the introduction of a more effective incident detection program, there would be an 11% reduction in the number of fatalities nationally. That would translate into 246 fewer fatalities in a year.

Using an estimated monetary cost of $111,870 for a nonfatal injury and $708,235 for a fatality and an estimated comprehensive cost of $560,018 for an injury and $2,074,533 for a fatality, he calculated the net benefit of avoiding fatalities. The comprehensive cost takes into account the additional cost due to the loss of the quality of life. By reducing the notification time from the average 5.2 minutes to 3 minutes on both urban interstates and rural freeways, the net monetary benefit is estimated to be $267,767,900 and the net comprehensive benefit to be $931,465,300.

It is important to understand that Evanco’s study deals exclusively with the reduction of detection times, not the whole incident duration. However, the results of this timely research project clearly demonstrate the importance of rapid incident detection in terms of saving lives as well as reducing the costs associated with traffic accidents. It is clear that rapid incident detection not only will reduce congestion due to incidents but will also reduce the number of fatalities. The possible improvement in public safety that can be achieved by an effective incident management program is an important benefit to any DOT trying to determine the benefits and the costs of a new or an existing incident management program.

### 4.3 Effect of Incident Detection Time on Overall Incident Duration

As mentioned in Chapter 3, overall incident duration time has several components, including incident detection and verification time, incident response time, and time to normal flow. Thus, it is important to have answers to the following questions:
• Is the incident clearance time affected by the length of incident detection time or type of detection source?

• Is the incident verification plus incident response time affected by the incident detection time and or source?

If the answer to the first question is “Yes,” it is clear that by reducing incident detection time we can also reduce the incident clearance time. Also, if the detection source can be shown to have a major effect on the incident clearance time, future investments can be channeled to that specific kind of detection source. The same arguments are valid for the second question.

A recent report [3] studied the effect of incident detection on the overall and individual components of incident duration using the I-880 incident database. The I-880 incident database was developed specifically for the California Freeway Service Patrol (FSP) study [4]. The incident data were recorded by probe vehicles traveling on the 9.2-mile section of the I-880 freeway in the city of Hayward, Alameda County. The database was complemented by the California Highway Patrol (CHP) computer-aided dispatch (CAD) logs. For the development of the incident duration models, Skabardonis and his colleagues at PATH at the Institute of Transportation Studies at the University of California, Berkeley, employed the CAD database. Their study tested several relationships that can answer the two questions posed at the beginning of this section. First, it was shown that incident clearance time is not significantly affected by the incident detection time or the incident detection source, but it is mainly affected by the incident type. Then the effect of incident detection time on the incident verification plus incident response time was tested. Incident detection time was found to be an insignificant independent variable for the incident verification plus response time. Further tests showed that incident verification plus response time are clearly affected by the incident type and incident detection source.

Those results show that the answer to both questions is “No.” The length of incident detection time is not a significant factor that affects incident response and clearance times. However, it was also observed that the detection source affects the verification and response times. Incidents detected as a result of a cellular phone call require longer times to verify and respond to compared to the incidents detected by FSP or CHP. That is obvious because an FSP or CHP officer who detects an incident is at the scene and ready to take immediate action, whereas a CHP officer has to be dispatched to the scene to verify an incident reported over a cellular phone.
Although incident detection and verification times do not have a direct effect on the response and clearance time, it is important to understand that the shorter the incident detection and verification time, the shorter the small incident duration (See Figure 1.2).

4.4 Incident Detection Issues

There are three basic issues concerning incident detection: surveillance issues, algorithmic issues, and verification issues. Each of these issues and its relevance to the incident detection process are discussed in detail in this section.

4.4.1 Surveillance Issues

Traffic surveillance can be defined as the process of measuring traffic flow characteristics and sending this information to the TOC. The traffic surveillance system is the main source of the traffic flow data employed by almost all the AID algorithms. The last decade has been an exciting time as far as traffic surveillance is concerned. Since the inception of ITS, many new and effective traffic sensors have been introduced. Although loop detectors are the most widely used sensing system, several new sensors using different technologies have been widely adopted by DOT’s throughout the country. The following detector technologies cited in [5] are currently used in traffic sensors.

- Inductive loop technology is an active detector technology that responds to ferrous mass (cars).
- Magnetometer technology is a passive detector technology that also responds to ferrous mass (cars).
- Infrared technology, which can be either active or passive. Passive infrared technology uses the contract in thermal radiation to detect vehicles, while active infrared technology makes use of reflected signals.
- Acoustic detection technology is passive and employs sound to detect vehicles.
- Ultrasonic detection technology is active and employs reflected sound to detect vehicles.
- Charged coupled devices (CCD) camera is a passive technology that uses the contrast in visible light.
Doppler radar detection is an active detection technology that uses frequency shift of reflected signal.

Pulsed radar technology is an active technology that makes use of reflected signals.

Although there is a large range of detector technologies, all sensors are evaluated according to the quality of surveillance data they provide. The factors considered to evaluate them are:

- Reliability;
- Performance under different environmental conditions;
- Data accuracy;
- Real-time performance.

In addition to those four factors, cost plays a pivotal role in the selection of any detector system. It is clear that a detector that provides excellent results in terms of the four factors will be highly undesirable if it is very expensive compared to the other available technologies.

Reliability of a sensor is most of the time on the top of the list of evaluation factors. Many traffic surveillance systems are plagued by the low reliability of loop detectors. Frequent malfunctions or breakdowns of sensors can seriously hamper the performance of the overall traffic management operations. It is often very expensive and impractical to fix or replace a sensor that is placed under the road surface.

Performance of a specific sensor under different environmental conditions is an important factor. Among other things, a study conducted by Hughes Aircraft [5] determined the best environmental conditions for different sensor technologies, as listed in Table 4.1. The table clearly shows that different sensors using different technologies can perform better under certain environmental conditions such as fog, rain, or smoke. A simple example is the inductive loop technology, which does not perform well when snow covers the road surface. It is important to choose the sensor that will perform well under the specific environmental conditions of the area where it will be deployed.

Data accuracy is another important factor that largely depends on the installation and calibration of the sensor. A sensor that is known to be very accurate can collect erratic data if it is not appropriately installed and calibrated. Another important issue is continuous monitoring of the performance of the sensor to ensure its accuracy, because over time sensors need to be
recalibrated. More important, accuracy of sensor evaluations should be made for the operational conditions for which they are designed. Some sensors are designed for low-volume roads. Therefore, testing those sensors under high-volume traffic conditions will produce unacceptable accuracy results. However, that does not mean the sensor is not accurate. It simply means the sensor is not tested under right conditions.

Finally, real-time performance of any sensor plays a crucial role in ensuring timely decisions. In the past, real-time performance was not an issue because the data were used for mostly off-line purposes. Today, the focus is on on-line applications, and sensors are expected to collect second-by-second data. Of course, that raises the issue of real-time performance, which easily can be addressed by the use of widely available high-speed communication technologies.

The selection of a specific sensor technology also affects the type of AID algorithms that can be used and vice versa. Different sensors can measure different traffic variables, and different incident detection algorithms need

Table 4.1

<table>
<thead>
<tr>
<th>Environmental Conditions</th>
<th>Clear Day</th>
<th>Clear Night</th>
<th>Hot Day</th>
<th>Light Wind</th>
<th>High Wind</th>
<th>Light Rain</th>
<th>Hard Rain</th>
<th>Light Snow</th>
<th>Hard Snow</th>
<th>Fog</th>
<th>Smoke</th>
<th>Weather Monitor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inductive Loop</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Magnetometer</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infrared (passive)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infrared (active)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acoustic (passive)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ultrasonic</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCD camera</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radar–Doppler</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radar–FMCW</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laser–Pulsed</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(From R. Weill et al., with permission from Elsevier Science, 1998)
different data types. Table 4.2 shows traffic flow parameters measured or calculated by various sensor technologies [5]. Thus, extreme care must be taken in the selection of the specific sensor technology of incident detection algorithm and making sure that they are compatible.

### 4.4.2 Algorithmic Issues

This section focuses on two types of algorithms used for automated incident detection on freeways. Until recently, most of the automated incident detection algorithms were based on traffic flow measurements made at one point. This family of algorithms is generally called *point-based algorithms*. The point measurement–based algorithms use the following approaches to detect incidents on the freeways:

- Comparative or pattern recognition;
- Statistics;
- Traffic model and theoretical algorithms;
- Artificial intelligence–based algorithms.
The other family of incident detection algorithms is called spatial measurement–based algorithms. They make use of video cameras and image-processing techniques, which are becoming more common in traffic-engineering applications.

The discussion in this section based on a comprehensive review presented in [6] and [7] and related papers [8-22] focuses more on the first family of algorithms, because they are by far the more common types of applications and they employ already existing and relatively cheap sensor technologies, such as loop detectors.

4.4.2.1 Comparative or Pattern Recognition–Based AID Algorithms

Comparative AID algorithms, that is, algorithms based on pattern recognition, were the first ones to be developed by traffic engineers. They rely on recognizing and differentiating unusual patterns of traffic from “normal” traffic conditions. This type of algorithm looks at the occupancy levels at the detector stations upstream and downstream of the incident. The basic principle of these algorithms is that an incident will create increased occupancy levels upstream of the incident and a decrease downstream. The measured values of the traffic flow are compared with predetermined threshold values using a decision tree logic. The algorithm determines the existence of an incident if the threshold values are exceeded. “California algorithms,” developed as a result of a 1973 FHWA-sponsored study, are the best known comparative/pattern recognition algorithms. The study produced 10 versions of the California algorithm. A decision tree that depicts the general logic of the California algorithm is shown in Figure 4.1. In that decision tree, measured traffic flow variables (occupancies) pass three sequential steps. At each step, the occupancies are compared with a predetermined threshold value. The first step compares the occupancy difference between the downstream and upstream stations with the threshold value. The next two steps look at the relative spatial and temporal differences of occupancies. An incident is declared if all three threshold values are exceeded.

Among those 10 California algorithms developed by [8], algorithms #7 and #8 are known to produce best results [7]. The decision tree for California algorithm #7 is shown in Figure 4.2.

4.4.2.2 Statistical AID algorithms

Statistical algorithms model the stochastic traffic flow patterns obtained from the loop detector data. Among the several models developed using statistical principles are as follows:

- The Standard Normal Deviation (SND), developed at the Texas Transportation Institute (TTI) by [9], is based on the assumption that
a sudden change in traffic flow pattern due to an incident is the sign of the occurrence of an incident. In this algorithm, the SND is defined as the number of deviations away from the mean. The algorithm compares occupancy averaged over 1-minute intervals with the historical values of the mean and the SND. If the SND exceeds a critical value, an alarm that signals the occurrence of an incident is triggered.

- The Bayesian algorithm, developed by Levin et al. [10], uses Bayesian statistical techniques and historical data to determine the probability of an incident signal being caused by downstream lane blocking [10]. It calculates the probability that the relative occupancy differences between detectors are caused by an incident.
The time series and filtering algorithms developed by [11–15] compare short-term predictions of traffic conditions to measured traffic conditions.

4.4.2.3 Traffic (Modeling) and Theoretical Algorithms

Theoretical algorithms actually employ the basic theories of traffic flow characteristics. Among the most notable of these types of AID algorithms is the McMaster algorithm, which makes use of the catastrophe theory to model the sharp changes in traffic flow. Use of the catastrophe theory was first proposed by [16, 17]. The algorithm develops a volume-occupancy template divided into four distinct areas, each corresponding to a particular state of traffic flow (Figure 4.3). As shown in Figure 4.3, state 1 represents uncongested traffic flow conditions, states 2 and 3 represent areas where congested flow conditions

![Decision tree for California algorithm #7](image)

**Figure 4.2** Decision tree for California algorithm #7 [8].

- The time series and filtering algorithms developed by [11–15] compare short-term predictions of traffic conditions to measured traffic conditions.

4.4.2.3 Traffic (Modeling) and Theoretical Algorithms

Theoretical algorithms actually employ the basic theories of traffic flow characteristics. Among the most notable of these types of AID algorithms is the McMaster algorithm, which makes use of the catastrophe theory to model the sharp changes in traffic flow. Use of the catastrophe theory was first proposed by [16, 17]. The algorithm develops a volume-occupancy template divided into four distinct areas, each corresponding to a particular state of traffic flow (Figure 4.3). As shown in Figure 4.3, state 1 represents uncongested traffic flow conditions, states 2 and 3 represent areas where congested flow conditions
occur, and state 4 represents traffic flow conditions at the downstream of a permanent bottleneck. The algorithm makes two basic comparisons between this figure and actual loop data. The first test determines if the actual detector is congested. If congestion exists, the algorithm tries to determine the source of congestion by examining the traffic state at a downstream detector. The McMaster algorithm is rated as one of the most accurate incident detection algorithms with an overall detection accuracy between 70% and 85% and a false alarm rate of 1% or less [7].

4.4.2.4 Artificial Intelligence–Based Algorithms

Some researchers use artificial neural networks (ANNs) to develop models for AID. An ANN consists of simple processing elements and neurons that are interconnected. The concept of ANNs is borrowed from the human brain. The idea is to train the ANN by feeding it with input and associated output data. As a result of that training process, ANN develops rules of associations among its neurons. For incident detection, input data consist of traffic flow variables such as volume, speed, and occupancy at both upstream and downstream detectors. Some researchers who have used ANNs for AID have reported successful results [18, 19].

![Figure 4.3 Illustration of volume-occupancy template for traffic state classification. (From: [17], with permission from the Transportation Research Board and the author.)](image-url)

Volume = Number of vehicles in 30 seconds

g(OCC) = K*a*occupancy, 0 < k < 1, 0, (k, a, b, and Vcrit are station-specific parameters.)

OCMAX = Maximum uncongested occupancy
4.4.2.5 Surface Street Incident Detection (SSID)

Surface street incident detection still remains one of the biggest challenges in the area of AID. The interrupted flow conditions due to the traffic signals create extra difficulties for the development of reliable AID algorithms. Some of the basic problems associated with surface street incident detection can be summarized as follows:

- Interrupted traffic flow conditions complicate the analysis of traffic flow data;
- Arterials are much longer than freeways and require more personnel and equipment for incident detection and verification;
- Most arterials are not instrumented with traffic detectors, which makes it impossible to use AID algorithms.

Several researchers [20–22] have recently attempted to develop incident detection systems for arterials. Among the most notable ones is the work presented by Bhandari et al. [20]. That project developed an arterial incident detection system for the ADVANCE project, an advanced traveler information system demonstration in the northwest suburbs of Chicago. To remedy some of the problems mentioned above, they used data from various sources, including fixed detectors, probe vehicles, and anecdotal sources. All the data was processed through the use of data fusion algorithms, and the likelihood of the occurrence of an incident at a given location was determined. One of the most important aspects of the algorithm is the use of anecdotal data, which basically are descriptions of incidents reported by trained and untrained field observers. Several other SSID algorithms developed as part of the ADVANCE project were using data fusion approaches. They produced incident detection rates that were between 66.7% and 87.0% [23]. A good review of the state of the SSID algorithms and research needs is given in [24].

4.5 Verification Issues: Evaluation of Incident Detection Systems

Three basic measures of effectiveness (MOEs) are used to evaluate incident detection algorithms:

- The detection rate (%) is the ratio of the number of detected incidents to the actual number of incidents in the data set.
• The false alarm rate (%) is the fraction of incorrect detections to the total number of algorithm applications.
• The time to detection (sec) is the average time required for the algorithm to detect an incident.

Those MOEs are not independent. For example, longer time to detection means lower false alarm rates. However, it is clear that there is a tradeoff between losing precision time and lowering false alarm rates. Another problem is the lack of standards in the evaluation methodology of AID algorithms; hence, the evaluation results are not comparable most of the time. A summary of the reported performance of various algorithms is given in University of California PATH ITS LEAP Web page [6]. The evaluation results of AID algorithms here are shown in Table 4.3. It is important to emphasize once more that the evaluation results are not obtained using a standard methodology. Thus, it may be misleading to compare the results with one another without considering the differences in the actual traffic and network conditions.

Table 4.3
Summary of the Evaluation Results of the Most Commonly Used AID Algorithms
(From: [6], with permission from UC Berkeley PATH ATMIS Group)

<table>
<thead>
<tr>
<th>Algorithm Type</th>
<th>Detection Rate (%)</th>
<th>False Alarm Rate (%)</th>
<th>Average Detection Time (secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic California</td>
<td>82</td>
<td>1.73</td>
<td>0.85</td>
</tr>
<tr>
<td>California #7</td>
<td>67</td>
<td>0.134</td>
<td>2.91</td>
</tr>
<tr>
<td>California #8</td>
<td>68</td>
<td>0.177</td>
<td>3.04</td>
</tr>
<tr>
<td>Standard Normal Deviate</td>
<td>92</td>
<td>1.3</td>
<td>1.1</td>
</tr>
<tr>
<td>Bayesian</td>
<td>100</td>
<td>0</td>
<td>3.9</td>
</tr>
<tr>
<td>Time Series (Autoregressive Integrated Moving Average)</td>
<td>100</td>
<td>1.5</td>
<td>0.4</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>92</td>
<td>1.87</td>
<td>0.7</td>
</tr>
<tr>
<td>Low-Pass Filter</td>
<td>80</td>
<td>0.3</td>
<td>4.0</td>
</tr>
<tr>
<td>Modified McMaster</td>
<td>68</td>
<td>0.0018</td>
<td>2.2</td>
</tr>
<tr>
<td>Multi Layer Feed Forward Neural Networks</td>
<td>89</td>
<td>0.01</td>
<td>0.96</td>
</tr>
<tr>
<td>Probabilistic Neural Networks</td>
<td>89</td>
<td>0.012</td>
<td>0.9</td>
</tr>
<tr>
<td>Fuzzy Sets</td>
<td>Good</td>
<td>Good</td>
<td>Up to 3 minutes quicker than conventional algorithms</td>
</tr>
</tbody>
</table>
4.6 Operational Field Tests

In addition to the conventional algorithms, there have been some recent attempts to use and evaluate more innovative and practical approaches for incident detection. Two of the most interesting and successful of these incident detection operational field tests are:

- The TRANSCOM TRANSMIT project implemented along a corridor in Staten Island, New York, centered in Interstate 287 and extending from the Verrazano Bridge across the New Jersey Turnpike to Routes 1 and 9 in New Jersey;

- The I-880 field experiment to evaluate the effectiveness of incident detection using cellular phones conducted on the 9.2-mile stretch of I-880 freeway in the city of Hayward, California (Alameda County).

4.6.1 TRANSCOM TRANSMIT Project

The TRANSMIT project was initiated to evaluate the feasibility of using electronic toll and traffic management (ETTM) equipment for traffic surveillance and incident detection purposes [20]. Toll tag readers installed along the roadway are also used to obtain vehicle surveillance data. The passage times of individual vehicles are kept track of by a central system which also calculated vehicle travel times by using this information. Incidents are detected by comparing actual vehicle travel times with historical vehicle travel times. If a predetermined number of vehicles are delayed at a certain location more than usual, an incident is identified. The system was evaluated by researchers from the New Jersey Institute of Technology (NJIT) in 1996. Table 4.4 summarizes the evaluation results [25].

In this study, between 9.8 and 15% operational false alarm rates were calculated by dividing the number of false alarms by the total number of alarms. Although that is a better measure of effectiveness for the evaluation of a specific AID algorithm, most of the time false alarm rates are calculated differently. Each AID system has a cycle of 5 to 10 seconds. At the end of each cycle, the system checks the existence of an incident. A cycle of seconds means 267,840 checks in a month (31 days). Thus, if an algorithm had 268 false alarms in a month, its false alarm rate would be 0.01. This gives a more comparable measure of the TRANSMIT system’s performance with respect to other AID systems using this in other places. When false alarm rates are calculated using this new method, they are found to be between 0.002% and 0.008%. However, even with such low numbers, the authors of [25] observed an average of 2
alarms for every three days, which might create operational problems for on-line applications. Finally, they concluded that operational false alarm rates gave a more realistic and better understanding of the system performance compared to extremely low false alarm rates which tend to mask the real performance of an AID program.

4.6.2 I-880 Field Experiment: Incident Detection Using Cellular Phones

The I-880 study attempted to evaluate the quality and adequacy of cellular phone information as part of advanced incident management systems. It also evaluated the effects of the timeliness of incident detection on incident duration and the effects of incident duration on congestion.

The study compared cellular phone incident data with incident data obtained from other detection sources. The major goal of the study was to assess the adequacy of cellular phones as an incident detection technique. Table 4.5 summarizes the comparison.

A close look at Table 4.5 shows that cellular phones have high false alarm rates. That is due basically to the reporting person’s judgment of whether a vehicle is involved in an accident. However, in other parts of the country cellular phones are found to be an excellent information source for incident detection. Although false alarm rates will remain a problem, cellular phones can be considered one of the fastest and cheapest ways of detecting incidents. Coupled with other conventional incident detection techniques such as safety patrols, CCTV cameras, and loop detectors, the reliability of the cellular phone information can be drastically improved.
4.7 Summary

This chapter briefly discussed different incident detection techniques. As the first step of incident management process, incident detection is important in any successful incident management program. Timely and quick incident detection also has been shown to save lives and money [2]. The evaluation results of some of the most common incident detection algorithms also were presented in this chapter. Among them, the California algorithms and the McMaster algorithm are the AID algorithms most widely used by the DOTs because of their proven performance in accurately detecting incidents and their low false alarm rates.

An important issue in getting high performance from AID algorithms is the importance of proper calibration of threshold values. The use of new technologies such as cellular phones and ETTM for incident detection is part of the recent operation field tests conducted in the United States. Those new approaches for AID aim at taking full advantage of already existing technologies such as toll tags and cellular phones to monitor the traffic conditions. They appear promising in terms of developing effective AID systems for a relatively low investment on areawide surveillance infrastructure, such as traditional loop detectors or more expensive vision-based cameras. It is extremely important to emphasize the role and the effectiveness of freeway patrol programs for reducing the detection and verification times of incidents. Several recent studies [3, 4] clearly show that those new incident detection techniques are still not as good as freeway patrol programs such as FSP and CHP in California. Although AID traditionally has been used for freeway incident detection, there is a

<table>
<thead>
<tr>
<th>Detection Source</th>
<th>Detection Rate</th>
<th>False Alarm Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Incidents</td>
<td>Other Events</td>
</tr>
<tr>
<td>Cellular Phone</td>
<td>37.9</td>
<td>1.2</td>
</tr>
<tr>
<td>California Highway Patrol (CHP)</td>
<td>25</td>
<td>4.3</td>
</tr>
<tr>
<td>Freeway Safety patrol (FSP)</td>
<td>17.1</td>
<td>4.9</td>
</tr>
<tr>
<td>Public Entity</td>
<td>13.3</td>
<td>0.6</td>
</tr>
<tr>
<td>Call Box</td>
<td>4.5</td>
<td>3.6</td>
</tr>
</tbody>
</table>
growing interest among researchers and practitioners for the development of AID algorithms for surface streets, too [24]. However, due to the lack of adequate surveillance on the surface streets and complex traffic environment compared to the freeways, surface street AID continues to be a challenging theoretical and practical problem for traffic engineers.

**Review Questions**

1. How would you determine the threshold values used in the California incident detection algorithm?

2. Choose two of the AID algorithms presented in this chapter and determine the surveillance needs for effectively using those algorithms.

3. Discuss the problems associated with calibrating and evaluating incident detection algorithms using traffic simulation packages.

4. Compare the two methods of false alarm rate calculations using a numerical example. Discuss the advantages and disadvantages of both methods.

5. Identify the AID techniques used in your state. Propose new AID techniques that can be used in your state and explain why.

**References**


**Selected Bibliography**

