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AN ASSESSMENT AND ANALYSIS OF USING DEDICATED SHORT-RANGE COMMUNICATIONS (DSRC) TECHNOLOGY FOR INCIDENT DETECTION ON RURAL FREEWAYS

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ABSTRACT OF DISSERTATION

Joseph D. Crabtree

AN ASSESSMENT AND ANALYSIS OF USING
DEDICATED SHORT-RANGE COMMUNICATIONS (DSRC) TECHNOLOGY
FOR INCIDENT DETECTION ON RURAL FREEWAYS

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ABSTRACT OF DISSERTATION
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A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy
in the College of Engineering
at the University of Kentucky

By
Joseph D. Crabtree
Versailles, Kentucky

Director: Dr. Nikiforos Stamatiadis, Professor of Civil Engineering
Lexington, Kentucky

2004

ABSTRACT OF DISSERTATION

AN ASSESSMENT AND ANALYSIS OF USING
DEDICATED SHORT-RANGE COMMUNICATIONS (DSRC) TECHNOLOGY
FOR INCIDENT DETECTION ON RURAL FREEWAYS

This report describes an assessment of using dedicated short-range communications (DSRC) technology to perform travel time monitoring and automated incident detection on a segment of rural freeway. The assessment used the CORSIM traffic simulation tool to simulate traffic and incidents on a segment of rural freeway. Output data from the simulation was subjected to post-processing to produce the "probe and beacon" data that would be produced by a DSRC-based system. An incident detection algorithm was developed, which used a travel time threshold and a counter. Travel times exceeding the threshold incremented the counter, while travel times below the threshold decremented the counter (unless it was at zero). An alarm was generated when the counter reached a pre-selected level. This algorithm was tested on selected data files, and the results were used to identify the "best" values of the threshold and counter alarm level. Using these "best" values, the algorithm was then applied to the "probe and beacon" data to determine how quickly the system could detect various traffic incidents. The analysis showed that the system could provide rapid and reliable detection of incidents.

During the simulation and analysis, several parameters were varied to observe their impacts on the system performance. These parameters included traffic volume, incident severity, percentage of vehicles with transponders, spacing of roadside readers, and location of the incident relative to the next downstream reader. Each parameter proved to have a significant effect on the detection time, and the observed impacts were consistent with logical expectations. In general, the time to detect an incident was reduced in response to (1) an increase in traffic volume, (2) an increase in incident severity, (3) an increase in transponder population, (4) a reduction in reader spacing, and (5) a reduction in distance from incident location to next downstream reader.

Preliminary estimates were developed of the costs associated with implementing a DSRC-based traffic monitoring system. The relationship between system cost and system performance was explored and illustrated.

Recommendations were developed and presented. These included further analysis based on traffic simulations, followed by a limited field deployment to validate the analysis results.

KEYWORDS: Incident Detection; Probe Vehicles; DSRC; Transponders; Travel Time

<u>   Joseph D. Crabtree   </u>

<u>   December 15, 2004   </u>

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By

Joseph D. Crabtree

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December 15, 2004
Date

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DISSERTATION

Joseph D. Crabtree

The Graduate School

University of Kentucky

2004

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Dr. Mei Chen	Dept of Civil Engineering, University of Kentucky
Dr. Donn Hancher	Dept of Civil Engineering, University of Kentucky
Dr. Issam Harik	Dept of Civil Engineering, University of Kentucky
Dr. Arnold Stromberg	Dept of Statistics, University of Kentucky
and	
Dr. Lisa Aultman-Hall	Connecticut Transportation Institute, University of Connecticut

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INTRODUCTION

One of the fundamental requirements of a traffic management system is the ability to determine when an incident has occurred so that proper responses can be initiated. Traffic incidents can result from a large variety of causes, including crashes, stalled vehicles, road maintenance or construction work, hazardous material spills, severe weather, rockslides, debris in the roadway, and many others. Some incidents cause only minor delays, while others result in severe and prolonged traffic backups. For any incident that affects traffic flow, it is essential that traffic management personnel become aware of the incident as quickly as possible after it occurs.

Responses to a traffic incident may take many forms, including dispatching emergency services, rerouting traffic, and providing up-to-date traffic condition information to travelers. When these responses occur quickly, lives can be saved, traffic congestion and delays can be minimized, secondary crashes can be prevented, and traffic flow can be restored to normal in the quickest possible manner. The crucial first step in any type of incident response is to detect the incident. Obviously, without a prompt detection, there can be no prompt response.

Many studies have documented the cost of traffic incidents and the value of rapid response. Traffic congestion (from all causes) is estimated to cost approximately $63 billion annually in the United States.[1] The National Highway Traffic Safety Administration (NHTSA) has reported that the cost of traveler delay due to traffic crashes in calendar year 2000 was $25.6 billion, which is 11 percent of the total cost associated with traffic crashes.[2] This NHTSA estimate does not include the direct cost of secondary crashes, nor does it include the cost of congestion and delay from other types of incidents (other than crashes). It has been estimated that ten to twenty percent of all crashes on freeways are caused by preceding (primary) incidents.[3] Obviously, there is a heavy cost associated with traffic incidents that generate congestion and delay. This cost can be reduced through prompt detection and rapid response.

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[1] "2004 Annual Urban Mobility Report;" Texas Transportation Institute; Texas A&M University; September 2004; http://mobility.tamu.edu

[2] Blincoe. L.J. et al; "The Economic Impact of Traffic Cashes 2000;" National Highway Traffic Safety Administration; DOT HS 809 446; May 2002; http://www.nhtsa.dot.gov/people/economic/EconImpact2000/

[3] Versavel, J.; "Sparing Lives, Saving Time: A Unified Approach to Automatic Incident Detection;" Traffic Technology International; Annual Review 2000; pg 189

Because of the importance of rapid detection of incidents, many different technologies and techniques for incident detection have been developed, implemented, and evaluated. This study focuses on the use of dedicated short-range communications (DSRC) technology for travel-time monitoring and incident detection on rural freeways.

RESEARCH OBJECTIVES

The objectives of this research were to:

a) Assess the feasibility of using a DSRC-based system to perform continuous travel-time monitoring and automated incident detection on a segment of rural freeway in Kentucky.

b) Identify an appropriate decision algorithm for determining, based on travel time data, that an incident has occurred. Apply this algorithm to data produced by traffic simulation, and refine the algorithm to achieve optimum performance.

c) Determine how the effectiveness of a DSRC-based incident detection system would be affected by selected variables, including traffic volume, percentage of vehicles with transponders, incident severity, spacing of roadside readers, and location of the incident relative to the next downstream reader.

d) Develop a rough estimate of the anticipated costs of such a system and describe the expected tradeoffs between cost and performance.

e) Develop recommendations regarding operational testing and implementation of a DSRC-based incident detection system on a segment of rural freeway in Kentucky.

LITERATURE REVIEW

The first step of this research was to conduct a thorough literature review. The review was designed to identify literature on the broad topic of incident detection, as well as on the narrower topic of using probe vehicles for incident detection. Using the Transportation Research Information Services (TRIS) Database, numerous resources were identified. Brief summaries of several directly related documents are presented in the Appendix. The literature review was used to assess and describe the current state of incident management, highlight best practices, identify key questions, and define areas where the current research could contribute to the knowledge base. The results of the literature review are discussed in the following sections.

Available Approaches and Technologies for Incident Detection

Methods of incident detection generally fall into four categories:

1) Detection based on data from traffic sensors
2) Detection based on images from cameras
3) Detection based on data from probe vehicles
4) Detection based on reports from the traveling public

Traditionally, detection using traffic sensors has depended on sensors installed in or along the roadway to continuously measure vehicle flow rates and speeds. Often, these sensors have been installed for the primary purpose of managing traffic operations, and they have a corollary value in incident detection. However, there have also been instances where detectors have been installed with the primary purpose of incident detection. Specific types of detectors that have been used for traffic monitoring and incident detection include the following:

- Loop detectors in pavement
- Roadside (or overhead) detectors using laser or radar
- Acoustic detectors
- Video cameras with video image processing

Many traffic management systems, particularly in urban areas, have included the deployment of video cameras for traffic monitoring. Because the images from these cameras are typically displayed in a traffic management center with continuous staffing, the images can be monitored by staff for any indication of an incident. Thus, video cameras provide a valuable

means for detecting incidents. These cameras offer an advantage over other types of detectors, in that they allow traffic management personnel to perform some degree of remote diagnosis when an incident occurs. This is particularly true when the ability exists to control cameras (i.e., pan, tilt, and zoom) from the traffic management center. Thus, video cameras can be valuable not only in detecting and verifying the incident, but also in tailoring the response to fit the situation.

The use of probe vehicles for incident detection can take many forms. One example of this approach is to have designated travelers who periodically report their position to a traffic management center, using some form of wireless communications.[4] Another approach is to have vehicles equipped with global positioning systems (GPS) and wireless communications, so that the vehicles themselves report their position (either periodically or continuously). An alternative to the GPS-based approach is the use of cellular telephones as probes.[5] Technology exists (and has been installed in some urban areas) that can determine the location of cellular telephones and track them as they move. With this type of technology, any vehicle containing a cellular telephone can function as a probe vehicle, as long as the phone is turned on.

A fourth type of probe-based detection is the "probe and beacon" approach. Under this approach, the position of the vehicle is determined only when it passes certain locations on the roadway network (e.g., Mouskos et al[6]; Hallenbeck et al[7]). This can be accomplished with a short-range communications device (such as a radio frequency transponder) on the vehicle and a corresponding reader on the roadside, or it can be accomplished using passive vehicle identification equipment on the roadside (such as automated license plate readers).

Most of the technologies described above have been deployed primarily for traffic management purposes; hence, most installations have been in urban areas. In general, the cost of deploying traffic sensors, video cameras, or cellular phone tracking systems has been prohibitive for rural areas. Thus, incident detection in rural areas still depends primarily on reports from the traveling public. The proliferation of mobile telephones has greatly enhanced the ability of

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[4] Balke, K.N. et al; "Benefits of Real-Time Travel Information in Houston, Texas;" Texas Transportation Institute, Texas A&M University; College Station, Texas; January 1995
[5] Mudge, R.R.; "Cell Phones as Data Probes: Background and Recent US Wireless Experience;" Presentation at ITS Mid-America Annual Meeting; Columbus, Ohio; September 2000.
[6] Mouskos, K.C. et al; "TRANSMIT System Evaluation;" Institute for Transportation; New Jersey Institute for Technology; June 1998.
[7] Hallenbeck, Boyle, and Ring; "Use of Automatic Vehicle Identification Techniques for Measuring Traffic Performance and Performing Incident Detection;" University of Washington, Seattle; October 1992.

travelers to report incidents. However, this method has serious limitations as well. Travelers often do not know what number to call to report an incident, so the incident report may be delayed in getting to the appropriate agency. Reports are often sketchy, inaccurate, or incomplete. This is particularly true with regard to the location of the incident, since many travelers in rural areas do not know how to determine and report their own location.

Incident Detection using DSRC

One technology that has great potential for use in travel time monitoring and incident detection is dedicated short-range communications, or DSRC. The use of DSRC technology for transportation-related applications has grown rapidly in the last ten years. This technology consists of vehicle-mounted transponders and roadside readers, which communicate with each other via radio frequency (RF) transmissions. As the name implies, the communication range is short, usually less than 50 meters (for technology currently in use). The most significant deployments of DSRC thus far have been for the purposes of electronic toll collection (ETC), commercial vehicle electronic screening, and international border crossings. Other promising near-term applications include facilities access control, parking access and payment, and commercial fleet management. Potential future applications of this technology are too numerous to list, but examples would include vehicle-to-vehicle safety systems (e.g., collision avoidance systems), in-vehicle signing, and data downloads to onboard navigational or entertainment systems. As DSRC-based systems proliferate, the number of transponder-equipped vehicles can be expected to increase exponentially. Currently, there are approximately fifteen to twenty million transponders on vehicles in the United States, and this number is growing daily. The Federal Communications Commission (FCC) has allocated a frequency band in the 5.9 GHz range for transportation applications of DSRC, and a national standard[8] has been adopted, so transponders may soon become standard equipment on all new cars and trucks.

This increasing population of transponder-equipped trucks and automobiles offers the potential for developing effective, low-cost systems for traffic monitoring and incident detection. With a few, strategically-located roadside readers, it should be possible to continuously monitor travel times between selected points and rapidly detect incidents that cause delays.

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[8] See http://www.standards.its.dot.gov/Documents/dsrc_advisory.htm.

One of the inherent advantages of using DSRC for incident detection is that it measures actual travel times for individual vehicles in the traffic stream. Since the primary concern of most travelers, other than safety, is travel time, then their primary means of judging the severity of an incident is the impact of that incident on their travel time. Thus, with DSRC-based incident detection, the system is measuring something that is of direct interest and importance to the traveler. Travel time data has value beyond its possible use for incident detection. For example, travel time data collected by a DSRC-based system could be communicated to travelers (via Advanced Traveler Information Systems, or ATIS), thus allowing those travelers to be better-informed and make improved decisions.

Kentucky's Experience with DSRC

Kentucky has been a national leader in deploying DSRC systems for commercial vehicle administration and enforcement. As the lead state for the ***Advantage I-75 Operational Test Project***, Kentucky began deploying DSRC at weigh stations along Interstate 75 in 1993. The success of that program led to its expansion, and DSRC technology is now deployed at 14 weigh stations in Kentucky. The 15th (and final) station is scheduled for installation in early 2005. Approximately 16.000 trucks are currently enrolled for electronic screening in Kentucky. Nationwide, there are approximately 275 weigh stations equipped with DSRC technology (which is about one-third of all weigh stations[9]), and approximately 300,000 trucks are enrolled in electronic screening programs.

Kentucky is a member of the North American Preclearance and Safety System partnership, or NORPASS.[10] NORPASS has ten member jurisdictions (nine states and one Canadian province), all of which have deployed (or are in the process of deploying) DSRC for commercial vehicle screening. All of the major electronic screening programs in North America use the same transponder technology. In fact, it is now possible for a trucker to participate in every electronic screening program and in the E-ZPass[TM] electronic toll collection system with a single transponder. As might be expected, the spread of electronic toll collection and electronic screening systems has created a corresponding growth in the percentage of trucks with

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[9] In 1995, there were 862 fixed weigh stations in the United States. See Stamatiadis, Graves, and Schmidt; "Best Practices for Commercial Vehicle Monitoring Facilities Design;" Report No. FHWA-SA-96-001; Federal Highway Administration; September 1995.
[10] See NORPASS web site at http://www.norpass.net.

transponders. Observations at a Kentucky weigh station on Interstate 75 in calendar year 2001 indicated that approximately 15 to 20 percent of the trucks were equipped with windshield-mounted DSRC transponders.

Prior Research on DSRC and Incident Detection

The TRANSMIT System Evaluation by Mouskos, et al[11], was one of the few studies that actually used DSRC technology for traffic surveillance and incident detection. It is perhaps the most significant example of installing closely-spaced roadside DSRC technology specifically for those purposes. The project installed 28 roadside DSRC readers along the Garden State Parkway and the New York State Thruway, at a spacing of 0.5 to 2.1 miles. The system made use of existing transponders deployed for the E-ZPass electronic toll collection system. The detection algorithm used was based on statistical comparisons of measured travel times with historical travel times for the same time period. The evaluation assessed performance of the roadside technology in terms of its success in detecting transponder-equipped vehicles and communicating the data to the operations center. It also assessed the performance of the incident detection system by comparing incidents detected by the system with incidents recorded by traffic operations personnel. The key performance measures were a "probability of detection" (which ranged from 67 to 95 percent) and a "probability of false alarms" (which ranged from 10 to 32 percent. The "mean time to detect an incident" could not be determined, but was recognized as an important performance measure.

A study by Hallenbeck, Boyle, and Ring[12] was a very early project (1992) that examined the potential benefits of using DSRC for traffic monitoring and incident detection. Since this study focused primarily on the use of transponder-equipped <u>trucks</u> as the probe vehicles, a secondary objective was to see whether trucks would provide an unbiased measure of traffic performance. For this study, three DSRC readers were installed on northbound Interstate 5 in Washington State, with an approximate spacing of one mile between readers. The project made use of the existing population of transponders that had been deployed for the HELP/Crescent project. Possible methodologies for the incident detection algorithm were explored, using either

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[11] Mouskos, K.C. et al; "Transmit System Evaluation: Final Report;" Institute for Transportation; New Jersey Institute for Technology; June 1998
[12] Hallenbeck, Boyle, and Ring; "Use of Automated Vehicle Identification Techniques for Measuring Traffic Performance and Performing Incident Detection;" University of Washington, Seattle; October 1992.

vehicle headways (for a single roadside reader) or travel times (for more than one reader). Unfortunately, the volume of transponder-equipped vehicles was insufficient to perform real-time traffic monitoring or incident detection. This project was unique in that it examined the use of DSRC for traffic monitoring and incident detection in a region with no electronic toll collection. It installed DSRC readers specifically for traffic monitoring, and it relied entirely on trucks to serve as probe vehicles.

Parkany and Bernstein[13] promoted DSRC as an attractive option for incident detection and offered three example, pattern-based algorithms for use with DSRC data. A simulation was used to test the algorithms and to compare them against an existing algorithm that used loop detector data. The algorithms were compared in terms of detection rate, false alarm rate, and time to detect. The results showed that even simple DSRC-based algorithms performed at least as well as implemented algorithms using other sensors. The report also included recommendations for further research, some of which have been incorporated into the objectives of the current project.

A study by Fremont[14] described the development and testing of a real-time, on-board, information system called ADAMS, originally developed by COFIROUTE and Renault, and then enhanced by an expanded partnership under the AIDA project, sponsored by the Ministry of Industry in France. The purpose of the ADAMS and AIDA demonstrations was to introduce new information services in the vehicles, for the comfort and safety of the drivers. The ADAMS system included vehicle-mounted DSRC transponders (5.8 GHz), onboard terminals (with smart-card readers and LCD display), various onboard sensors, roadside DSRC readers, a communications network, and a traffic management center. Communications between the vehicle-mounted transponders and the roadside readers was two-way. The system was installed on a 90-km section of the A10 Paris-Poitiers motorway. There were 26 roadside beacons (or readers) installed, with the spacing between beacons varying from 5 km to 10 km. Incident detection was only a small part of this study, and it was not the primary emphasis. Automated incident detection was anticipated to be a future addition to the system, and it noted that "algorithms will be developed and tested." No evaluation had been performed; however, the

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[13] Parkany and Bernstein; "Design of Incident Detection Algorithms Using Vehicle-to-Roadside Communication Sensors;" Transportation Research Record #1494; "Traffic Operations, Traffic Signal Systems, and Freeway Operations 1995;" Transportation Research Board; 1995

study determined that using DSRC for automated incident detection could be very cost effective, since "it is quite impossible to implement classic AID systems (like cameras and image processing systems) on large parts of interurban highways." The study was particularly significant in that it included a substantial deployment of roadside DSRC technology (26 readers) along a single roadway with fairly close reader spacing. A substantial portion of the roadway segment included in the study was in a non-urban area. Unfortunately, no evaluation of the system was available.

Balke[15] provided an excellent overview of all available incident detection algorithms. His work included a summary and description of each available algorithm, along with an assessment of each algorithm based on previously published results. He did not attempt to use actual field data to evaluate the algorithms. The focus was on algorithms that used inductive loop detectors, and all existing (and known) incident detection algorithms were described and assessed. No specific evaluation was performed; rather, the incident detection algorithms were assessed based on the available literature. The report included a discussion of performance measures, including the relationship among detection rate, false alarm rate, and time to detect. Thus, it served as a useful compilation of information on existing incident detection algorithms and on the relationships that exist among the key performance measures.

Research Needs Identified by the Literature Review

The literature review was extremely helpful in identifying some apparent gaps in the current base of knowledge. These gaps indicated areas where the current research study could make significant contributions. These areas include:

- Performance of a DSRC-based incident detection system
  - How is it affected by varying key system parameters?
  - What level of performance is possible?
  - What is the relationship (and trade-off) among the measures of effectiveness?
- Using DSRC for incident detection in a rural freeway environment
  - How well can it work?

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[14] Fremont, Guy; "Using In-Vehicle Systems and 5.8 GHz DSRC for Incident Detection and Traffic Management;" Fourth World Congress on Intelligent Transportation Systems; Berlin, Germany; October 1997

[15] Balke, Kevin N.; "An Evaluation of Existing Incident Detection Algorithms;" Texas Transportation Institute; Research Report 1232-20; Texas A&M University; College Station, Texas; November 1993.

- o Can a simple detection algorithm perform well?
- o How much would it cost to actually deploy such a system?
- o Is it feasible to deploy such a system?
- o What would be some guidelines and recommendations for deploying?

These identified needs played a substantial role in defining the research objectives for the current study.

RESEARCH APPROACH AND METHODOLOGY

To accomplish the objectives of this research project, the following tasks were performed. With the exception of the Literature Review, which has already been discussed, specific details of each task are provided in the discussion that follows.

1. Literature Review
2. Study Design
3. System Modeling and Simulation
4. Post-Processing of Simulation Output
5. Development of Detection Algorithm
6. Application of Detection Algorithm to Data
7. System Performance Assessment (and Regression Analysis)
8. Cost Assessment
9. Development of Recommendations

Study Design

Before proceeding with the study, it was necessary to develop a "study design," i.e., to decide on the direction the study would take and the methodologies that would be used. Some of the key decisions made during the study design phase are described in the following.

It was determined that the incident detection system should be assessed using a traffic simulation tool rather than attempting a real-world installation and test. This offered the advantages of lower initial cost and increased flexibility, while providing the opportunity to vary each parameter individually while holding all other parameters constant. This highly controlled environment would be ideal for assessing the impact of each parameter on the performance of the incident detection system.

When the study requirements were compared to the capabilities of commercially available traffic simulation packages, it became apparent that the simulation output data would require post-processing to convert it from vehicle position data to "probe and beacon" data. This post-processing would require development of one or more computer programs to read the simulation output file and perform the necessary conversion.

An important component of the study design was identifying the fixed parameters of the simulation, the parameters to be varied (so their effects could be studied), and the specific values

of those parameters that would be used for the analysis. The parameters selected for the analysis (and their values) are shown in Table 1 (fixed parameters) and Table 2 (variable parameters).

Table 1. Fixed Parameters for Simulation and Analysis

Category	Parameter	Value
Freeway Segment Characteristics	Total segment length	135,000 ft (25.57 mi)
	Number of Links	15 (at 9000 feet each)
	Number of lanes	Two lanes (one direction)
	Terrain	Flat
	Intervening interchanges	None
Incident Characteristics	Incident location	81,840 ft (15.5 mi) from beginning of segment
	Time of occurrence	1800 seconds (30 minutes) after initialization
	Incident length	40 feet
	Location of warning sign	0 feet
	Duration of incident	900 seconds (15 minutes)
Traffic Characteristics	Entry headways	Normally distributed
	Lane split for entering vehicles	40/60 (left/right)
	Truck percentage breakdown	20% single unit 40% semi (med. load) 35% semi (full load) 5% double bottom trailer
General	Total simulation time	3000 seconds (50 minutes) after initialization
	Time frame included in analysis	Chopped off and ignored first 900 seconds after initialization

Some of the parameters in Table 1 were chosen for simplicity. Examples would be the flat grade and the lack of intervening interchanges. Other factors, such as the segment length, incident location on the segment, and total simulation time, were chosen to allow adequate time and space for the incident to develop and be detected by the system. Early trials of the simulation helped to refine the selected values. The first 900 seconds of each simulation were "chopped off" (i.e., ignored) to ensure that the segment was completely filled with traffic before any analysis of travel times was conducted.

Table 2. Variable Parameters for Simulation and Analysis

Parameter	Values Tested	Where Varied
Traffic Volume	Heavy (3000 vph, 30% trucks)	Simulation
	Light (1500 vph, 40% trucks)	
Incident Severity	No incident	Simulation
	Minor (Lane 1 blocked, lane 2 10% rubberneck factor)	
	Moderate (both lanes blocked for three minutes, then lane 2 open with 50% rubberneck factor for duration of incident	
Percentage of Vehicles with Transponders	25% of trucks, 5% of cars (Case "a")	Post-processing
	50% of trucks, 10% of cars (Case "b")	
	75% of trucks, 15% of cars (Case "c")	
	100% of all vehicles (Case "d")	
Spacing of Roadside Readers	Two miles apart	Post-processing
	Four miles apart	
	Six miles apart	
	Eight miles apart	
	Ten miles apart	
Distance from Incident Location to Next Downstream Reader	0.5 mile	Post-processing
	1.5 miles	
	2.5 miles	
	3.5 miles	
	4.5 miles	
	5.5 miles	
	6.5 miles	
	7.5 miles	
	8.5 miles	
	9.5 miles	

In selecting parameters to be varied, the primary consideration was to determine those factors most likely to affect the ability of the system to detect the incident (and the time it would take to do so). In general, every factor that could be varied was varied, if there was a reasonable expectation that the factor would affect the system performance. One exception was the presence of intervening interchanges. This would theoretically impact the performance of the incident detection system, but it was determined to be beyond the scope of this initial analysis.

Choosing the actual values to be tested for each parameter involved the application of real-world data coupled with engineering judgment. Real-world values were obtained for the

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traffic volume and percentage of trucks on Interstate 75 in southern Kentucky, as well as for the percentage of trucks with transponders on that same route. The first scenario for the percentage of transponders (25% of trucks, 5% of cars) was selected to approximate the current condition, while the other scenarios represented possible future conditions. The primary purpose here was to provide sufficient variability in each parameter so that its impact could be properly assessed.

As shown in Table 2, five different parameters were selected to be varied in the simulation and analysis. Only two of these parameters were varied in the simulation; the remaining parameters were varied in the post-processing of the simulation output. Six different simulations were required to cover the possible values of traffic volume and incident severity. Each simulation was run ten times, using a different set of random number seeds for each run. Thus, the simulations generated 60 output files. These files were then subjected to post-processing.

In the course of post-processing the simulation output, the remaining three parameters were varied. These parameters generated 120 possible valid combinations. It should be noted that the last two parameters (i.e., the reader spacing and the distance to next downstream reader) were somewhat interrelated, in that not all combinations of these parameters were valid for consideration. For example, the distance to the next downstream reader could not be 2.5 miles if the readers were spaced two miles apart. This is illustrated in Figure 1. There were 30 valid combinations of reader spacing and distance to next downstream reader. So, when coupled with four possible values of the percentage of vehicles with transponders, this generated 120 unique combinations. When each of these 120 combinations was applied to the 6 different simulations, the result was 720 unique combinations to be assessed. Of course, as stated previously, each simulation was run ten times with different random number seeds, so there were actually 7,200 individual scenarios to analyze.

The overall study design is illustrated as a block diagram in Figure 2. This figure shows how the five selected parameters were varied to create the 720 unique combinations to be analyzed.

Figure 1. Relationship Between Reader Spacing and Incident Location

Reader Spacing (miles between readers)

	2	4	6	8	10
0.5					
1.5					
2.5					
3.5			Valid Combinations		
4.5					
5.5					
6.5					
7.5		Invalid			
8.5		Combinations			
9.5					

Incident location (miles to next reader)

Figure 2. Block Diagram of Overall Study Design
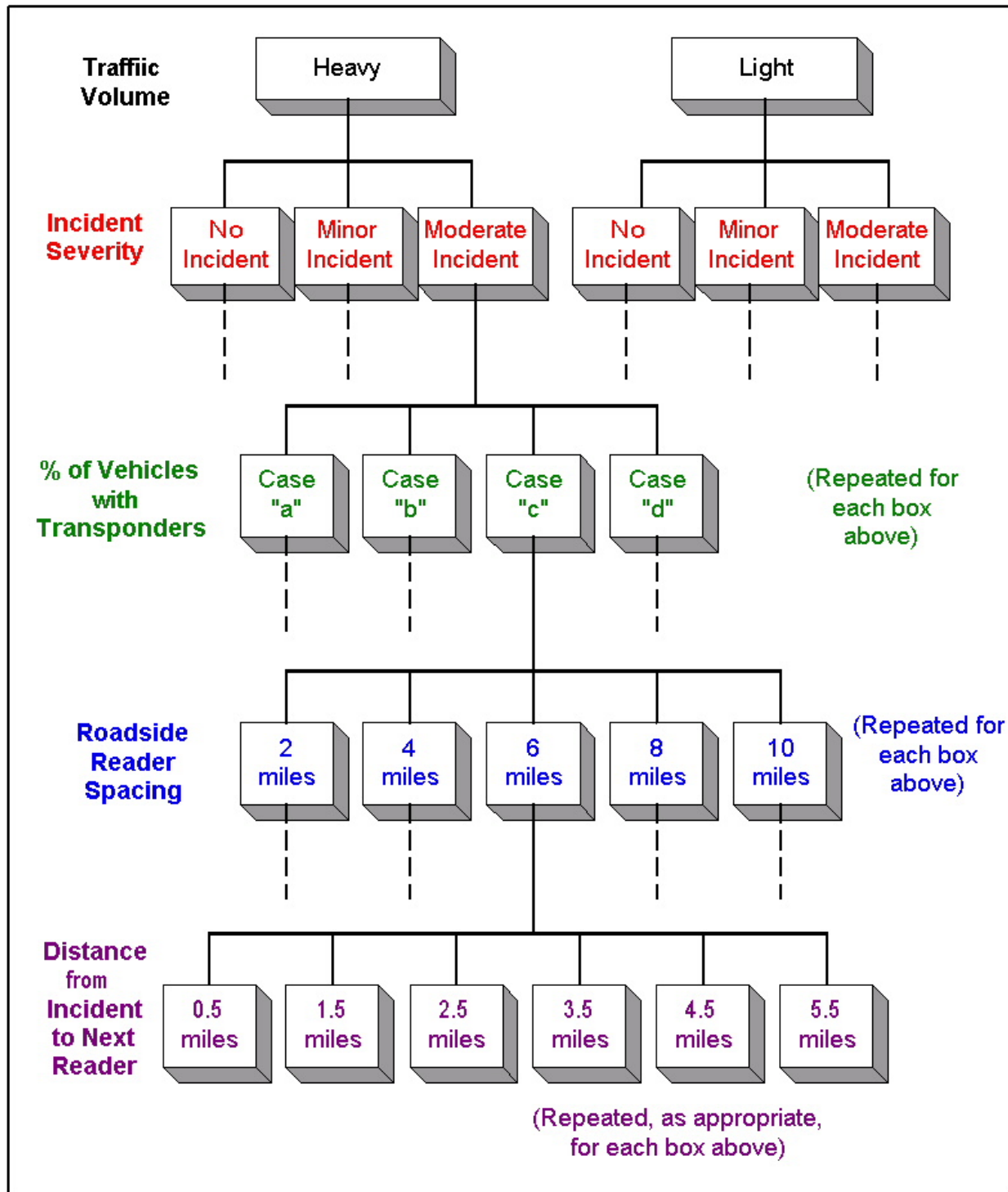
System Modeling and Simulation

The freeway simulation tool selected for use in this study was the CORSIM software, which is part of the TSIS[16] package, version 5.0. Factors influencing this decision included prior experience with the software, its ready availability, its capabilities, and the ease of obtaining technical support. The TSIS package proved to be reasonably straightforward to use, and the simulations were run with no major difficulties. The primary output file produced by each execution of the simulation was a "time step data" file, or TSD file. This binary file contained the position of every vehicle on the freeway segment for each one-second time increment (or time step) of the simulation.

In accordance with the study design, the CORSIM simulation was run for each of the following six scenarios:

- Heavy Traffic, No Incident (HTNI)
- Heavy Traffic, Minor Incident (HT1B)[17]
- Heavy Traffic, Moderate Incident (HTMO)
- Light Traffic, No Incident (LTNI)
- Light Traffic, Minor Incident (LT1B)
- Light Traffic, Moderate Incident (LTMO)

For each scenario, the simulation was run ten times, using different random number seeds for each run. This generated 60 different time-step-data files.

Post-Processing of Simulation Output

In order to be useful for assessing a DSRC-based incident detection system, the data in the TSD file needed to be converted to "probe and beacon" data. This "post processing" of the TSD file involved the following steps:

- Read through the TSD file, strip off the header information, convert the data from binary to ASCII format, and carry forward only the data elements that will be needed for the analysis.

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[16] Traffic Software Integrated System; Federal Highway Administration; see www.fhwa-tsis.com
[17] "HT1B" was the author's shorthand notation for "heavy traffic, one lane blocked."

- Sort the data by vehicle ID, then by simulation time.

- Convert the two variables representing the vehicle's position (the LINKID and vehicle's position on that link) to a single variable representing the position of the vehicle on the total segment. (This simplifies future comparisons between vehicle positions and reader positions.)

- Randomly assign transponders to vehicles using the appropriate percentages for the scenario being assessed. Create a new data file with only the transponder-equipped vehicles included. (This step must be performed four times for each input file, using the four different "cases" for the percentages of vehicles with transponders.)

- Convert the vehicle position data to "probe and beacon" data by determining when a transponder-equipped vehicle will go past a roadside reader and creating a data record for each such event. (This step must be performed 30 times for each input file, to account for all the valid combinations of reader spacing and distance to the next downstream reader.)

The post-processing was accomplished using a series of Fortran programs written by the author. Fortran was chosen due to the author's prior experience and familiarity with that programming language. The only problems encountered were the size of the files (a typical TSD file was in excess of 100 megabytes), which made sorting and similar functions unwieldy, and the sheer number of data files that required processing. For example, the last step in the bulleted list above was carried out for 240 different input files, and generated 7,200 unique output files.

The end result of the post-processing was a set of 7,200 text files containing "probe and beacon" data. Figure 3 shows a portion (i.e., the first few records) of the resulting data file for one of the "heavy traffic, minor incident" scenarios. This particular file is for random run number one, transponders on 25 percent of the trucks (i.e., case "a"), readers spaced two miles apart, and one-half mile from the incident to the next downstream reader.

Figure 3. Portion of Typical Output File Resulting from Post-Processing

Reader	Time	VehID
126720	946	114
126720	926	190
126720	947	192
126720	949	195
126720	931	197
126720	927	201
126720	997	215
126720	990	218
126720	984	220
116160	930	225
126720	1046	225
126720	987	228
126720	1003	230
126720	1018	233
126720	995	246
116160	905	250
126720	1031	250

Once the post-processing was complete, an additional program was run to calculate travel times for those vehicles that passed more than one roadside reader during the simulation. Plots of the travel times were then prepared. These plots were used by the author for several purposes, including: (1) verifying that the simulations and post-processing routines had worked properly; (2) gaining further understanding of the travel time distributions (both before and after the incident occurrence); and (3) identifying the best approach to use for the incident detection algorithm.   Samples of the travel time plots are shown in Figures 4, 5, and 6. These figures represent the scenario with heavy traffic, random run number one, transponders on 25 percent of the trucks (i.e., case "a"), readers spaced two miles apart, and one-half mile from the incident to the next downstream reader. Figure 4 is the "no incident" scenario, Figure 5 is the "minor incident" scenario, and Figure 6 is the "moderate incident" scenario.

Figure 4. Sample Graph of Travel Times for "No Incident" Scenario

HTNI-01a0201
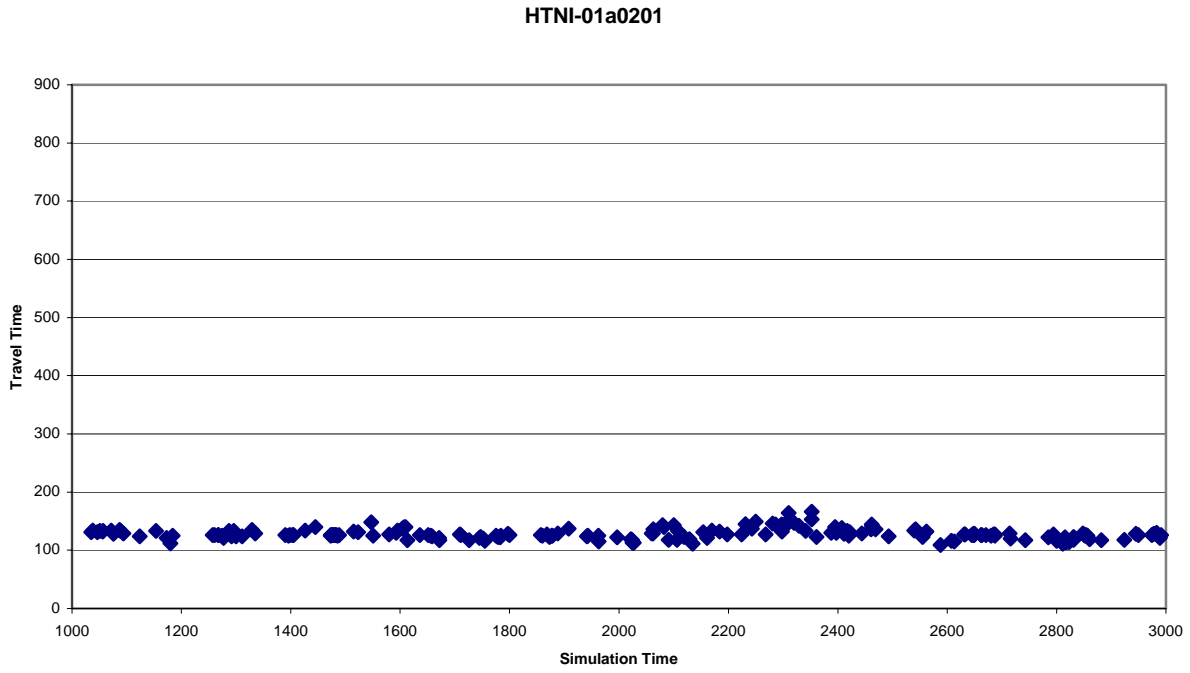
Figure 5. Sample Graph of Travel Times for "Minor Incident" Scenario

HT1B-01a0201
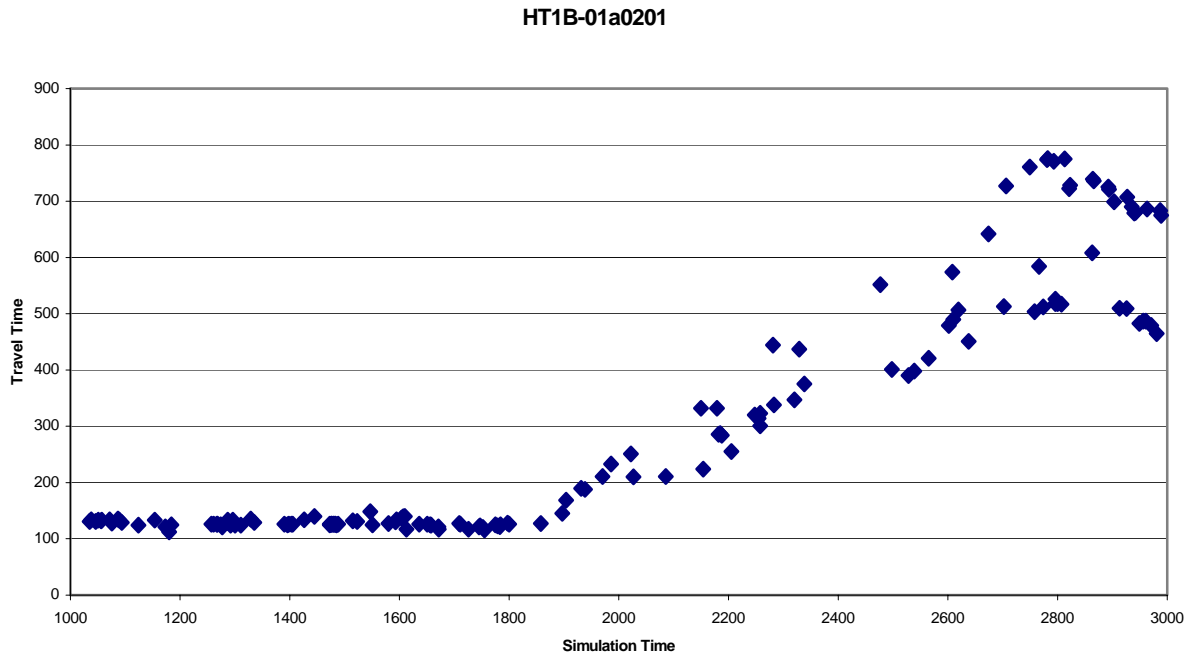
Figure 6. Sample Graph of Travel Times for "Moderate Incident" Scenario

HTMO-01a0201
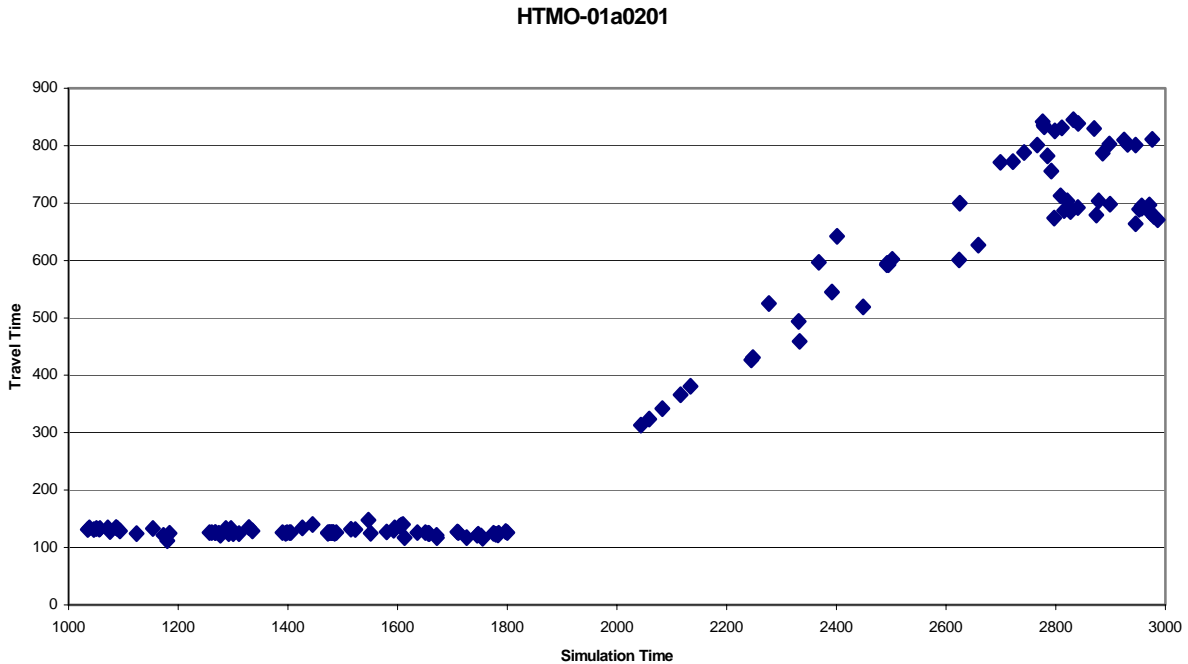
Development of Detection Algorithm

After the simulation output files had been post-processed to create the 7,200 "probe and beacon" data files, the next step was to apply the incident detection algorithm. Development of the algorithm was one of the more intriguing components of the study. Much of the available work on developing and evaluating incident detection algorithms has focused on two challenges. The first challenge is using data from fixed-point traffic sensors (e.g., loop detectors in the pavement) to estimate travel time or delay on a roadway segment. The second challenge is distinguishing between recurring congestion and incident-related congestion. For this study, which is focusing on a DSRC-based incident detection system on a segment of rural freeway, these challenges are not applicable. A DSRC-based system measures travel time directly, so if travel time increases, then something has happened to reduce vehicle speeds and/or to create delay. And, for most rural freeway settings, recurring congestion is not an issue. So, when congestion and delay occur, they are due to an incident and they need to be detected.

With this in mind, the original intent for this study was to develop an incident detection algorithm based on a statistical test (such as a t-test) using the mean travel time. The logic

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behind such an approach was as follows. For normal circumstances (free from incident), travel times will follow some random distribution. When the system observes a value (or several values) that differs from the mean, it could be the result of an incident or it could simply reflect the distribution of values. So, how does the system know when an incident has occurred? The most accurate answer is, it doesn't know. The system never actually <u>knows</u> (from the transponder data alone) that an incident has occurred. However, it can determine the probability that an incident has occurred, based on what has been observed.

One approach to this analysis would be to select a "null hypothesis" that no incident has occurred—that the "after" observations are drawn from the same population as the "before" observations. The alternative hypothesis is that something has occurred to change the situation, so that the "after" observations are drawn from a population with a different (i.e., larger) mean than the "before" observations. For a given confidence level (or a given "alpha"), the algorithm can either reject or fail to reject the null hypothesis. If it rejects the null hypothesis, then it has concluded (with a confidence level of "one minus alpha") that an incident has occurred.

In this case, "alpha" represents the probability of a "type one" error, i.e., of rejecting the null hypothesis when it is actually true. The designers should choose "alpha" based on their determination of an acceptable risk of a "false alarm" (concluding that an incident has occurred when it has not). If they set "alpha" very low, they can virtually eliminate the possibility of a type one error, but in so doing they increase the chance of a type two error, which is failing to reject the null hypothesis when it is false. This type of error would cause the system to fail to recognize an incident when one has occurred, or, in more practical terms, to require more data points (and hence more time) to recognize the incident. So, setting "alpha" very low would make the system less likely to generate false alarms, but it would also make the system slower to detect incidents, since more data points would be required to reject the null hypothesis. This is illustrated in Figure 7, which shows (for a given value of detection rate) the shape of the expected relationship among the other three parameters; namely the selected "alpha" value, the time to detect an incident, and the rate of false alarms. It is reasonable to assume that for incidents causing significant delay, the detection rate should be 100 percent, given sufficient time and data points.

**Figure 7. Qualitative Relationship Among Alpha, Time to Detect,
    and False Alarm Rate**
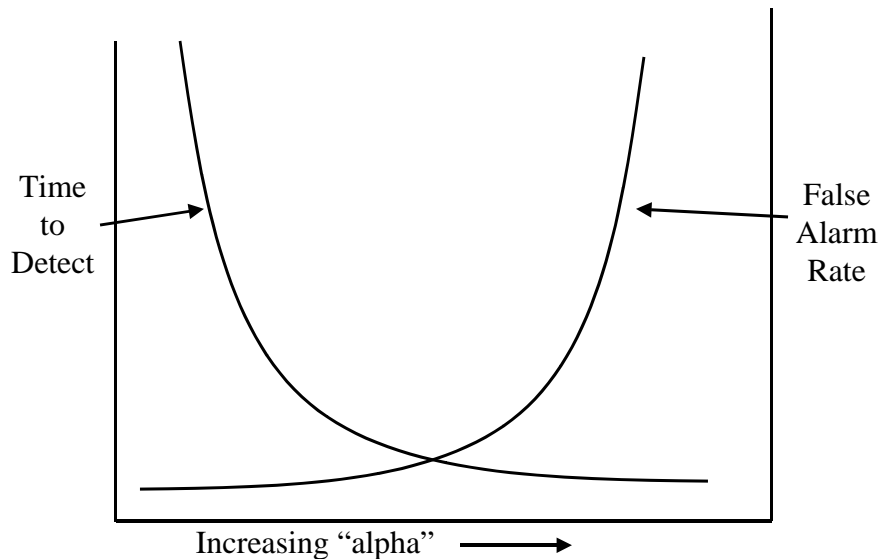
The statistical analysis of this problem is quite straightforward. It consists of examining the means of two samples and trying to determine if they come from the same population (i.e., have the same mean) or from different populations (with different means). This can be accomplished using a simple t-test. However, when it comes to actually applying such a statistical test to incident detection, there are several issues that make the problem more interesting. These include the following:

1) Since the analysis logic will not know when (or if) an incident has occurred, it will need to keep a running mean of the "before" observations and treat each new observation as a potential "after." It will need to know when to start keeping a running mean of the "after" observations, based on some sort of clue that an incident may have occurred.

2) Obviously, not all incidents are the same. Some will result in longer delays than others, and thus will be easier to detect statistically. Others may result in shorter delays and may require more data points to confirm.

3) For serious incidents (e.g., where the roadway is completely blocked), the first indication may be that the system stops getting data from a specific roadside reader. The logic will need to identify such a condition and know when to declare that an

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incident has occurred. This raises interesting questions about what will happen if a reader ceases to function, since a reader failure could produce the same indications as a complete roadway blockage.

4) Of course, in a real world application, the system will not just be looking at a single pair of readers. It will be looking at multiple readers, and each two consecutive readers will constitute a pair, with their own analysis.

Through the early stages of this research project, it was the author's intention to develop a detection algorithm based on a statistical test of means, as described above. Such a test is quite appropriate to the situation, and the challenge of programming the test for the travel-time data was quite appealing to the author. However, when it came down to analyzing the actual data from simulated incidents, it quickly became apparent that such an approach, while quite appropriate, was not necessary. For any incident severe enough to produce a significant increase in travel times (significant to the traveler, that is), the increase was of such a magnitude to be detectable with more straightforward tests. So, the task of programming the t-test for the mean travel time was deferred, perhaps to be used in a future project.

After plotting and assessing the travel time data, the approach (or algorithm) that was chosen for implementation was based on setting a "threshold" value for travel time. The threshold value was selected to represent a significant increase over the normal travel time, i.e., an increase that would be regarded as a significant delay to a traveler. Any travel time value that came in exceeding the threshold would increment a counter. Any travel time that came in under the threshold would decrement the counter (unless the counter was at zero). When the counter reached a pre-selected level, an alarm would be generated. This approach is similar to techniques used for quality control applications, such as the Individual Observation Control Chart.

An obvious question is: "Why was a counter needed?" Why not just generate an alarm for any travel time that exceeded the threshold? The counter was necessary to account for the possible spurious behavior of individual vehicles/drivers. A vehicle might stop by the side of the road to change drivers, make a phone call, or change a flat tire. In the case of vehicles traveling together, several vehicles may stop by the side of the road. Or, in the case of an intervening interchange or rest area, a percentage of all vehicles may experience "delay" that is not

associated with any incident. Thus, the appropriate value for the counter "alarm level" could vary based on the characteristics of the segment being monitored.

This same argument explains why it is necessary to decrement the counter for travel times that come in below the threshold. If this were not done, then the occasional data points with high travel times would eventually drive the counter to the alarm point. For a true incident situation, travel times should increase for all vehicles in the traffic stream, not just for an occasional vehicle.

With this type of detection algorithm, there are two user-selected values that will impact the performance of the system: the travel time threshold and the counter alarm level. Obviously, in the selection of these values, there is a trade-off between detection time and false alarm rate. In general, the lower the threshold and counter alarm level, the more quickly the system will detect incidents, but the more false alarms will be generated. Higher values for the threshold and counter alarm level will reduce the frequency of false alarms, but will also delay the detection of incidents. The general shape of this relationship is shown in Figure 8. The shape of this graph is identical to Figure 7; only the labels have been changed.

Figure 8. Qualitative Relationship among Threshold, Counter Alarm Level, False Alarm Rate, and Time to Detect
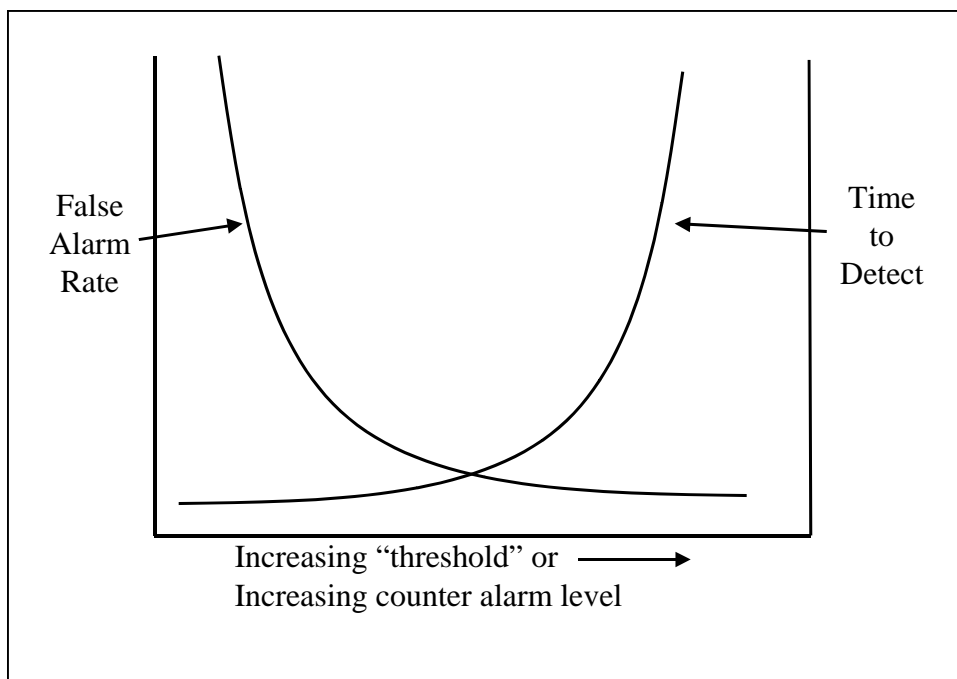
Since the incident detection algorithm requires comparing individual travel times to the "normal" travel time, it was necessary to define the "normal" travel time. For the sake of this analysis, it was decided to use the mean travel time for the appropriate "no incident" scenario as the normal travel time. Any individual travel time that exceeded the mean travel time by an amount equal to (or exceeding) the threshold would increment the alarm counter.

One additional consideration in actually programming the incident detection algorithm was the necessity for the system to "infer" data. In other words, when a vehicle was late arriving at a downstream reader (i.e., its travel time exceeded the mean travel time) by an amount equal to the alarm threshold, the system needed to create a data point as soon as this situation occurred. It was not acceptable to wait until the vehicle actually arrived at the downstream reader, because doing so would delay detection of the abnormal travel time. In fact, for a complete blockage of the roadway, vehicles would not arrive at the downstream reader until after the incident had been cleared. So, the algorithm was programmed with the capability to determine an "overdue" time for each vehicle at the downstream reader, and to replace the actual arrival time with the overdue time when appropriate. The effect of this "data inference" is illustrated in Figure 9, which plots travel time versus simulation time for the "HT1B-01a0201" scenario. This plot uses the same data as Figure 5, except that arrivals at the downstream reader have been created whenever a vehicle is late arriving by an amount equal to the threshold (30 seconds in this case). The net effect is to "chop off" all travel times at the threshold level, and, of course, these "inferred arrivals" occur earlier in the simulation, since the program does not wait for the actual arrival to create a data point. This capability will lead to more rapid detection of incidents.

Figure 9. Plot of Travel Times for Minor Incident Scenario (with inferred travel times)

HT1B-a0201
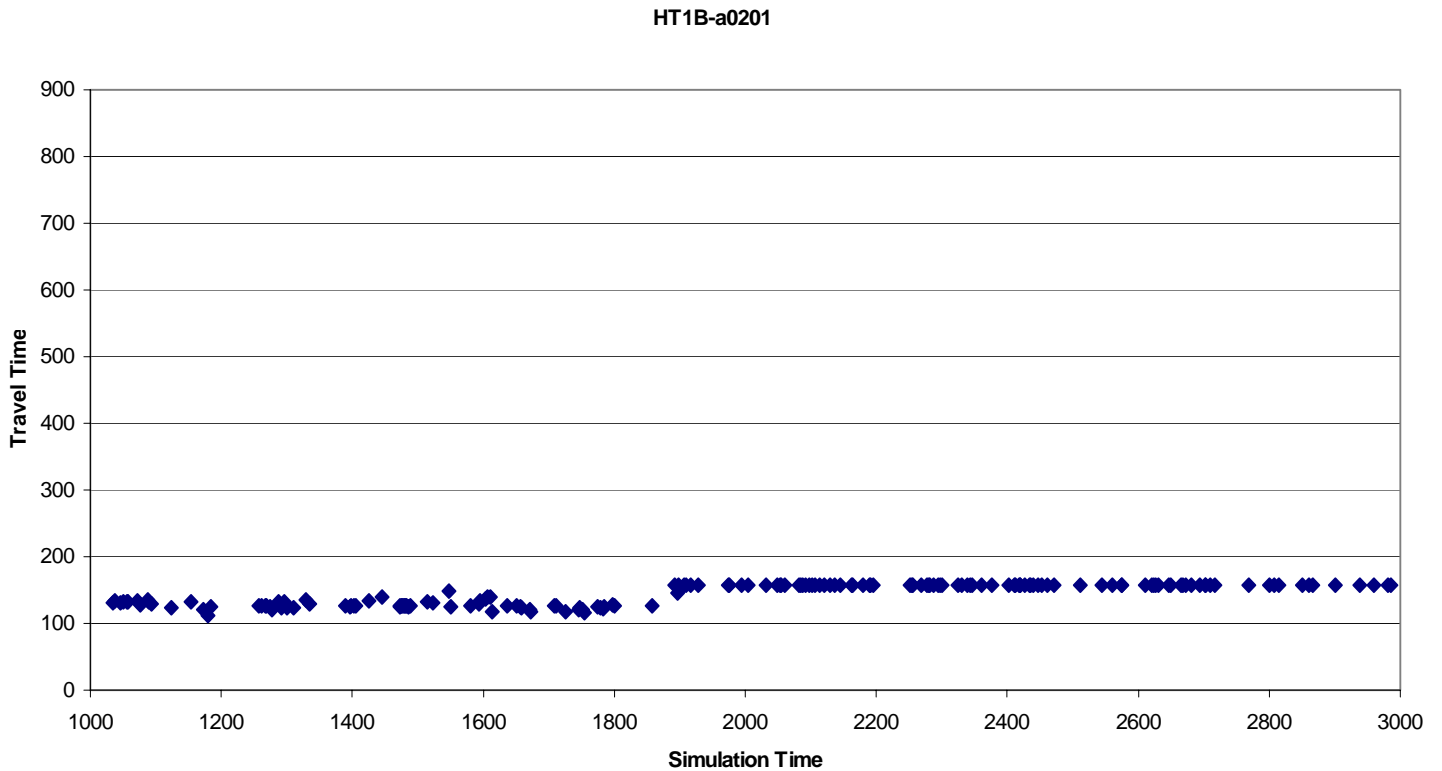
Application of Detection Algorithm to Data

The trade-off between detection time and false alarm rate was of some interest to the author, and so it was investigated for different values of the threshold and the counter alarm level. It was desired to select a counter alarm level that was high enough to avoid spurious alarms (such as from two or three vehicles traveling together and stopping on the roadside), and yet was low enough to provide for quick incident detection. So, the counter alarm level was initially set at five, and the detection algorithm was run using thresholds of 30, 45, and 60 seconds. For each of these values, the algorithm was run on 24 different scenarios (selected to represent a wide range of conditions), and the results were used to determine a detection rate, false alarm rate, and average time to detect for each scenario. In order to gain some understanding of the effect of varying the counter alarm level, the algorithm was run again (on all 24 scenarios) using a threshold of 30 seconds and a counter alarm level of ten. Again, the

results were used to determine a detection rate, false alarm rate, and average time to detect for each scenario.

For the purposes of this study, the false alarm rate was calculated (and hence defined) as follows. For a given scenario (e.g., heavy traffic, minor incident, 25 percent of trucks with transponders, two-mile reader spacing, one-half mile from incident to downstream reader), the false alarm rate was determined by applying the incident detection algorithm to the ten "no incident" files corresponding to this same scenario. Since these files represented scenarios without incidents, then any alarm generated on these files would be a false alarm. So, if no alarms were generated for any of these files, then the false alarm rate was zero. If alarms were generated for three of the ten files, then the false alarm rate was 30 percent, and so on.

The detection rate was defined as the percentage of files (for a given "minor incident" or "moderate incident" scenario) for which the algorithm successfully detected the incident before the end of the simulation. The average time to detect was defined as the elapsed time (averaged over the ten files for each scenario) from the occurrence of the incident until the alarm was generated. Files where the incident was not detected or where the detection occurred early (due to a false alarm) were excluded from the calculation of the average.

The ultimate purpose of this analysis was to identify the "best" values for the threshold and the counter limit, so that these "best" values could then be applied to all 480 incident scenarios. Of course, it was recognized early in the analysis that there might not be a single "best" value for the threshold or for the counter limit. Instead, different values might need to be selected for different scenarios. In particular, it was recognized that the threshold might need to vary based on some measure of the amount of "spread" in the travel time distribution. To implement this, the algorithm was modified to select a threshold for a particular scenario based on the standard deviation of the travel times for the corresponding "no incident" scenario. This modified algorithm was then applied to the 24 selected scenarios in order to assess its performance.

The results of the algorithm assessment are presented and discussed in the "FINDINGS" section of this report.

System Performance Assessment (and Regression Analysis)

Using the "best" values of the threshold and the counter alarm value (based on the algorithm analysis), the detection algorithm was then run on all 4,800 output files[18] (for the minor incident and moderate incident scenarios) generated by the simulation and post-processing. This generated 4,800 values of the amount of time required to detect an incident.[19] These values represented 480 scenarios, with ten independent runs (with different random number seeds) for each scenario. An average time to detect was determined for each of the 480 scenarios, and these values were organized into four tables. The tables were analyzed for trends, so that the effects of varying key parameters could be identified and described. To verify the trends that were observed in the tables, a regression analysis was conducted to assess the effect of each of the key parameters on the detection time. The dependent variable in this analysis was the time to detect an incident. The independent variables were the traffic volume, the incident severity, the percentage of vehicles with transponders, the reader spacing, and the distance from the incident to the next downstream reader. The SAS statistical package was used for this analysis.[20] The results of the analysis are presented in the "FINDINGS" section of this report.

Cost Assessment

Using the author's prior experience with implementing DSRC-based systems for commercial vehicle electronic screening, a rough cost estimate was developed for implementing a travel-time monitoring and incident detection system on a segment of rural interstate. The results are presented in the "FINDINGS" section of this report.

Development of Recommendations

Based on the results of the algorithm assessment, the regression analysis, and the cost assessment, the author developed recommendations for further testing and implementation of a DSRC-based incident detection system. These recommendations are presented in the "RECOMMENDATIONS" section of this report.

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[18] As previously discussed, the simulation and post-processing generated 7,200 output files. One-third of these files were for "no incident" scenarios. The remaining 4,800 were for "minor incident" and "moderate incident" scenarios. These are the files to which the incident detection algorithm was applied.

[19] There were some scenarios where the algorithm failed to detect the incident, so the actual number of values was less than 4,800. This is discussed in the "FINDINGS" section.

[20] SAS Institute, Inc.; Cary, NC; See http://www.sas.com.

FINDINGS

Application of Detection Algorithm to Data

As previously described, the post-processing of the simulation output data resulted in a set of 7,200 data files, each containing "probe and beacon" data. Each record in such a file represents an event where a transponder-equipped vehicle passes a roadside reader. In order to assess the performance of the incident detection algorithm, the algorithm was applied to 24 different scenarios, selected to represent a wide range of conditions. For each scenario, the results were used to determine a false alarm rate, a detection rate, and an average time to detect (as defined in the "METHODOLOGY" section). This process was carried out using alarm thresholds of 30, 45, and 60 seconds (with a counter alarm level of 5), and then repeated with a threshold of 30 seconds and a counter alarm level of 10. The results are presented in Tables 3 through 6. The following abbreviations are used in the tables to represent the selected scenarios.

HT1B = heavy traffic, minor incident

HTMO = heavy traffic, moderate incident

LT1B = light traffic, minor incident

LTMO = light traffic, moderate incident

0201 = reader spacing of two miles, one-half mile from incident to next reader.

0605 = reader spacing of six miles, 4.5 miles from incident to next reader.

1010 = reader spacing of ten miles, 9.5 miles from incident to next reader.

"a" = percentages of trucks and cars with transponders are 25% and 5% , respectively.

"c" = percentages of trucks and cars with transponders are 75% and 15% , respectively.

Table 3. Algorithm Results (Threshold = 30 sec, Counter Alarm Level = 5)

	Avg Time to Detect (seconds)			Detection Rate (%)			False Alarm Rate (%)	
HT1B	a	c		a	c		a	c
0201	153	125		100%	100%		30%	30%
0605	412	386		100%	100%		20%	50%
1010	740	706		100%	100%		20%	30%
HTMO	a	c		a	c		a	c
0201	116	89		100%	100%		Same as HT1B	
0605	360	331		100%	100%			
1010	677	653		100%	100%			
LT1B	a	c		a	c		a	c
0201	365	288		60%	90%		0%	0%
0605	542	483		56%	88%		0%	10%
1010	842	753		56%	80%		10%	60%
LTMO	a	c		a	c		a	c
0201	154	102		100%	100%		Same as LT1B	
0605	382	329		100%	100%			
1010	669	611		100%	100%			

Table 4. Algorithm Results (Threshold = 45 sec, Counter Alarm Level = 5)

	Avg Time to Detect (seconds)			Detection Rate (%)			False Alarm Rate (%)	
HT1B	a	c		a	c		a	c
0201	174	149		100%	100%		0%	0%
0605	452	407		100%	100%		0%	20%
1010	774	739		100%	100%		10%	10%
HTMO	a	c		a	c		a	c
0201	132	103		100%	100%		Same as HT1B	
0605	383	350		100%	100%			
1010	697	672		100%	100%			
LT1B	a	c		a	c		a	c
0201	373	371		50%	70%		0%	0%
0605	594	545		56%	67%		0%	0%
1010	884	803		50%	50%		10%	30%
LTMO	a	c		a	c		a	c
0201	169	117		100%	100%		Same as LT1B	
0605	399	346		100%	100%			
1010	685	631		100%	100%			

Table 5. Algorithm Results (Threshold = 60 sec, Counter Alarm Level = 5)

	Avg Time to Detect (seconds)			Detection Rate (%)			False Alarm Rate (%)	
HT1B	a	c		a	c		a	c
0201	199	171		100%	100%		0%	0%
0605	470	435		100%	100%		0%	0%
1010	815	772		100%	100%		0%	0%
HTMO	a	c		a	c		a	c
0201	147	118		100%	100%		Same as HT1B	
0605	398	370		100%	100%			
1010	712	685		100%	100%			
LT1B	a	c		a	c		a	c
0201	473	385		40%	50%		0%	0%
0605	720	531		40%	40%		0%	0%
1010	1015	816		30%	40%		0%	0%
LTMO	a	c		a	c		a	c
0201	184	132		100%	100%		Same as LT1B	
0605	414	361		100%	100%			
1010	702	650		100%	100%			

Table 6. Algorithm Results (Threshold = 30 sec, Counter Alarm Level = 10)

	Avg Time to Detect (seconds)			Detection Rate (%)			False Alarm Rate (%)	
HT1B	a	c		a	c		a	c
0201	225	149		100%	100%		10%	20%
0605	486	409		100%	100%		10%	20%
1010	820	740		100%	100%		0%	0%
HTMO	a	c		a	c		a	c
0201	161	111		100%	100%		Same as HT1B	
0605	413	355		100%	100%			
1010	718	672		100%	100%			
LT1B	a	c		a	c		a	c
0201	393	353		50%	70%		0%	0%
0605	737	597		60%	70%		0%	0%
1010	931	832		40%	44%		0%	20%
LTMO	a	c		a	c		a	c
0201	240	130		100%	100%		Same as HT1B	
0605	468	357		100%	100%			
1010	753	645		100%	100%			

Using a threshold of 30 seconds with a counter alarm level of five (Table 3) results in a 100 percent detection rate for most of the scenarios. The exceptions are the "light traffic minor incident" cases (LT1B), where the detection rate ranges from 56 to 90 percent. It should be noted here that the combination of light traffic and a minor incident often resulted in little or no delay to the vehicles in the traffic simulation. Specifically, when light traffic allowed lane changes at will, the impact of a single lane closure was minimal. Therefore, it is feasible that some of these scenarios will be difficult to detect, even with the best algorithm settings.

Table 3 shows an apparent problem with using a threshold of 30 seconds with a counter alarm level of five. There were significant percentages of false alarms in most of the scenarios. The only exceptions were for light traffic scenarios with close reader spacings.

Increasing the threshold to 45 seconds (Table 4) reduced the number of false alarms, but false alarms were still observed for the scenarios with long reader spacings. The higher threshold exacerbated the problem of failing to detect incidents for the "light traffic minor incident scenarios," but all other scenarios remained at 100 percent. And, as expected, increasing the threshold caused increases in the average time to detect. These increases ranged from eight seconds to 83 seconds.

When the threshold was further increased to 60 seconds (Table 5), the algorithm was able to eliminate all false alarms for the scenarios being studied. The trade-off for this improvement was a further decline in the detection rate for the "light traffic minor incident" scenarios (still 100 percent for all other scenarios) and a further increase in the average time to detect for most scenarios.

Of course, there are actually two potential strategies for reducing the false alarm rate. One is to increase the threshold, as illustrated in Tables 3 through 5. The other strategy is to increase the counter alarm level. Table 6 shows the results for a threshold of 30 seconds and a counter alarm level of ten. It can be seen that increasing the counter alarm level from five to ten did reduce the number of false alarms, but false alarms still occurred for a large number of scenarios. And, of course, it resulted in a corresponding increase in the average time to detect, as well as a drop in detection percentage for the "light traffic minor incident" scenarios. Since it was possible to eliminate all false alarms by simply increasing the threshold from 30 seconds to 60 seconds, it was determined that the more effective way to eliminate false alarms is to select an

appropriate value for the threshold. Therefore, the decision was made to set the counter alarm level back at five and to focus attention on selecting the "best" value for the threshold.

This analysis demonstrated that there is no single setting for the threshold that is best for all scenarios. Instead, it was apparent that the threshold should vary based on the characteristics of the scenario being analyzed. The most critical characteristic would be the amount of "spread" in the distribution of travel times (for incident-free traffic flow). Therefore, it was determined that the threshold should vary based on the standard deviation of travel times (calculated for the corresponding "no incident" scenario). After assessing which threshold values worked best for each scenario and comparing the threshold values to the standard deviation for each scenario, it was determined that the threshold should be set at one-third the standard deviation. In addition, it was determined that the minimum value for the threshold should be 20 seconds and the maximum value should be 60 seconds. Since the analysis had already shown that a threshold of 60 seconds would eliminate all false alarms, there was no reason to use higher values. On the minimum side, extremely small threshold values could create false alarms and there was no practical need to detect extremely small increases in travel time.

The incident detection algorithm was reprogrammed to calculate the threshold based on the standard deviation of travel times, as described above. It was then applied to the 24 selected scenarios, and the results were used to calculate a detection rate, false alarm rate, and average time to detect for each scenario. The results are shown in Table 7. As can be seen in the table, this approach completely eliminated false alarms (for the selected scenarios), and it resulted in 100-percent detection for all but the "light traffic minor incident" scenarios.

Table 7. Algorithm Results (Threshold based on Std. Dev., Counter Alarm Level = 5)

	Avg Time to Detect (seconds)			Detection Rate (%)			False Alarm Rate (%)	
HT1B	a	c		a	c		a	c
0201	165	135		100%	100%		0%	0%
0605	469	435		100%	100%		0%	0%
1010	815	772		100%	100%		0%	0%
HTMO	a	c		a	c		a	c
0201	123	94		100%	100%		Same as HT1B	
0605	397	369		100%	100%			
1010	712	685		100%	100%			
LT1B	a	c		a	c		a	c
0201	335	265		90%	100%		0%	0%
0605	720	531		40%	40%		0%	0%
1010	1015	816		30%	40%		0%	0%
LTMO	a	c		a	c		a	c
0201	145	92		100%	100%		Same as HT1B	
0605	414	361		100%	100%			
1010	702	650		100%	100%			

System Performance Assessment (and Regression Analysis)

To assess the performance of the incident detection system, and to determine the effects of varying key parameters, the incident detection algorithm was applied to all 4,800 output files (for the minor incident and moderate incident scenarios) generated by the simulation and post-processing. The end result of this process was a single data file with 4,800 records. A printout of the first few records of that file is shown in Figure 10. Each record in the data file contained the values of six variables. Five of the variables were the parameters that were varied in the study design (i.e. traffic volume, incident severity, percentage of vehicles with transponders, roadside reader spacing, and distance from incident to next reader), while the sixth variable was the time that elapsed between incident occurrence and incident detection. Of the 4,800 files processed, there were 612 where the algorithm failed to detect the incident before the end of the simulation. All of these failures were for "light traffic, minor incident" scenarios). There were also two cases where the algorithm generated a false alarm (i.e., it generated an alarm before the incident occurred). For these situations, the detection time was left blank in the resulting data file, and these blank records were ignored in subsequent processing.

For each specific combination of parameters (i.e., for each unique scenario), there were ten values of the time to detect. This resulted from the fact that each simulation was run ten times, with different random number seeds for each run. As a result, it was possible to calculate an "average time to detect" for each scenario. This calculation was carried out, and the results are shown in Tables 8 through 11. Each individual table represents a specific combination of traffic volume and incident severity. Each quadrant within a table represents a specific case of the percentage of transponders on vehicles (i.e., cases "a, b, c, and d" as they were defined in Table 2). Each cell within a table shows the average detection time for a given combination of reader spacing and distance from the incident to the next downstream reader. Obviously, any missing values (i.e., blank detection times) were not included when calculating the average detection time.

Figure 10. Portion of Data File Containing Incident Detection Times

Volume	IncSev	TransPop	RdrSpac	Dist	DetTim
1500	Minor	A	2	0.5	661
1500	Minor	A	2	0.5	117
1500	Minor	A	2	0.5	166
1500	Minor	A	2	0.5	
1500	Minor	A	2	0.5	454
1500	Minor	A	2	0.5	486
1500	Minor	A	2	0.5	443
1500	Minor	A	2	0.5	406
1500	Minor	A	2	0.5	157
1500	Minor	A	2	0.5	121
1500	Minor	A	2	1.5	716
1500	Minor	A	2	1.5	153
1500	Minor	A	2	1.5	222
1500	Minor	A	2	1.5	698
1500	Minor	A	2	1.5	521
1500	Minor	A	2	1.5	567
1500	Minor	A	2	1.5	496
1500	Minor	A	2	1.5	463
1500	Minor	A	2	1.5	211
1500	Minor	A	2	1.5	179
1500	Minor	A	4	0.5	695
1500	Minor	A	4	0.5	
1500	Minor	A	4	0.5	281
1500	Minor	A	4	0.5	

Tables 8 through 11 are extremely useful in looking for the effects of specific parameters on the detection time. For example, it is quite easy to observe the effect of the distance from the incident to the next downstream reader. This effect can be observed by scrutinizing any column of any table. By moving down any column (within a given quadrant), the effect of varying the downstream distance, while holding all other parameters constant, can be observed. It is apparent from all the tables that increasing the downstream distance causes a substantial increase in the average detection time.

Table 8. Average Detection Times for Light Traffic, Minor Incident

LT1B		Reader Spacing (miles)									
		2	4	6	8	10	2	4	6	8	10
Distance to Next Reader (miles)	0.5	335	417	553	520	492	274	395	468	369	433
	1.5	423	474	509	504	500	304	453	479	425	404
	2.5		525	598	541	558		499	494	460	510
	3.5		599	661	636	619		562	536	523	527
	4.5			720	707	686			618	598	575
	5.5			779	854	769			684	665	687
	6.5				936	913				722	725
	7.5		Case "a"		919	932		Case "b"		834	837
	8.5					1025					897
	9.5					1015					951
Distance to Next Reader (miles)	0.5	265	367	369	403	356	219	353	394	463	465
	1.5	285	399	499	386	476	279	473	441	452	506
	2.5		492	463	442	535		517	464	503	585
	3.5		555	481	471	500		580	493	521	550
	4.5			531	529	550			623	582	610
	5.5			619	610	633			735	729	673
	6.5				672	692				822	812
	7.5		Case "c"		699	733		Case "d"		793	801
	8.5					778					769
	9.5					816					849

Table 9. Average Detection Times for Light Traffic, Moderate Incident

LTMO	Reader Spacing (miles)									
Distance to Next Reader (miles)	2	4	6	8	10	2	4	6	8	10
0.5	145	169	184	179	175	103	127	142	139	136
1.5	203	227	241	239	235	161	186	199	198	194
2.5		285	299	298	294		244	257	257	254
3.5		343	357	356	354		302	314	314	312
4.5			414	414	413			373	371	371
5.5			472	472	471			430	429	429
6.5				529	529				488	487
7.5	Case "a"			587	587	Case "b"			546	545
8.5					644					603
9.5					702					661
0.5	92	117	131	128	128	73	103	110	108	104
1.5	150	176	190	186	185	130	164	169	166	163
2.5		233	248	245	243		221	227	225	223
3.5		291	304	305	300		279	285	283	280
4.5			361	362	360			343	342	339
5.5			419	419	419			400	401	398
6.5				477	477				459	456
7.5	Case "c"			535	535	Case "d"			516	516
8.5					592					573
9.5					650					630

Another trend that can be observed is the effect of the roadside reader spacing. By examining the rows in any table (from left to right, within a given quadrant), the effect of increasing the reader spacing, while holding all other parameters constant, can be observed. The effect of increasing the reader spacing is not nearly as pronounced as that of the downstream distance. It can be seen that for small values of reader spacing (i.e., two to four miles), an increase in the reader spacing causes a corresponding increase in the average detection time. However, for the larger values of reader spacing (six, eight, and ten miles), there seems to be little or no effect. This pattern seems to hold true for all of the tables.

Table 10. Average Detection Times for Heavy Traffic, Minor Incident

HT1B		Reader Spacing (miles)									
		2	4	6	8	10	2	4	6	8	10
Distance to Next Reader (miles)	0.5	165	197	209	204	211	138	176	178	176	184
	1.5	227	267	271	267	268	214	242	249	238	246
	2.5		333	340	347	350		304	313	314	304
	3.5		397	403	414	413		369	375	387	371
	4.5			469	474	485			446	449	448
	5.5			528	542	557			508	526	530
	6.5				602	635				585	607
	7.5		**Case "a"**		666	696		**Case "b"**		654	673
	8.5					751					732
	9.5					815					796
Distance to Next Reader (miles)	0.5	135	170	167	162	172	110	154	158	151	153
	1.5	202	234	238	226	232	186	222	227	221	221
	2.5		297	302	306	293		284	294	289	280
	3.5		361	370	374	362		348	360	359	349
	4.5			435	436	437			420	423	424
	5.5			495	502	501			481	485	490
	6.5				565	579				555	566
	7.5		**Case "c"**		633	641		**Case "d"**		614	621
	8.5					706					685
	9.5					772					754

In order to observe the effect of the percentage of vehicles with transponders, the observer must compare individual cells from quadrant to quadrant within a given table. For example, comparing the same cell in the four quadrants of Table 10 (in the order "a, b, c, and d") will show the effect of increasing the percentage of vehicles with transponders, while holding all other parameters constant. The general pattern observed is that the average detection time decreases as the percentage of vehicles with transponders increases. This pattern holds true consistently for all scenarios except the "light traffic minor incident" scenarios (Table 8). It is noteworthy that these were also the only scenarios where some incidents were not detected, resulting in missing values. These missing values could potentially skew the averages and prevent the expected patterns from being observed.

Table 11. Average Detection Times for Heavy Traffic, Moderate Incident

HTMO		Reader Spacing (miles)									
		2	4	6	8	10	2	4	6	8	10
Distance to Next Reader (miles)	0.5	123	148	150	148	149	112	135	136	133	137
	1.5	187	210	214	212	210	178	199	202	196	199
	2.5		270	277	277	274		259	265	263	259
	3.5		332	339	340	338		321	329	327	322
	4.5			397	401	401			387	390	387
	5.5			459	463	464			448	453	451
	6.5				524	527				513	515
	7.5		Case "a"		586	589		Case "b"		574	578
	8.5					648					637
	9.5					712					703
Distance to Next Reader (miles)	0.5	94	117	121	120	122	77	98	104	101	96
	1.5	164	180	185	183	184	150	160	167	165	162
	2.5		242	246	247	246		225	229	229	227
	3.5		308	309	310	309		292	291	292	289
	4.5			369	372	372			355	354	354
	5.5			434	433	434			420	415	415
	6.5				495	497				479	479
	7.5		Case "c"		560	559		Case "d"		545	540
	8.5					619					603
	9.5					685					671

Observing the effect of incident severity requires comparing a specific cell in one table with the same cell in another table. For example, comparing a given cell in Table 10 with the same cell in Table 11 will show the effect of increasing incident severity while holding all other variables constant. The general pattern observed here is that increasing the incident severity results in more rapid detection.

The effect of varying the traffic volume can also be observed by comparing the same cell in two different tables. An example would be to compare a specific cell in Table 8 with the same cell in Table 10. The general pattern observed here (for minor incidents) is that a heavier volume of traffic results in more rapid detection. However, when the same comparison is performed for moderate incidents (i.e., comparing Tables 9 and 11), the effect of traffic volume is much less consistent. This would seem to indicate an interaction between traffic volume and incident severity with regard to their effects on the detection time.

In order to verify the relationships that are apparent in the tables, and to determine if the observed effects of the parameters are statistically significant, a regression analysis was performed on the detection time data. The analysis used the "raw" data, with 4,800 individual detection times (less missing values), rather than the "reduced" data with 480 mean detection times. The SAS statistical package, version 7, was used to perform the analysis. The regression model set the detection time as the dependent variable. The five independent variables were traffic volume, incident severity, percentage of vehicles with transponders, roadside reader spacing, and distance from incident to next reader. Actual numerical values were used for the traffic volume, the reader spacing, and the distance to next reader (as shown in Table 2). For the other variables, values were assigned as follows:

- Incident severity
  - Minor = 1
  - Moderate = 2
- Percentage of vehicles with transponders
  - Case "a" = 1
  - Case "b" = 2
  - Case "c" = 3
  - Case "d" = 4

The regression analysis resulted in an R-squared value for the model of 0.829. The parameter estimates for the independent variables were as follows:

- Intercept   503.26209
- Traffic Volume   -0.04714
- Incident Severity -138.11953
- Transponder %   -19.34680
- Reader Spacing   3.03601
- Distance to Reader 61.85608

For each parameter estimate, the "t value" was of such a magnitude that the "Pr > |t|" was less than 0.0001. So, each independent variable was determined to be a significant predictor of the detection time. The largest "t value" was for the distance to the next reader, while the smallest was for the reader spacing.

It is interesting to note the signs (i.e., positive or negative) of each of the parameters listed above and see if they agree with the patterns observed in Tables 8 through 11. The negative values of parameters above would indicate that increasing the traffic volume, the incident severity, or the percentage of vehicles with transponders should result in a reduced time to detect. On the other hand, increasing the roadside reader spacing or the distance from the incident to the next reader should cause an increase in the time to detect. These findings are reasonable, and they corroborate the trends observed in Tables 8 through 11.

A second regression analysis was run to look for possible interactions between the independent variables. This analysis showed several statistically significant interactions between variables, with the strongest interaction between traffic volume and incident severity. This is consistent with the observations from Tables 8-11. A major factor in creating and shaping this interaction was the way in which incidents were defined for the simulation (see Table 2). Specifically, for minor incidents, the traffic volume had a substantial impact on determining whether traffic backups occurred (or how long it took for a backup to occur). However, for moderate incidents, where the roadway was completely blocked, traffic backups (and associated delays) would occur immediately, regardless of the traffic volume. This is what was observed in the tables and verified by the regression results.

With regard to overall system performance, the following can be observed:
- For a roadside reader spacing of two miles, the average detection time ranged from 73 seconds to 423 seconds. Excluding the "light traffic minor incident" (or LT1B) scenarios, which were inherently difficult to detect due to minimal traveler delay, the average detection time ranged from 73 seconds to 227 seconds. So, for any incident causing significant traveler delay, the system detected the incident in one to four minutes.
- When the roadside reader spacing was four miles, the average detection time ranged from 98 seconds to 599 seconds. Excluding the "LT1B" scenarios, the largest average detection time was 397 seconds. So, using a four-mile reader spacing, the system detected significant incidents in 1.5 to 6.5 minutes.
- For a reader spacing of six miles, the smallest average detection time was 104 seconds and the largest was 779 seconds. Excluding the "LT1B" scenarios, the

largest average detection time was 528 seconds. So, with this reader spacing, the system detected significant incidents in 1.5 to nine minutes.

- When the reader spacing was eight miles, the average detection time ranged from a minimum of 101 seconds to a maximum of 936 seconds. Excluding the "LT1B" scenarios, the largest average detection time was 666 seconds. So, an eight-mile reader spacing generated detections (for significant incidents) in the range of 1.5 to 11 minutes.

- Finally, for a roadside reader spacing of ten miles, the smallest average detection time was 96 seconds, and the largest was 1025 seconds. Excluding the "LT1B" scenarios, the largest average detection time was 815 seconds. So, with a ten-mile reader spacing, the system was able to detect significant incidents in 1.5 to 14 minutes.

One question that may be raised is, "How well could a DSRC-based incident detection system perform today, with the current population of transponders on vehicles?" In the experimental design, with regard to the percentage of transponders on vehicles, Case "a" was selected to approximate the current condition. So, it is possible to assess how a system would perform today by examining the Case "a" quadrants of Tables 8 through 11. If the intent is to exclude the "LT1B" scenarios, then Table 8 can be ignored. Examining Tables 9, 10, and 11 shows that, for a reader spacing of two miles, the average detection time (for Case "a") ranges from two to four minutes. When the reader spacing is four miles, the detection time is 2.5 to 6.5 minutes. For a six-mile reader spacing, the detection time is 2.5 to nine minutes. When the reader spacing is eight miles, the average detection time ranges from 2.5 to 11 minutes. And, for a reader spacing of ten miles, the detection times range from 2.5 to 14 minutes.

In summary, for today's transponder population levels, the "best case" scenario (where an incident occurs just upstream of a reader) could be detected within two minutes or so (regardless of the reader spacing). For the "worst case" scenario (where the incident occurs far upstream of a reader) the incident could be detected in four minutes for a two-mile reader spacing, and this time increases by about 2.5 minutes for every two-mile increase in the reader spacing. This relationship can be expressed by the formula:

$DT_{wc} = 1.5 + (1.25) * RS$

where DT_{wc} is the detection time in minutes for the "worst case" scenario (as defined above), and RS is the reader spacing in miles.

The relationship between roadside reader spacing and average time to detect (for the current population of transponders) is illustrated in Figure 11. The three lines on this graph represent the "best case" detection time, the "worst case" detection time, and the calculated detection time using the formula above.

This analysis demonstrates a relationship that was observed earlier when looking for patterns in Tables 8 through 11. The reader spacing itself has very little impact on the average detection time (when all other parameters are held constant). However, the reader spacing is extremely significant, because it defines the upper limit of the distance from the incident to the next downstream reader. Obviously, the distance from the incident to the next reader cannot exceed the reader spacing.

Figure 11. Relationship Between Reader Spacing and Detection Time (for Current Levels of Transponders on Vehicles)
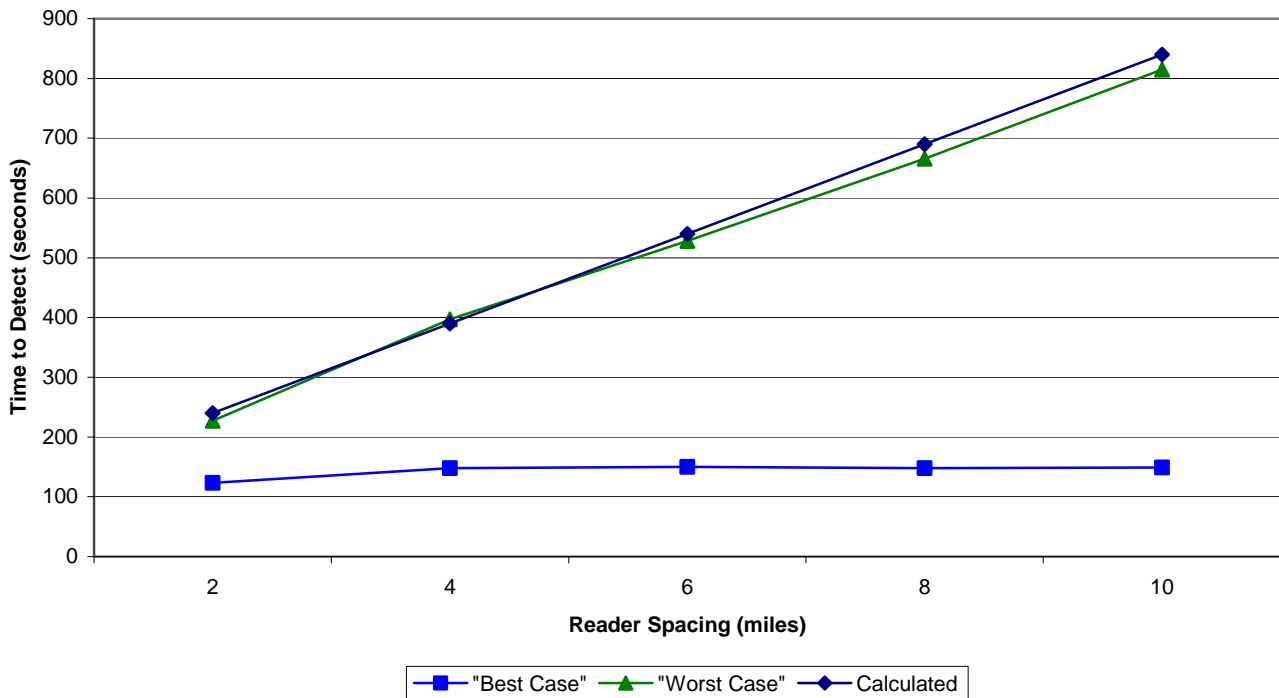
Cost Assessment

The cost of deploying a DSRC-based system for traffic monitoring and incident detection can be divided into the following elements:

- Cost of system hardware
- Site preparation and installation costs
- Software development and system integration
- Ongoing operations and maintenance costs

The cost of system hardware would include the DSRC readers, antennas, associated wiring, roadside equipment cabinets, poles, and mast arms. It would also include a computer to receive the "probe and beacon" data, calculate travel times, and run the detection algorithm. Depending on the communications and electrical power options selected, the hardware costs could also include radio-frequency modems (for point-to-point communications), solar panels, and batteries.

The cost of site preparation and installation would be greatly influenced by the communications and electrical power options selected. The use of solar power and wireless communications could eliminate the need for substantial trenching, conduit, and cabling to bring electrical power and hardwire communications to each site. In any case, site preparation would include concrete foundations for antenna poles. Equipment cabinets can be pole-mounted or placed on separate foundations. Initial installation of poles, mast arms, and antennas typically involves a lane closure, with associated costs for traffic control.

Software development costs, while always difficult to predict, should not be excessive. The system functionality is straightforward and the algorithm has already been programmed and tested. The primary task of software development will be converting the system from a post-processing environment to a real-time operation. The calculation of a "rolling mean" for travel time will also need to be included in the program.

The ongoing operations and maintenance costs will include the cost of any utilities used (electrical power, phone connections, wireless communications, etc.), the cost of routine preventive maintenance, and the cost of troubleshooting and repairing system failures. The Kentucky Transportation Cabinet has substantial experience in maintaining DSRC systems at weigh stations throughout the state, and these systems have not been expensive to maintain. The

utilities cost will be driven primarily by the type of communications selected for the system. Communications is vital to the system functionality. Each time a roadside reader reads a transponder, that information must get to the central processing computer[21]. So, a communications network must be established which includes each reader and the central system.

The following are preliminary cost estimates for developing and installing a DSRC-based incident detection system.

Initial Per-Site Costs (for roadside equipment procurement and installation)[22]
- DSRC Reader, with antennas and associated connectors
  - $8,000 to $15,000[23]
- Poles, mast arms, equipment cabinet, etc.
  - $5,000
- Solar panels, RF modems, batteries, etc.
  - $2,000
- Site preparation and installation
  - $8,000

Initial System-Wide Costs
- Software Development and System Integration
  - $50,000
- Computer and Peripherals for Central Processing
  - $3,000
- Miscellaneous (communications setup, etc.)
  - $2,000

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[21] There are also options involving distributed processing, which would require only reader-to-reader communications for normal operations. For such a system, communications with a "traffic management center" would still be required whenever an alarm was generated by the system.

[22] These estimates assume a bi-directional installation, with one DSRC reader connected to two antennas (one for each direction). They also assume the use of solar power, along with RF modems for reader-to-reader communications.

[23] The wide range in reader costs is due to the recent entrance of a new vendor, with prices about one-half of the historical norm.

<u>On-Going Costs</u>

- High-Speed Wireless Communications Service
    - $1,200 per year
- Maintenance of Central System Hardware and Software
    - $5,000 per year
- Maintenance of Roadside Systems
    - $3,000 per site per year

<u>Costs of a "Typical" Deployment</u>

Using the approximate unit costs listed above, deployment of a DSRC-based incident detection system with ten roadside installations would have a total initial cost in the range of $285,000 to $355,000. The annual cost for operations and maintenance would be approximately $36,000.

<u>Performance versus Cost</u>

In designing an incident detection system, there will be a trade-off between performance and cost. The primary factor impacting system cost will be the reader spacing. This relationship is best illustrated by looking at an example. If a system were being designed to cover 120 miles of rural Interstate (in both directions), using today's population of transponders on vehicles, the following five options would be available. (Of course, other options would be available as well, but these will serve for illustration.)

- <u>Option 1</u> – Deploy 13 roadside readers, spaced ten miles apart.
    - Estimated system cost (initial) -- $354,000 to $445,000
    - Estimated annual O&M cost -- $46,000
    - Detection Time – 2.5 to 14 minutes.

- <u>Option 2</u> – Deploy 16 roadside readers, spaced eight miles apart.
    - Estimated system cost (initial) -- $423,000 to $535,000
    - Estimated annual O&M cost -- $55,000
    - Detection time – 2.5 to eleven minutes.

- Option 3 – Deploy 21 roadside readers, spaced six miles apart.
    - Estimated system cost (initial) -- $538,000 to $685,000
    - Estimated annual O&M cost -- $70,000
    - Detection time – 2.5 to nine minutes.

- Option 4 – Deploy 31 roadside readers, spaced four miles apart.
    - Estimated system cost (initial) -- $768,000 to $985,000
    - Estimated annual O&M cost -- $100,000
    - Detection time – 2.5 to 6.5 minutes.

- Option 5 – Deploy 61 roadside readers, spaced two miles apart.
    - Estimated system cost (initial) -- $1,458,000 to $1,885,000
    - Estimated annual O&M cost -- $190,000
    - Detection time – two to four minutes.

These five options are illustrated in Figure 12, which shows the time to detect an incident ("best case" and "worst case") plotted against the system cost. Figure 12 clearly shows the effect of changing the reader spacing. A shorter distance between readers will reduce the time to detect the "worst case" incident, but it will also increase the system cost. There is a "law of diminishing returns" evident in the figure. At the left side of the graph, moderate increases in system cost result in large reductions in the "worst case" detection time. Moving to the right of the graph, it becomes increasingly expensive to achieve further reductions in the detection time. While this analysis is for an extremely large deployment, covering 120 miles of freeway, it could easily be scaled down to any size deployment being considered. The shape of the relationship should remain the same; only the numbers along the axes will change.

Figure 12. Relationship Between System Cost and Detection Time (for a 120-mile Deployment)
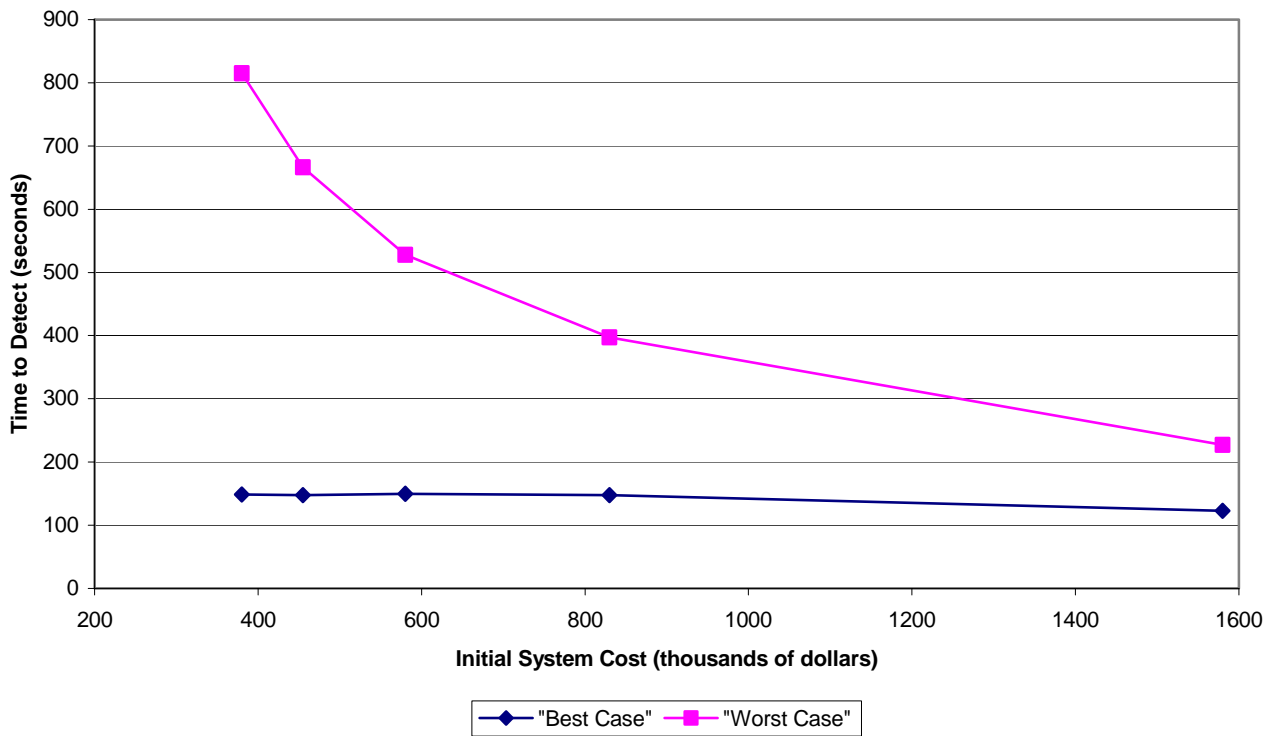
It may be of interest to know how the relationship between system performance and system cost will be affected by increasing numbers of transponders on vehicles. Figure 13 shows the "worst case" detection time plotted against the system cost (as in Figure 12), but includes four curves. Each curve represents a different percentage of transponders on vehicles, as defined in the study design. It can be seen that increasing the number of transponders on vehicles will reduce the "worst case" detection time. However, it is also apparent that the performance with current levels of transponders is reasonably close to the best performance that can be expected in the future, even with 100 percent of vehicles equipped with transponders.

In designing and deploying a DSRC-based system, the relationship between performance and cost will need to be considered. Specifically, decisions will need to be made regarding the speed of detection that is needed. In other words, how quickly must the system detect incidents in order to be valuable? And, of course, the amount of available funding will always be a factor in choosing among options.

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Figure 13. Relationship Between System Cost and "Worst Case" Detection Time for Varying Percentages of Vehicles with Transponders
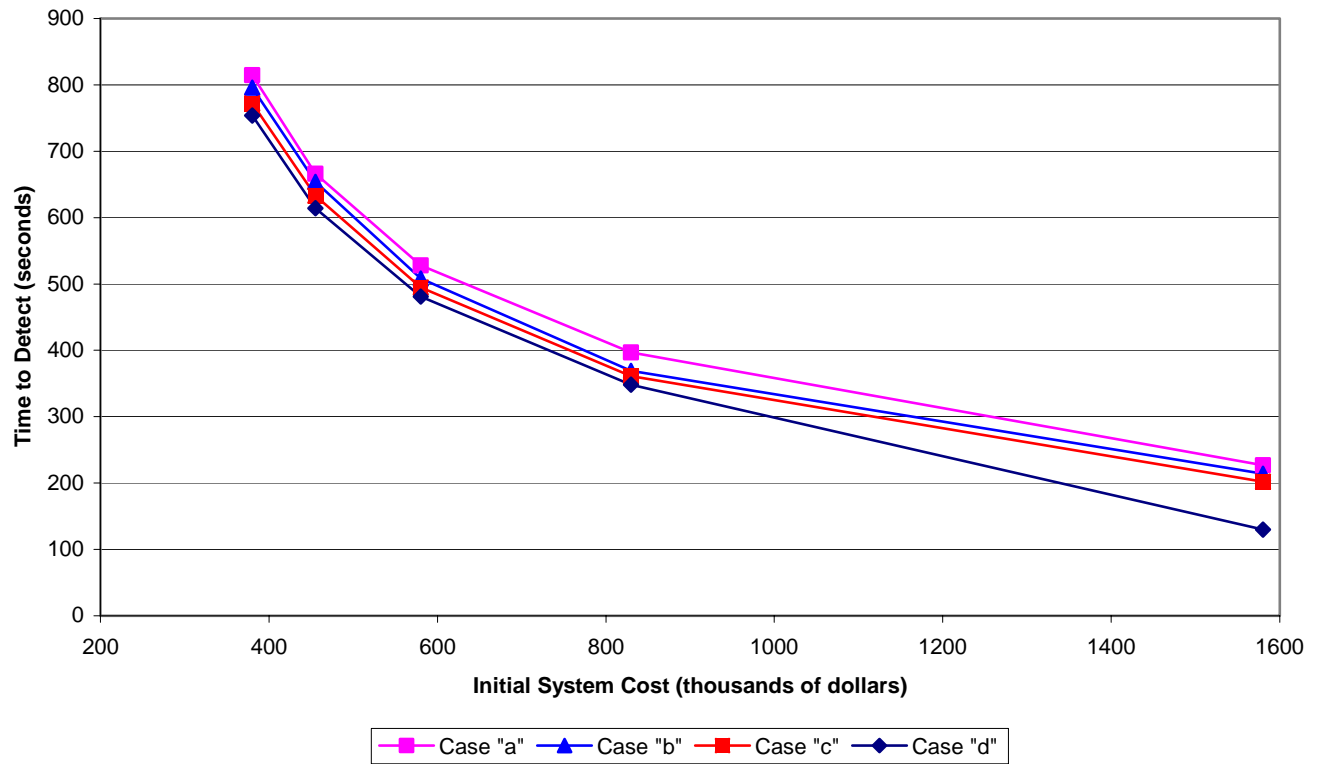
CONCLUSIONS

The findings of this study indicate that a DSRC-based incident detection system could provide rapid and reliable detection of incidents on a rural freeway. This is true for current levels of transponders on vehicles, so such systems could be effective now, without waiting for the transponder population to increase. A straightforward incident detection algorithm, based on Individual Observation Control Chart techniques (e.g., a threshold and a counter), can provide excellent results. The specific algorithm used herein, with the threshold based on the standard deviation of travel times for the "no incident" condition, proved to be effective at producing timely detections while virtually eliminating false alarms.

All of the variable parameters examined in this study proved to be significant predictors of the time to detect, and the observed relationships were in accord with expectations based on logical reasoning. Of the five parameters studied, only the spacing between the roadside readers can be selected by the designer of an incident detection system. The other four parameters are characteristics of the traffic or the incident itself. For any incident severe enough to cause significant traveler delay (i.e., delay of 60 seconds or more), the primary determinant of the detection time was the location of the incident relative to the next downstream reader. Of course, the incident location cannot be chosen, but the worst-case scenario (i.e., the maximum possible distance from the incident to the next downstream reader) can be constrained by choosing an appropriate value for the roadside reader spacing. In choosing this value, the designer must consider the relationship between performance and cost. This relationship shows diminishing returns as the reader spacing becomes shorter and shorter.

Caution must be exercised in transferring the findings of this study directly to deployments in the real world. As discussed previously in this report, situations will exist in real-world operations that do not occur in simulations. Vehicles will stop along the roadside for driver changes or mechanical repairs. Vehicles will exit at intervening interchanges, and they may or may not re-enter the freeway at a later time. Travel times will be affected by snow, rain, fog, or other environmental conditions. Readers and communication devices will experience failures. All of these factors (as well as others not mentioned) have the potential to affect the performance of an incident detection system.

The selected detection algorithm has the capability to account for the behavior of individual vehicles and the possibility of intervening interchanges. This is accomplished by use of a counter alarm level. The counter alarm level can be adjusted to match the characteristics of a specific freeway segment. Use of a "rolling mean" of travel times should provide the capability to adjust for gradual changes in travel times due to environmental conditions. Finally, it will be important to provide equipment monitoring capabilities, so that equipment failures can be distinguished from roadway blockages.

RECOMMENDATIONS

The findings of this study demonstrate that DSRC technology has significant potential for travel time monitoring and incident detection on rural freeways. The technology offers the promise of providing rapid, reliable, and cost-effective detection of incidents. These findings should provide sufficient justification to move toward the goal of deploying such a system. However, there are issues that merit further exploration before undertaking a full-scale operational deployment. Therefore, the following recommendations are provided:

1. The "probe and beacon" data produced by the simulations and post-processing should be subjected to further analysis. In particular, the following areas of exploration are recommended.
    a. Experiment with other values of the threshold and the counter alarm level to gain a more complete understanding of these factors.
    b. Better define the relationship among detection rate, false alarm rate, and time to detect. Replace the "generic" curves illustrating this relationship with actual curves based on plotted data.
    c. Experiment with other types of detection algorithms. Explore the quality control literature for candidate approaches.
2. Actual DSRC data should be collected on a rural freeway segment to validate the simulation results. This could make use of currently installed DSRC readers (used for commercial vehicle screening), or it could involve a separate (perhaps temporary) installation.
3. A pair of DSRC readers should be deployed on a rural freeway to collect actual travel time data for a specified time period. This would assist in identifying differences in behavior between simulated and real traffic. It could also be used to assess the impact of an intervening interchange. This would provide the first opportunity to apply the incident detection algorithm to real-world data rather than simulation data.
4. A more detailed simulation should be developed to replicate actual conditions on a selected section of rural Interstate. These conditions would include terrain, intervening interchanges, and actual traffic patterns at those interchanges. The data from this

simulation should be processed, analyzed, and used to develop more refined recommendations regarding the incident detection algorithm and a possible real-world deployment.

5. A project steering committee should be created to oversee the process of creating functional requirements and specifications for a permanent field deployment of a DSRC-based incident detection system. These functional requirements and specifications should then be used to develop more accurate cost estimates for deploying.

6. If deemed appropriate, based on the results of the previous recommendations, project funding should be sought to begin deploying DSRC-based traffic monitoring and incident detection on a selected segment of rural freeway.

APPENDIX

SUMMARIES OF KEY DOCUMENTS IDENTIFIED

IN LITERATURE REVIEW

TRANSMIT SYSTEM EVALUATION: FINAL REPORT

Authors: Kyriacos C. Mouskos, Ph.D.
Edip Niver, Ph.D.
Louis J. Pignataro, Ph.D.
Stuart Lee
Nicholas Antoniou
Leonidas Papadopoulos

Published by: Institute for Transportation, NJIT

Date: June 30, 1998

Summary:

This report presents evaluation results of TRANSCOM's System for Managing Incidents and Traffic, otherwise known as TRANSMIT. This system uses ETTM (electronic toll and traffic management) equipment for traffic surveillance and incident detection. The evaluation had two goals:

1) Assess the performance of the TRANSMIT system.
2) Assess the costs, benefits, and institutional issues of the TRANSMIT system.

The evaluation was conducted in 1996.

Detection Technology:

TRANSMIT uses DSRC technology (ETTM equipment) compatible with the E-ZPass system. Technology was installed on a 21-mile stretch of the Garden State Parkway (GSP), from the Hillsdale Toll Plaza to the New York State Thruway (NYST), and along the NYST from the Tappan Zee Bridge to the Spring Valley Toll Plaza. A total of 28 tag readers were installed at intervals of 0.5 to 2.1 miles.

Of course, the other "piece" of the technology puzzle is the transponder on the vehicle. Market penetration rates for the study varied from 1.59% to 16.5% on the GSP and from 5.29% to 73.84% on the NYST.

Incident Detection Methodology/Algorithm:

The incident detection algorithm is based on statistical comparison of measured travel times with historical travel times for the same time period (i.e., time of day and day of week). When the number of vehicles arriving late at a downstream reader reaches a predetermined level, an alarm is generated to indicate a possible incident.

TRANSMIT used an incident detection algorithm developed by PB Farradyne, Inc. The expected link travel times are estimated using the historical probability distribution (assumed normal) for specific time intervals. When vehicles fail to arrive at the downstream reader at the expected time, the probability of an incident increases, while the probability of a false alarm

decreases. These probabilities continue to change with each vehicle that doesn't arrive when expected. When the confidence level of the possible occurrence of an incident reaches its user-set threshold, an alarm is triggered.

This is a probability-based algorithm. The actual probability formulas are shown and described on pages 19-21 of the report.

Evaluation of the Technology:

The evaluation assessed the "detection rate," i.e., the success rate of the roadside readers at recording the passage of transponder-equipped vehicles, and the "transmission rate," i.e., the success rate of the system for transmitting the detection information back to the Operations Information Center. For most roadside readers, the detection rate was near 100 percent, although a few readers experienced lower rates. The transmission rate was near 100 percent (98.8 to 100.0) for all reader locations except one.   That one location was the only one using a radio link.

Evaluation of the Incident Detection System:

Based on incident data for January through April, 1996.

The study included 136 major incidents on the NYST and 62 on the GSP.

Based on a comparative analysis of incidents recorded by the TRANSMIT system versus incident record data recorded by NYST and GSP personnel.

Performance was quantified in terms of:

- Probability of detecting incidents
    - NYST was 91% (worst case) to 95% (best case)
    - NJT was 67% to 79%
- Probability of false alarms and false alarm rates
    - Percentage of total alarms that were false was 10% (best case) to 22% (worst case) on NYST
    - Percentage of total alarms that were false was 16% to 32% on NJT

The TRANSMIT system compared very favorably with other incident detection algorithms reported in the literature.

Note: Mean time to detect an incident could not be estimated, but was recognized as an important parameter, which should be incorporated into a future, more comprehensive evaluation.

Evaluation of Costs, Benefits, and Institutional Issues:

The costs of installing and operating a TRANSMIT roadside detection site were compared with the costs of alternative detection technologies, i.e., inductive loops, video image

detection, and microwave radar. The TRANSMIT cost ranged from 55% to 73% of the cost of the alternative technologies.

The TRANSMIT system offered several advantages over other technologies. The principal advantage lies in its ability to identify vehicles at successive locations, thus providing the basis for determining space mean speed and link travel time, as well as for origin-destination studies, fleet management, transit management, volume estimation, etc.

Privacy of the identity of the vehicle was identified as a key institutional issue. The TRANSMIT system was designed to ensure anonymity of all vehicles.

Other Comments:

The TRANSMIT system can provide direct estimates of the link travel time and link space mean speed.

Use of Automatic Vehicle Identification Techniques for Measuring Traffic Performance and Performing Incident Detection

Authors: Hallenbeck, ME; Washington State Transportation Center
            Boyle, T (Graduate Research Assistant)
            Ring, J (Graduate Research Assistant)

Summary:

The primary objective of this study was to determine the possible benefits of using Automatic Vehicle Identification (AVI) systems for monitoring the performance of traffic and detecting incidents. A secondary objective was to determine whether the truck fleet tagged as part of the HELP Project, or even the entire truck population, would provide an unbiased measure of traffic performance.

Detection Technology:

DSRC (truck-mounted transponders and roadside readers). Three AVI readers were purchased for the project and installed on Interstate 5, south of the Tacoma Central Business District. They were installed on the northbound side, roughly one mile apart. Data from the readers went to the HELP/Crescent database in Santa Clara, California, and then to the research team.

Algorithm(s):

This report talked about two different ways to use DSRC data for monitoring traffic performance. One method uses data from a single reader location to count the volume of tagged vehicles that pass and the headways between tagged vehicles. The other way is to use the data from two or more locations to determine travel times (and hence average speeds) between the locations. Both of these techniques can be used simultaneously. The "single reader" method detects incidents more quickly if the incident occurs just downstream of the reader or if the roadway is completely blocked. For all other situations, the two-or-more-reader approach is better.

There are four factors that interact to determine the detection times possible with the AVI travel time technique:

- Headway between tagged vehicles

- Distance between AVI readers

- Speed of vehicles on the roadway

- Number of vehicles that must be monitored to detect a change in traffic conditions (and make it statistically significant)

Some trade-offs can be made among these factors to maintain detection times within a desired range.

"Because of the complex interaction of these variables, it is not possible to provide a single table or figure that summarizes the time required for detecting changes in travel time (or vehicle speed) using the travel time technique. The complexity of estimating detection times is further increased if statistical levels of confidence are associated with these variables. (That is, vehicles do not always arrive at the rate indicated by the headway. Their arrival rate is really a distribution, which will affect the actual response time of the AVI monitoring system.

There are tables in the report that present expected detection times for varying conditions. The authors indicate that any of the four factors can be a limiting factor in determining response time of the system. It appears that each table presents detection times as a function of headway and number of vehicles needed, for given values of speed and reader spacing. By varying the speed and the reader spacing, and producing additional tables for each combination, the relationship among the variables was portrayed.

The report stated that the mathematical algorithms needed to operate the AVI system are straightforward and easily programmed.

Results:

The volume of tagged vehicles in the field test was insufficient to perform real-time traffic performance monitoring or incident detection. They only had 40 to 45 tagged vehicles per day.

Nevertheless, the authors concluded that AVI-based systems can produce superior traffic performance data for use in both real-time control systems and more general transportation planning and engineering analyses. The impediments to using AVI technology in this manner are not technical, but fiscal and political.

Using VRC Data for Incident Detection

Authors: A. Emily Parkany (MIT)
          David Bernstein (MIT)

Summary:

This is a preliminary and theoretical look at using Vehicle-Roadside Communications (VRC) technology for incident detection purposes. It includes a discussion of the types of data that can be obtained from VRC and the general ways such data can be used for incident detection. Several new algorithms are described, along with a preliminary evaluation of their performance (based on simulation).

Detection Technology: DSRC

Detection Methodology/Algorithms:

The report lists several ways that VRC data can be used to determine that an incident has occurred. Incident detection algorithms will incorporate one or more of these indicators:

1) Increased travel time between two readers
2) Lower volumes or headways at one reader compared to an upstream reader
3) Vehicles not reaching the downstream reader.
4) Multiple reading of the same transponder at a reader
5) Abnormal number of lane changes
6) Few vehicles in certain lanes
7) Variance in travel times

Algorithms are developed (and flow charts are provided for the decision process) for each of the following indicators:

a) Travel time and travel time variance
b) Upstream/downstream headway comparisons
c) Density comparisons
d) Lane-specific headways

Results:

A preliminary evaluation of the algorithms was conducted using a microsimulator developed at MIT. Preliminary results were very promising. For example, the travel time changes/variance algorithm yielded a one-minute time to detect for heavy flow and a three-minute time to detect for light flow. No false alarms were generated during a one-hour simulation period.

For comparison, the same simulation was used to test the California #7 algorithm. It failed to detect the incident during heavy flow and detected the light-flow incident in five minutes. It also generated five false alarms during the one-hour simulation.

Comments:

Of the "indicators" listed, four of them (1,3,4, and 7) seem applicable to rural freeway applications. Determining volumes or headways requires an extremely high market penetration, so #2 is not likely to be applicable in the near future. Also, a typical, single-antenna DSRC installation will not do lane discrimination, so #5 and #6 will not be applicable unless they are of sufficient value to justify the extra expense.

Much of the complexity of these algorithms seems targeted at distinguishing between incidents and recurring congestion. If that is not an issue (which it may not be for a rural freeway), then the algorithm can be much simpler. For a rural freeway application, it may be quite sufficient to look just at travel times. However, the information in this report may be useful if there is a need to add complexity to the algorithm.

It is worth noting that this report (and the other Parkany/Bernstein report) is focused on toll applications of DSRC. These systems typically have lane discrimination capabilities, and they typically have many more reader locations than a typical CVO application.

Design of Incident Detection Algorithms Using Vehicle-to-Roadside Communication Sensors

Authors: Emily Parkany
                 David Bernstein

Published by: Transportation Research Board
                 In Transportation Research Record #1494, "Traffic Operations, Traffic Signal Systems, and Freeway Operations 1995"

Date: 1995

Summary:

       This report is similar to the 1993 paper (describing the same research), but is more detailed and exhaustive, as it was prepared for publication by TRB. It promotes Vehicle-Roadside Communications (VRC) technology as an attractive option for incident detection and offers three example, pattern-based algorithms for use with VRC data. A simulation was used to test these algorithms and to compare them against an existing (California #7) algorithm that uses loop detector data.

       Included are discussions of categories of data that can be used for incident detection, numbers of sensors, read only versus read-write systems, and penetration rates.

       Recommendations for future research are included.

Detector Technology: DSRC

Detection Methodology and Algorithms:

       This report advocates using systems deployed for electronic toll collection (ETC) to also monitor traffic flow and detect incidents (perhaps with some additional reader sites). It states that traditional algorithms, designed for point data collection, are probably not best for VRC systems, which collect point-to-point data.

       Three example pattern-based algorithms are presented for consideration. These include a Headways Algorithm (using travel times and headways), a Lane Switches Algorithm, and a Lane Monitoring Algorithm. A verbal description and a flow chart are provided for each algorithm.

       Using a microscopic traffic simulator, the algorithms were tested for 40 minutes (including a 20-minute warm-up) on a 12-mile section of 3-lane freeway (including six miles of warm-up. A variety of incidents (minor to serious) were simulated. The performance of the algorithms was measured in terms of detection rate, false alarm rate, and time to detect. For comparison purposes, the same simulation was applied to the California #7 algorithm, using point data from loop detectors.

Results:

       Even simple VRC-based algorithms perform at least as well as implemented algorithms using other sensors. Additionally, compared with other simple VRC-based algorithms

developed, implemented, and tested during the course of this research, these specific algorithms and their corresponding logics seem to give the most promising results.

Performance measures used to evaluate these algorithms were detection rate, false alarm rate (per time and per algorithm repetition), and average time to detect. For each algorithm, results were presented for the "best" threshold values; i.e., those that provided the best combination of detection rate, false alarm rate, and average time to detect. The performance measures for the three VRC-based algorithms were compared with the corresponding measures for the California Algorithm #7.

In general, the performance of the VRC-based algorithms was superior to the California Algorithm #7. All three of the VRC algorithms had a substantially higher detection rate, two of them had a lower time to detect, and one had a lower false alarm rate.

Conclusions:

All three of the pattern-based algorithms performed reasonably well, and demonstrated that VRC has significant potential for use as a stand-alone sensor for incident detection. The algorithms performed much better than did the California algorithm. They are applicable to a wide variety of conditions, which further increases their value.

Recommendations for further research:

The authors provided a number of ideas to spark future research. These included the following possible extensions to the research:

1. Testing the algorithms with field data.
2. Use thresholds that are functions of the flow. (Would require developing threshold-flow relationships).
3. Developing threshold functions that incorporate other variables, such as the percentage of vehicles with tags.
4. Further work in refining algorithm calibration.
5. Investigating the relationship between detector spacing, time to detect, and false alarm rate.
6. Investigate how different percentages of tagged vehicles and different types of tagged vehicles will affect algorithm performance.
7. Combining VRC data with data from other detector types.
8. Investigate other types of algorithms, other than pattern-based. For example, statistical methods (including times series and filtering), catastrophe theory, artificial neural networks, and use of a traffic flow model.
9. Cost-benefit analysis of VRC-based incident detection versus incident detection based on other sensors.

Comments:

See comments on the previous Parkany and Bernstein paper, "Using VRC Data for Incident Detection." Those comments are applicable to this paper, as well.

Benefits of Real-Time Travel Information in Houston, Texas

Authors: Balke, Kevin N.
                  Ullman, Gerald L.
                  McCasland, William R.
                  Mountain, Christopher E.
                  Dudek, Conrad L.

Published by: Texas Transportation Institute
                  Texas A&M University
                  College Station, Texas 77843-3135

Date: January 1995

Summary:

Describes some of the possible benefits and uses of real time travel time information in major cities in Texas. Reports on an actual system in North Houston, which can be used to detect incidents. Detection rates are comparable to loop-based systems, but false alarm rates are higher. A survey of commuters (small sample) indicated that the information provided by the system was useful and credible. Having accurate travel time information available led to increased usage of variable message signs by the Texas DOT. Fuel savings benefits were estimated at 9,000 to 18,000 gallons per year.

Technology Used:

      Phase 1: Cell phones in probe vehicles. Drivers called in at designated points.

      Phase 2: Automatic Vehicle Identification (AVI -- transponders and roadside readers)

System/Study Design:

      Phase 1 – Approximately 200 probe vehicles. Drivers call in on cell phones. Stations 4-6 miles apart.

      Phase 2 – Used transponder-equipped vehicles as probes, with roadside beacons. No information provided on number of probe vehicles or beacon spacing.

      Real-Time Travel Information System – RTTIS

Detection Algorithm:

      Standard Normal Deviate (SND) Incident Detection Algorithm, developed by Dudek and Messer. Referenced "Incident Detection on Urban Freeways," in Transportation Research Record #495 (1974).

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

> With x-bar values calculated for every 15 minutes of the peak period of every weekday.

Detection Rate – comparable to loop-based systems

False Alarm Rate – higher than loop-based systems

Time to Detect – No information available.

Used incident logs to identify probe vehicles that were traveling the facilities during incident conditions – then simulated the performance of the algorithm to detect actual incidents in the field.

z-statistic: Using SND = 2.0, 97.72% of travel times will fall within interval.

If SND = 4.0, 99.9968% will fall within interval.

They tested travel times at SND = 2.0, 2.5, 3.0, 3.5, and 4.0. If a probe-measured travel time exceeded the computed threshold, an alarm flag was set.

Reviewer's note: If they set flag based on a single data point, that could explain their high false alarm rate. An alternative is to use lower thresholds (if needed), but multiple data points.)

False alarm rate was calculated as follows:

F.A. Rate = (false incident alarms / total probe-measured travel times) x 100%

Results:

The authors included a comparison of this system and algorithm with other algorithms, based on reported performance of other algorithms.

Algorithm	Detection Rate	False Alarm Rate
SND—probe travel times	70%	5.2%
California	82%	1.73%
Modified California #8	68%	0.177%
SND—loop detectors	92%	1.3%
McMaster	68%	0.0018%

The authors were not able to assess average detection time.

Reviewer's note: The validity of this type of direct comparison is questionable. We need to account for differences in parameters, such as detector spacing, traffic volumes, percentage of vehicles equipped as probes, choice of algorithm thresholds, etc.

Traveler Survey:

Most participants said the information provided by the system directly influenced their travel behavior.

Other Benefits of System:

Use of changeable message signs by the Texas DOT went from approximately once per month to 12.3 times per month.

Method for Selecting Among Alternative Incident Detection Strategies

Authors: Balke, Kevin N.
                   Ullman, Gerald L.

Published by: Texas Transportation Institute
                   Texas A&M University
                   College Station, Texas 77843-3135

Date: August 1992; Revised February 1993

Summary:

      This report lists and describes a number of existing strategies for incident detection. It then attempts to assess each strategy in terms of its cost and its effectiveness. In addition, a method for selecting among alternative incident detection strategies is provided. The method uses incremental benefit-cost analysis. An illustration of this method is provided, using data from the motorist assistance patrol in Houston, Texas.

Incident Detection Technologies:

      The report lists ten existing incident detection strategies.

1. Motorist Assistance Patrols
2. Electronic Surveillance Systems
3. CCTV
4. Stationary Observers
5. Law Enforcement Patrols
6. Aerial Surveillance
7. Motorist Aid Call Boxes and Telephones
8. CB Radio Monitoring Systems
9. Cellular Telephone Call Numbers
10. AVI Systems

      It is interesting to note that the report contains a description of each of these, with the lone exception of AVI systems.

Comments:

      Focus of report is how to assess strategies using benefit-cost analysis, including incremental benefit-cost analysis.

Using In-Vehicle Systems and 5.8 GHz DSRC
for Incident Detection and Traffic Management

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Summary:

This paper reports on the development and testing of a real-time, on-board, information system called ADAMS, originally developed by COFIROUTE and RENAULT, and then enhanced by an expanded partnership under the AIDA project, sponsored by the Ministry of Industry in France.

The system described in this report is fairly sophisticated and elaborate. The purpose of the ADAMS and AIDA demonstrations was to introduce new information services in the vehicles, for the comfort and safety of the drivers.

Technologies:

The ADAMS system includes vehicle-mounted DSRC transponders (5.8 GHz), onboard terminals (with smart-card readers and LCD display), various onboard sensors, roadside DSRC readers, a communications network, and a traffic management center.

Information flow between transponders and roadside readers is two-way. When a vehicle enters the "capture zone" of a roadside reader, the following information is uploaded from the vehicle: average speed since last beacon, rapid speed reductions encountered (along with location), fog encountered (with location—indicated by use of fog lamps), heavy rain encountered (with location—indicated by use of high-speed wipers), and incident information (with location—entered by driver using onboard terminal). Information on safety alerts is downloaded from the roadside reader to the vehicle, where it is displayed for the driver.

Information gathered from vehicles and from other sources is used to generate safety alerts. These alerts are communicated to AIDA-equipped vehicles via the roadside readers and to other vehicles via changeable message signs and/or highway advisory radio.

In addition to safety alerts, the system can provide information on services available in the area (including restaurant availability and wait times), the price of petrol, and traffic conditions.

The system was installed on a 90 km section of the A10 Paris-Poitiers motorway. The section consisted of two parts: the city of Orleans and the Orleans to Paris portion. There were 26 roadside beacons (or readers) installed, with the spacing between beacons varying from 5 km to 10 km.

Incident Detection Algorithms:

Incident detection was only a small part of this study, and it did not seem to be the primary emphasis. Automated incident detection was anticipated to be a future addition to the system, and it said that "algorithms will be developed and tested."

Comments:

The report indicated that using DSRC for automated incident detection could be very cost effective, since "it is quite impossible to implement classic AID systems (like cameras and image processing systems) on large parts of interurban highways." Studies in Europe have shown that systems like AIDA could reduce accidents by 20%.

This report was written at a preliminary phase of the AIDA project, and it indicated that an evaluation would be performed.

Travel Time Computation Using Vehicle Probe Tags

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Summary:

This paper describes the Automated Vehicle Identification (AVI) project of the TransGuide Model Deployment Initiative in San Antonio, Texas. The AVI system consists of 53 tag reader locations and 78,000 vehicle probe tags. The system was designed to measure the traffic conditions along selected roadways within the San Antonio area by measuring travel times between selected locations. The data collected by the AVI system is made available to the TransGuide Advanced Traffic Management System through the TransGuide data server.

TransGuide is a collection of point speed detectors, closed circuit television cameras, and traveler advisory equipment. One of its primary functions is to monitor current traffic conditions. The AVI project of the MDI added a new traffic monitoring capability to the TransGuide system. Installation of the AVI system was anticipated to be completed in the Spring of 1998.

This system is unique in that the deployment of AVI technology for this project had travel time measuring, not toll collection, as its objective.

Another unique aspect of this system is that it provided coverage not just for freeways (as is typical for toll collection systems), but also for arterial streets.

Incident Detection Technology:

The stated objective of this system is travel time measurement, not incident detection. The technology used for travel time measurement is Amtech DSRC readers and Amtech passive toll tags. Readers were deployed at 53 locations, and 78,000 tags were distributed.

Incident Detection Algorithm:

The report did not mention specific algorithms for incident detection, but it did refer to software being custom-developed for the AVI system. The software had the functions of

collecting the tag read data, calculating travel times, transmitting the data to the TransGuide data server, and archiving the data. (Note that this does not mention incident detection.) The report did talk about the software calculating average travel times. If a single vehicle is significantly above or below the current average, its measurement is not included in the average. However, the software can also recognize trends and start including differing values in the average to reflect those trends.

Comments:

        This seems to be an impressive system. This report was written before the system was deployed.

Comparative Performance Evaluation of Incident Detection Algorithms

Authors: Stephanedes, Yorgos J.
              Chassiakos, Athanasios P.
              Michalopoulos, Panos G.

Date: January 1992

Summary:

The objective of this study was to investigate the performance limitations of conventional automated incident detection systems and define the specifications for a new algorithmic logic that can lead to improved detection performance.

All tests employed a unified system of performance assessment, suitable for direct algorithm evaluation.

Incident Detection Technology:

This study used data collected by presence detectors embedded in the roadway. The authors made the point that video detection systems could be used in place of the embedded loops.

Incident Detection Algorithms:

    Comparative:
            California
            California #7
    Time Series
    McMaster
    HIOCC
    WILLSKY
    CREMER
    Proposed new algorithm

Detailed testing was performed for two types of existing algorithms: Comparative (California-type) and Time Series, in addition to the proposed new algorithm.

The authors stated that they were in the process of testing the McMaster algorithm and "plan to incorporate its most appealing features in more sophisticated algorithms under development."

The proposed new algorithm used filtered detector output (values averaged over short time periods) to reduce the incidence of false alarms that are due to short-term traffic inhomogeneities. It is simple to implement, requires no additional data, and is less sensitive to random fluctuations of traffic.

The primary factors used for the comparison were detection rate, false alarm rate, and mean time to detect. To compare algorithms to one another, the authors developed an operating characteristics curve for each algorithm. The curves showed detection rate plotted versus false alarm rate. Mean time to detect was shown in a separate table.

Results/Conclusions:

The evaluation revealed that comparative evaluations, employing three test variables, can distinguish incidents from other traffic phenomena more effectively than single-variable time-series algorithms that use statistical forecasting of traffic. At all detection levels, the comparative algorithms produce 30 to 50 percent fewer false alarms than time-series algorithms.

Tests with the new algorithm indicate a decrease of 50 to 70 percent in false alarm rates compared to comparative algorithms and a 70 to 80 percent reduction compared to time-series algorithms. The mean time to detect is comparable to existing algorithms.

Even though the proposed new algorithm produced superior results to the existing algorithms evaluated, the authors still questioned whether the false alarm rate was low enough to be acceptable for operational use. For example, they projected that this false alarm rate would generate approximately 1.5 false alarms per hour at a 50 percent detection rate.

Comments:

The preparation of operating characteristics curves appears to provide a good way to evaluate and compare algorithms. It allows direct comparison of algorithms and provides information that is transferable. This is much more valuable than coming up with a single value of detection rate, false alarm rate, and mean time to detect for each algorithm. These values will vary based on your choice of threshold (and other factors), and there is usually a tradeoff among them.

An Evaluation of Existing Incident Detection Algorithms

Authors: Balke, Kevin N.

Published by: Texas Transportation Institute
              Research Report 1232-20
              Texas A&M University System
              College Station, Texas

Date: November 1993

Summary:

"The objectives of this research were as follows:

1. Using the literature, assess the existing incident detection algorithms in terms of their reported operational performance, ease of calibration, ease of implementation, and data requirements;
2. Determine which algorithms, if any, are currently being used in select freeway management systems in the United States and Canada; and
3. Recommend which of he currently available incident detection algorithms should be considered by TxDOT for possible inclusion into the initial implementation ot their freeway surveillance and control systems."

This report provides a good overview of all available incident detection algorithms, as of 1993. It includes discussions of:

- Incident traffic patterns
- Situations that cause false alarms
- Relationship between detection rate, false alarm rate, and time to detect.
- Existing incident detection algorithms
- Advanced incident detection techniques

The report includes a summary and description of each available algorithm.

The study included site visits to selected freeway management centers.

The assessment of existing algorithms included the following:

- Reported performance
  - Detection rate
  - False alarm rate
  - Time to detect
- Data requirements
- Ease of Implementation

- ■ Ease of Calibration
- ■ Operational Experience
- ■ Summary

It should be noted (and it was noted by the author) that "the assessment of the performance of the incident detection algorithms was based on the results published in the available literature. No attempt was made to use actual field data to compare the performance of the algorithms. Since algorithm performance is very dependent on the design of the system and how well the algorithms is calibrated for the system, the research assumes that the results published in the literature by other authors are accurate and objective."

Incident Detection Technology:

"The study was limited to a review of incident detection algorithms that use data from inductive loop detectors only. Although the report does contain a section on other potential means of detecting incidents (such as video imaging or the use of automatic identification systems), a detailed assessment of these techniques was not performed."

Incident Detection Algorithms:

- ■ Existing incident detection algorithms
  - o Comparative
    - ▪ California
    - ▪ Modified California
    - ▪ All purpose
    - ▪ Pattern recognition
  - o Statistical
    - ▪ Standard normal deviate
    - ▪ Bayesian
  - o Time Series
    - ▪ ARIMA
    - ▪ High Occupancy
  - o Smoothing or Filtering
    - ▪ Exponential Smoothing
    - ▪ Low-Pass Filtering
  - o Modeling
    - ▪ Dynamic
    - ▪ McMaster
  - o Low Volume Incident Detection Algorithms

- ■ Advanced Incident Detection Techniques
  - o Artificial Intelligence
    - ▪ Fuzzy sets
    - ▪ Neural networks
  - o Automatic Vehicle Identification (AVI)
  - o Video Image Processing

Findings/Conclusions:

This report contains a brief discussion of the relationship among detection rate, false alarm rate, and time to detect. A graphical representation of that relationship is presented.

Most algorithms reported difficulty in detecting incidents in low volume conditions.

Most evaluations of incident detection systems/algorithms have been off-line. Very few have been tested in an operational setting. "There is no single study that compares the performance of all the existing algorithms using the same set of data. Further, very few of the algorithms have actually been evaluated in an on-line study." "Unfortunately, the algorithms are seldom evaluated under similar operating conditions.

A table presents the best detection rate, false alarm rate, and detection time for each of the existing algorithms. Readers are cautioned against using the table for direct comparisons.

All in all, there is very little difference in the performance of the existing algorithms. The detection rate ranged from 70 to 100 percent, with most in the 85 to 95 percent range. False alarm rates were reported to be below 1.5 percent for most algorithms.

The California #7, California #8, and McMaster algorithms reported detection rates lower than some of the other algorithms, but their false alarm rates were significantly lower. In general, the algorithms with the higher detection times also tend to have lower false alarm rates. This makes sense, since the additional tests required to confirm an incident (and thus avoid a false alarm) add to the time required to detect.

Most of the algorithms require the same amount and type of data. Most use occupancy (or a derivative of occupancy) as the control measure. Some also use volume and/or speed.

In summary, no single algorithm appears to be superior. The California #7, California #8, and McMaster algorithms were recommended as the most logical choices for the Texas DOT to consider.

Findings/Conclusions from Site Visits:

Of the seven locations visited, only four are actively using an algorithm to detect incidents. Three of these are using a California algorithm. Toronto recently switched to the McMaster algorithm. As a rule, the systems did not have quantitative data on the performance of their algorithms.

System operators reported being pleased with the perforance of their algorithms. However, on-site observations revealed that they did not rely heavily on the algorithm to alert them to an incident. (Toronto was an exception.) They usually relied on other mechanisms, such as radio reports or CCTV systems, to alert them to incidents on the freeway.

The other three locations had previously been using a California algorithms, but had discontinued use due to the high number of false alarms. These problems may have been related to poor calibration.

Recommendations:

As stated above, the California #7, California #8, and McMaster algorithms were recommended as the most logical choices for the Texas DOT to consider.

My Comments:

This report includes useful information, as highlighted above. Limitations include the fact that it is not a direct comparison of algorithms; it only echoes what previous authors have claimed about the algorithms. Also, it does not provide any useful information on detection using DSRC. All of the algorithms evaluated are based on loop detector data.

Traffic Monitoring and Incident Detection (1995-1997)

Author: Crowthorne & Berkshire

Published by: Current Topics in Transport, No. 120

Date: December 1997

Summary:

This is a collection of abstracts for research that was conducted in the area of Traffic Monitoring and Incident Detection in the years of 1995-1997. Some of these abstracts are of interest for my work, and some of them are not. The ones that appear to be of interest are listed below:

- ODISSEY Freeway Control, Lopez and Peck, Traffic Technology International, 1997, pp 110-112.
  ODISSEY is a motorway management and control system developed in Spain. It uses various algorithms (including HIOCC and California) to detect any unusual disturbances of the traffic.

- Incident Detection with Probe Vehicles: Performance, Infrastructure Requirements, and Feasibility; Papageorgiou, Pouliezos, Petty, and Skabardonis; Transportation Systems, Preprints of the 8th Symposium, International Federation of Automatic Control; Chania, Crete, Greece; June 1997.
  The authors develop an incident detection algorithm based on information received in real-time from probe vehicles. They present a model that allows them to estimate the upper bound detection rate for a given density of probe vehicles. They demonstrate their algorithm using data from I-880 in California. They conclude that a probe-vehicle-based algorithm is feasible and avoids some of the infrastructure problems facing loop-based algorithms.

- Image Processing Oriented Incident Detection Algorithms Using Artificial Neural Networks: Papageorgiou, Pouliezos, and Hsu; Transportation Systems, Preprints of the 8th Symposium, International Federation of Automatic Control; Chania, Crete, Greece; June 1997.
  This paper developed a new traffic parameter, lane-changing rate (LCR) to recognize the possible use of new technologies, such as image processing, for traffic sensing. Using the artificial neural networks, the authors developed a new incident detection algorithm, LCR-algorithm by combining conventional traffic parameters with lane changing rate. The performance of the new algorithm was found to be superior to other well-known detection algorithms.

- BEATRICS Radar System for Automatic Incident/Congestion Detection; Nuttall, Roussel, Petrucci, and Lion; Traffic Technology International, Annual Review Issue, 1996; pages 121-124.

     This article describes the BEATRICS traffic management radar sensor, which was developed to provide automatic detection of traffic incidents and congestion. BEATRICS was installed in France in 1994. It can rapidly and directly detect incidents up to 1000m away.

- Multiple Zone Radar Detection by RTMS; Nuttall and Manor; Traffic Technology International, Annual Review Issue, 1996; pages 126-130.

     This article reports tests of the Remote Traffic Microwave Sensor (RTMS) with encouraging results. This is a low-cost general purpose, all weather traffic sensor. It provides information on presence, volume, occupancy, and speed, from up to 60m away. Incident detection is just one of the applications described for which this technology is suitable.

- Laser Sensors for Traffic Monitoring and Control; Nuttall and Myers; Traffic Technology International, Annual Review Issue, 1996; pages 137-138

     This article reviews the development and operation of two laser-based sensors that are applicable to vehicle detection and classification.

- Advanced Video-Based Incident Detection; Nuttall and Lebre; Traffic Technology International, Annual Review Issue, 1996; pages 147-148.

     This article describes the Advanced Real-Time Imaging System (ARTIS), which is being used to monitor traffic on sections of roadways in France. ARTIS is a video-based incident detection system.

- Video-Based Solutions for Data Collection and Incident Detection; Nuttall, Bogaert, and Lemaire; Traffic Technology International, Annual Review Issue, 1996; pages 150-156.

     This article describes the range of video-based technologies developed by Traficon. More than 1,000 of these sensors are in use worldwide.

- Applying Neural Networks to Automatic Incident Detection; Ito, Namai, and Kojima; Traffic Technology International, August/September 1996; pp. 32-35.

     This article shows how the application of neural network decision processes to video-based detection will significantly increase the accuracy of AID systems in Japan.

- Development of Artificial Neural Network Models for Automated Detection of Freeway Incidents; Hensher, King, Oum, and Dia; World Transport Research: Proceedings of the 7th World Conference, Volume 2; Modeling Transport Systems; 1996; pp. 107-122.

     This paper describes the development of new incident detection techniques based on artificial neural networks. These models have the potential to provide faster and more fault-tolerant operation.

- The Use of Electronic Toll and Traffic Management Systems for Freeway Incident Detection; Kelly; Texas A&M University; August 1998.

This paper discusses the use of ETTM technologies for incident detection. The cost of such systems compares favorably with loop-based systems and offers the advantage of lower indirect cost to the motorists.

■ Arterial Incident Detection Using Fixed Detector and Probe Vehicle Data; Sethi, Bhandari, Koppelman, and Schofer; Transportation Research, Part C; Elsevier Science Ltd., Oxford, Great Britain; April 1995.

This paper describes incident detection algorithms using two distinct data sources: fixed traffic detectors and probe vehicles. The algorithms were developed and calibrated using simulated data for the ADVANCE ITS Operational Test.

■ Autoalert: Automated Acoustic Detection of Incidents; Whitney and Pisano; ITS-IDEA Program Final Report; Transportation Research Board; December 1995.

This project included the design, preliminary evaluation, and feasibility demonstration of an acoustic traffic sensor system that applies new signal processing algorithms to passive acoustic data to achieve incident detection.

■ A Simple Detection Scheme for Delay-Inducing Freeway Incidents; Lin and Daganzo; Transportation Research, Part A; Elsevier Science Ltd., Exeter; 1995; pp. 141-155.

This paper describes a freeway incident detection scheme that does not rely on complicated theories. It compares the occupancy information for two neighboring loop detectors. It can also detect the termination of a detected incident. It can be applied to any homogeneous site with little calibration. Default parameters can be used, with degraded performance. Tests were encouraging. The scheme was effective in distinguishing non-recurrent from recurrent congestion.

Cell Phones as Data Probes:
Background and Recent US Wireless Experience

(Presentation at ITS Mid-America Annual Meeting)
September 7, 2000

Richard R. Mudge, Ph.D.
US Wireless

1. Regulatory: FCC Rule

    a. Mandated wireless carriers to locate E911 calls by October 2001

    b. Sets standards (within 100 meters 67% of time)

    c. Choice of technology (network or handset based)

2. Electromagnetic Noise degrades the accuracy of all position location techniques

    a. Gaussian noise

        i. Affects all forms of communications

        ii. Mitigation: provide enough transmission power

    b. Multipath noise

        i. Cannot be mitigated as such

3. Pattern recognition makes use of Multipath rather then trying to mitigate it

    a. "Map" the actual multipath signatures and then match transmissions to their known patterns.

    b. Identifies locations based on their unique multi-path signature.

4. Characteristics

    a. Low technology cost (compared to alternatives)

    b. Passive—uses cell phones as anonymous data probes

    c. Great flexibility in defining links and/or time periods

    d. Scalable

    e. Digital

  f. Adaptable

  g. Covers all roads and locations

  h. Can track vehicles and other mobile assets for management purposes.

  i. Variety of reporting formats available

5. Planned or current deployments

  a. Washington, DC

  b. Baltimore, MD

  c. Hampton Roads, VA

  d. Oakland, CA

  e. Billings, MT

  f. San Diego, CA

  g. San Francisco and San Jose, CA

  h. New Hampshire, Vermont, Maine

Implementation of Incident Detection Algorithms
(Reviewed Abstract Only)

Authors: Al-Deek, H.M.
                 Ishak, S.

Published by: University of Central Florida, Orlando
                   Dept of Civil and Environmental Engineering

Date: May 1999

Summary:

Report focused on implementation of an online incident detection (I.D.) system that was added to an existing traffic surveillance system on Interstate 4. The I.D. system was developed at the ITS Lab at the University of Central Florida (UCF), and it operated over a dial-up connection to the I-4 Surveillance and Motorist Information System (SMIS).

Real-time data from loop detectors was fed to the I.D. system every 30 seconds. Two I.D. algorithms were tested: California Version 7 and Speed-Based Incident Detection Algorithm (SBIDA).

System was operated and tested for almost one year.

Detection Technology:

In-pavement loop detectors.

Algorithm(s):

California version 7

SBIDA

Results:

Both algorithms performed better in peak periods than in off-peak.

Overall performance was low in terms of detection rate and false alarm rate.

Overall, SBIDA had slightly higher detection rate, but much higher false alarm rate.

Performance of Automatic ANN-Based Incident Detection on Freeways
(Reviewed Abstract Only)

Authors: Ishak, S.
                 Al-Deek, H.

Published by: American Society of Civil Engineers
                 Journal of Transportation Engineering

Date: July 1999

Summary:

  This study explored the application of artificial neural networks (ANNs) to automatic incident detection on freeways. It used real-world traffic data collected by the traffic surveillance system on Interstate 4 in Orlando, Florida.

Detection Technology:

  Not specified in abstract. Probably in-pavement loop detectors.

Algorithm(s):

  Two ANN models were explored: Multi-Layer Feed Forward and Fuzzy Adaptive Resonance Theory (ART). These models were compared to each other and to California algorithms #7 and #8.

Results:

  Fuzzy ART algorithm generally outperformed the Multi-Layer Feed Forward and both California algorithms.

AIDDS: A System for Developing and Testing Incident Detection Algorithms
(Reviewed Abstract Only)

Authors: Papageorgiou, M. (Tech University, Crete)
                Pouliezos, A. (Tech University, Crete)
                Hourdakis, J. (Minnesota University)

Date: June 1997

Summary:

       Paper presents a computer program designed to assist researchers in testing incident detection algorithms. The program allows the user to assign individual threshold sets in every section and use multiple algorithms simultaneously. Three algorithms are included in the version presented in this paper.

       Some unique features of the program include the ability to combine measurements from the field to create "pseudo" detectors, the ability to automatically judge if a detection is valid, and the ability to combine incident detection algorithms to improve detection performance.

Detection Technology:

       Not specified.

Algorithm(s):

       Includes DELOS, California #7, and California #8

Results:

       Not specified.

Detection of Incidents and Compression Waves in Freeways
(Reviewed Abstract Only)

Authors: Papageorgiou, M. (Tech University, Crete)
                  Pouliezos, A. (Tech University, Crete)
                  Chassiakos, A.P. (Patras University, Greece)
                  Stephanedes, Y.J. (Minnesota University)

Summary:

This report presents a method (implemented in a computer algorithm) to distinguish between incidents and compression waves in freeway traffic. It is based on shock wave propagation characteristics. It is used to improve the performance of an existing incident detection algorithm (DELOS).

Detection Technology:

Not specified. Abstract mentions using occupancy data from adjacent sensors along the freeway.

Algorithm(s):

DELOS (augmented by the subject computer algorithm)

Results:

The computer algorithm resulted in superior performance to DELOS in terms of detection and false alarm rates.

Using Probe-Measured Travel Times to Detect Major Freeway Incidents in Houston, Texas
(Reviewed Abstract Only)

Authors: Balke, K.
                Dudek, C.L.
                Mountain, C.E.

Summary:

        This was a pilot study to test the feasibility of using probe-provided travel time
information to detect freeway incidents. It was considered to be a prelude to installing an AVI
system for collecting traffic and travel time information from probe vehicles.

        200 commuters equipped with cellular phones were used to collect travel time and
incident information from three facilities on the north side of Houston. Historical travel time
patterns were developed for known incident-free conditions.

        11 months of data were analyzed to determine when a probe travel time exceeded the
expected travel time for incident-free conditions, using the statistical principle of standard
normal deviates.

Detection Technology:

        Commuters with cell-phones reporting travel times and incidents.

Algorithm(s):

        Statistical analysis; standard normal deviates

Results:

        Detection rates and false alarm rates were worse than reported for other incident
detection algorithms.

        Study indicated that some level of incident detection could be achieved using travel time
information provided by probe vehicles.

Transferability of Freeway Incident Detection Algorithms
(Reviewed Abstract Only)

Authors: Stephanedes, Y.J.
                Hourdakis, J.

Published by: Transportation Research Board
        In Transportation Research Record No. 1554, "Advanced Traffic Management Systems
        and High-Occupancy Vehicle Systems"

Date: 1996

Summary:

        This paper focused on evaluating a new incident detection algorithm that distinguishes
incidents from recurrent congestion and other traffic disturbances using exponential smoothing.
The algorithm was tested using loop detector data from Interstate 35 in Minnesota and Interstate
880 in California.

Detection Technology:

        In-pavement loop detectors.

Algorithm(s):

        New algorithm. No name given. Uses exponential smoothing.

Results:

        The new algorithm was compared with major algorithms of comparable type (not
specified in abstract), and was found to be superior at all times. The strong performance at the
two different sites indicated a strong transferability potential.

Survey of Advanced Technology Deployment in Traffic Management Centers with an Emphasis on New Sensor Technologies and Incident Detection
(Reviewed Abstract Only)

Authors: Parkany, E.
                 Shiffer, G.

Published by: University of California-Irvine
                 Institute of Transportation Studies

Date: July 1996

Summary:

      This report describes a survey that was conducted of various traffic management centers (TMCs) throughout the U.S.. The purpose of the survey was to identify the current traffic sensors and incident detection algorithms used by those centers, as well as their interest in various research areas and topics under development.

Detection Technology:

      Not specified in abstract.

Algorithm(s):

      Not specified in abstract.

Results:

      Not specified in abstract.

Techniques for Detection of Incidents and Traffic Disturbances
(Reviewed Abstract Only)

Authors: Stephanedes, Y.J.
                Chassiakos, A.
                Vassilakis, G.

Published by: Minnesota University
              Center for Transportation Studies

Date: April 1994

Summary:

        The first phase of this research project had two objectives: (1) evaluate the performance of major existing incident detection algorithms; and (2) develop an improved algorithm. This research developed and tested algorithms that efficiently detect incidents at low levels of false alarms.

        The second phase of the project focused on: (1) describing, classifying, and analyzing major types of traffic disturbances and their characteristics; (2) developing strategies for detecting major traffic disturbances based on their distinctive features; and (3) developing strategies for modeling the propagation of detected traffic disturbances and predicting the traffic conditions in the area of the disturbance.

Detection Technology:

        Not specified in abstract.

Algorithm(s):

        Not specified in abstract. New algorithm developed.

Results:

        New algorithm is reported to efficiently detect incidents at low levels of false alarms. No specifics are given in the abstract.

Simulation of Freeway Incident Detection Using Artificial Neural Networks
(Reviewed Abstract Only)

Authors: Ritchie, S.G.
             Cheu, R.L.

Summary:

The authors hypothesize that spatial and temporal traffic patterns can be recognized and classified by an artificial neural network (ANN). They investigate the application of such models for the automated detection of lane-blocking incidents on a one-mile section of urban freeway.

Data for training the ANN came from a microscopic freeway traffic simulation model, which was calibrated for the actual freeway test section.

Detection Technology:

Not specified.

Algorithm(s):

ANN-based model

Results:

Not specified.

On-Line Testing of the McMaster Incident Detection Algorithm Under Recurrent Congestion
(Reviewed Abstract Only)

Authors: Hall, F.L.
                Shi, Y.
                Atala, G.

Summary:

        This report documents the development and testing of improved logic for the McMaster incident detection algorithm. The logic was subjected to three levels of testing: an off-line test (using 39 days of data from the Freeway Management System on the Queen Elizabeth Way in Ontario); an on-line test with the results reported to a file; and a full on-line test with results reported to the system operator (covering 64 weekdays). The results of the testing are presented.

Detection Technology:

        Not specified in abstract.

Algorithm(s):

        McMaster

Results:

        For the on-line test, the system detected 19 of 28 incidents (68%). Average and median time to detect were 2.1 minutes and 1.0 minute, respectively, after the time recorded in the operator's log. False alarm rate was one false alarm in every 6.4 operator shifts (i.e., 20 in 64 days).

Congestion Identification Aspects of the McMaster Incident Detection Algorithm
(Reviewed Abstract Only)

Authors: Persaud, B.N.
               Hall, F.L.
               Hall, L.M.

Summary:

        This report presents an incident detection algorithm that can provide a determination of
whether congestion is recurrent or caused by an incident. The logic uses flow, occupancy, and
speed (if available) from a single station to automatically detect congestion near that station. The
logic was tested off-line and on-line.

Detection Technology:

        Not specified in abstract.

Algorithm(s):

        McMaster

Results:

        Testing showed a good false alarm rate and a high detection rate (exact values not
specified in abstract). Some incidents were detected earlier than system operators identified
them.

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    Transportation Research Engineer
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1989-1992
    Plant Maintenance Manager
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1987-1989
    Manufacturing Supervisor
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1983-1987
    Nuclear Propulsion Officer
    United States Navy

1979-1983
    Transportation Research Engineer
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Scholastic and Professional Honors:

Selected for Eno Transportation Foundation Fellowship (one of 20 nationwide); April 1999

Intelligent Transportation Society of America 1998 Award for "Outstanding Achievement in Commercial Vehicle Operations;" Presented to Kentucky Transportation Cabinet and Kentucky Transportation Center for their role in the Advantage I-75 Operational Test Project and the CVISN Model Deployment.

Southern Section, Institute of Transportation Engineers; "Best Technical Paper Award;" April 1981.

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Awarded National Science Foundation Fellowship for Graduate Study (one of 50 nationwide); 1978.

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Professional Publications:

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