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16. Abstract:

Automatic Vehicle Identification (AVI) is a mature technology having high reliability for vehicle detection. San Antonio TransGuide recently installed a number of AVI readers alongside inductive loop detectors placed on the same freeway sections, allowing side-by-side performance comparison. The principal objective of this study is to perform a systematic comparative evaluation of the performance of AVI as a basis for incident detection and traffic state estimation for public information dissemination (through the Internet, Advanced Traveler Information System (ATIS), and/or variable message signs). A starting point is to investigate the quality of traffic state estimates, especially prevailing speeds and trip times, under low market penetration of toll tags. The project provides an extensive calibration and testing of AVI algorithms for incident detection, and compares their respective performance. The project also makes recommendations regarding further expansion of the AVI system and assesses the system's role within the overall Traffic Management Center (TMC) and ITS architecture.

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by

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EXECUTIVE SUMMARY

The principal objective of this study is to perform a systematic comparative evaluation of the performance of Automatic Vehicle Identification (AVI) as a basis for incident detection and traffic state estimation for public information dissemination (through Internet, Advanced Traveler Information System (ATIS) and/or variable message signs).

The study accomplished its objectives primarily through analysis of extensive field data, made possible through the unique setup in San Antonio. Frequent site visits to the San Antonio Traffic Management Center (TMC) were initiated to gather data and exchange knowledge with the TMC personnel to resolve some technical difficulties that affected the integrity and interpretation of the AVI data. Through evaluation of the on-line AVI system such difficulties should be avoided in any future AVI implementations. The confidence, delay, and availability of the AVI data for ATIS applications is evaluated in this report based on results from the study period analysis. The breadth and depth of coverage by AVI in San Antonio is discussed and adequacy of the data under current low market penetration of toll tags is established. Cost-benefit analysis of the AVI system is provided.

Considerable effort is devoted to developing, calibrating, and testing incident detection algorithms using the input from the inductive loop detectors and AVI. Performance comparison between these algorithms is conducted and recommendations in this regard are provided.

Several important practical insights and recommendations are provided as a result of the study, along with some potential areas of further research that enables best utilization of AVI, especially in light of rapidly increasing computation capabilities. Overall, AVI data, even under low penetration levels, is a valuable and generally reliable source of traffic state estimates. Coupled with additional sources, it can greatly enhance the performance of incident detection procedures.

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CHAPTER 1 INTRODUCTION

As travel demands continue to grow throughout the world, it is no longer feasible to continue building new roads. The focus has therefore shifted from increasing the size of networks to improving their overall efficiency. Implementation of Intelligent Transportation Systems (ITS) carries high promise of more efficient use of existing transportation networks through the use of advanced information processing and communication technologies to manage transportation systems and control the flow of vehicles.

The main elements of ITS are Advanced Transportation Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS). While ATMS's are aimed at assisting control center operators in managing traffic networks, ATIS's provide assistance to travelers in order to reach a particular destination via a private vehicle, public transportation or a combination of the two. ATMS's provide tools for managing data coming into the control center, processing this data and generating roadway information for dissemination via ATIS, detecting and resolving incidents, and, finally, controlling the traffic network. ATMS's rely mainly on real-time traffic data collection for incident detection, traffic flow monitoring, and information dissemination to the public.

Incident-related congestion results in billions of dollars a year in lost productivity, property damage, and personal injuries. According to the Federal Highway Administration (FHWA), in 1986 incidents accounted for 60 percent of the vehicle-hours lost to freeway congestion (Lindley 1986). In addition, the FHWA predicts that by 2005, incidents will account for 70 percent of all delay caused by urban freeway congestion associated with a users' cost of $35 billion (Gordon 1996). In addition to the material losses incurred as a result of incidents, they have extensive detrimental effects on safety and air pollution. An important part of any Traffic Management System (TMS) is its ability to detect incidents quickly and react accordingly. By definition, an incident is an unexpected event that temporarily disrupts the flow of traffic on a segment of roadway (Solomon 1991). A stalled vehicle, spilled debris on the roadway, bad weather, and a four-car accident are all examples of incidents of different magnitudes. To detect accidents at the earliest time and reduce the delay in the implementation of emergency response, many TMS's have been implemented along corridors where traffic volumes are high and the risk of accidents is significant. Fast and accurate detection of road accidents can assist in the implementation of efficient emergency response measures thus resulting in reduced severity of personal injury and reduced traffic disruption costs. Also, to speed up the time required to get back to normal operating conditions after an incident occurs on a facility, dynamic route guidance systems are being designed in such a way to provide motorists with in-vehicle information about incidents and how to avoid incident links (Catling 1994).

Early incident detection and clearance are based on patrol vehicles and passing motorists in addition to various automatic incident detection (AID) methods. AID is possible due to the very nature of incidents that result in changes in the flow of traffic. Typically, an incident results in a sudden, short-term decrease in road capacity leading to a speed reduction, and possibly queues, in addition to an increase in travel times. Many public,

private, and academic agencies throughout the world and particularly the U.S. are investing considerable amounts of effort and resources into developing efficient traffic management systems that exploits the capabilities of recent developments in traffic conditions' sources of information. Traditionally, inductive loop detectors (ILDs) have been the most common source of data for automated incident detection. A recent development is the application of Automatic Vehicle Identification (AVI) techniques, commonly referred to as vehicle probes, for incident detection purposes.

ATIS's constitute a primary component of fully deployed ITS's. An ATIS can be defined as a system that can provide useful travel information to users before or during a trip, often to aid in route, departure time, and/or other trip-related choices. In other words, it is defined as "groups and systems of technologies that aid in the collection, collation and dissemination of traveler information before and during trips" (Gilroy, Puentes, and Schuman 1998). The Metropolitan Model Deployment Initiative of the FHWA, defines the ATIS component as providing "the ability to collect and disseminate information about various modes of travel over the regional transportation network" (FHWA 1998).

Three main components of an ATIS are data acquisition, data fusion, and communication of value-added information (ITS America 1998). Examples of ATIS dissemination devices include, but are not limited to, variable message signs, traveler information kiosks, the Internet for transmission and display of traffic conditions on desktop/portable monitors, and a growing array of wireless devices. Information is collected and provided to users in many forms including, but not limited, to: traffic conditions, incident information, weather and roadway conditions, as well as local event information. The overall scope of ATIS is broader than just traffic data; however, the focus here is on traffic information available from AVI systems. A full ATIS involves the successful fusion and dissemination of data and information.

ATIS's require a different level of data resolution than other ITS's, and transportation applications. For example, a transportation-planning study would require travel times and demand patterns on an hourly or perhaps daily aggregation level. A real-time traveler information system may require a 5 or 10 minute aggregation level. An advanced traffic management system employing dynamic traffic assignment may require updated data every 30 seconds. The data refresh rate is only limited by the frequency of data provided from the field. The transportation management system, or detection technology, defines the refresh level and often computes the averages from raw field data. A working knowledge of the data requirements is essential for effective evaluation of AVI for ATIS applications.

1.1 MOTIVATION AND OBJECTIVES

Automated incident detection consists of two main requirements, data collection and, naturally, an incident detection algorithm. The data required for the calibration of incident detection algorithms consists of traffic stream measurements as well as incident logs. Until recently, most surveillance systems have been location-based where traffic occupancy, flow rate, or point speeds pertaining to a point location of the roadway were collected (FHWA

1985). These stream measurements are best collected using ILD's or video image processors (VIP).

AVI technology was first introduced in the United States during the early 1960s in the railroad industry. It was not until recently that new options for AVI use started to be considered seriously mainly due to recent technological advances and because of the important role AVI plays in integrated Intelligent Vehicle Highway Systems (IVHS) (Bernstein and Kanaan 1993). The potential advantage of AVI technology over fixed location detectors resides in its ability to collect both point data as well as point-to-point data, which are expected to provide a better representation of traffic conditions. While the development of algorithms to be applied on data collected using fixed-location detectors has been extensively researched, incident detection algorithms making use of data collected using probe vehicles are still in the early stages of development. Also, the reviewed literature showed that very little work has been done to assess the incremental benefit obtained from fusing data from multiple sources.

While the development of algorithms has been a dynamic area of research, the data used for testing and calibrating the algorithms has been for the most part inadequate. This inadequacy is due to the fact that the data used to compare the different sources is most often generated through some simulation software rather than being collected at a traffic management center. Therefore, the results might not be representative of a real traffic network. Lacking in the current literature is an experiment where real data from the different types of detectors is collected from a traffic management center and used to evaluate the relative benefits of each detector source. TransGuide, San Antonio's Traffic Management Center (TMC), has made such an undertaking possible due to its state-of-the-art installations along Interstate 35. These installations include ILDs and surveillance cameras, as well as AVI along the same network.

AVI systems continue to evolve with new technologies and demands from the transportation industry. The quality of obtainable data in light of the requirements for ATIS applications must be investigated to ensure efficient advances for both technologies. The opportunity presently exists to analyze and investigate on-line AVI systems for assessing the application of such data to ATIS applications. The analysis will be of interest to departments of transportation at the local and national level that are considering AVI systems for emerging ATIS applications. Accurate link travel time data from potentially large samples of vehicles is a new data source for transportation applications. Assessing the quality of link travel time data in response to the demands of ATIS is important for the overall ITS initiative.

The goals of this research are to exploit the unique TransGuide installations to evaluate the potential of AVI as a source of data for incident detection and ATIS applications and to investigate the incremental benefits AVI provides when used in addition to ILDs. Hence, the objectives of this study are to:

- Review existing traffic detectors while focusing on AVI and its different uses,

- Review existing incident detection algorithms currently used with ILD data and select the ones suitable for testing in this research,

- Review some of the proposed AVI algorithms that have been tested using simulated data and select the ones suitable for testing using real data in this research,

- Collect appropriate quantities of both real-time traffic detector data and corresponding incident reports to be used for both testing and evaluating the incident detection algorithms,

- Analyze and compare the performance of the detector and algorithm combinations selected for testing, and

- Identify the quality and applicability of data from an AVI system, for ATIS purposes.

1.2 REPORT ORGANIZATION

This chapter introduces the study. Chapter 2 describes the TransGuide installation that is used as a test bed for this research. Also, included are descriptions of the components of incident management, sensor technology, algorithms, and, finally, detection and response. Chapter 3 describes the logic behind several incident detection algorithms used with data collected from ILDs. Promising AVI incident detection algorithms are also described. Chapter 4 describes the traffic and incident data used in the evaluation of the presented algorithms. Also, the chapter summarizes the main limitations of the data used. Chapter 5 details the calibration process of the algorithms chosen for evaluation. Chapter 6 presents the performance results of the different fixed detector algorithms and probe vehicle algorithms implemented. Finally, conclusions are drawn and recommendations are made in the final chapter of this document.

CHAPTER 2 INCIDENT MANAGEMENT COMPONENTS

Incident management includes detecting and verifying the incident, responding with emergency vehicles and information for other motorists, clearing the incident, and monitoring traffic movements until normal traffic conditions return (Cullip et al. 1995). Typical traffic management programs consist of conventional and Automatic Incident Detection (AID) methods. Conventional incident detection systems consist of police patrols, motorist reports using cellular phones or call boxes and surveillance cameras.

A Police Patrol (PP) or Motorist Assistance Program (MAP) is the most commonly used traffic management approach. Unlike AID systems, when an incident is detected by a PP it does not need to be verified. Well-trained police officers can provide concise and accurate incident information. Generally, the first officer to arrive on-site can often start direct response actions following predefined procedures. The detection time using a PP depends on the staffing level. However, one of the shortcomings of this approach is its inability to detect all incidents with a reasonable staffing level.

The cellular phone is quickly becoming a major source of information about incidents as its market penetration level is witnessing an unprecedented growth. In the 1-880 field experiment conducted using the California Highway Patrol (CHP) Computer Aided Dispatch (CAD) incident database, it was concluded that 44 percent of accidents were reported by cellular phone while only 34 percent were reported by PP. The reported false alarm rate using cellular phones approached 8 percent and could be greatly reduced by the use of advanced cellular phone locating technologies in the near future (Skabardonis 1998). Cellular phones perform reasonably well in terms of correct reporting of incident locations, availability of information about the incident type, and the number of vehicles involved. Some of the weaknesses of cellular phones include a very low rate of detecting other events, higher false alarm rates, and limited information on the incident severity. Also, incidents detected using cellular phones need verification and the reports fail to show when the incident is cleared. When an incident is reported, an officer is dispatched to the scene to verify the existence of that incident before taking response actions, hence making the detection time longer. The verification and response time are greatly affected by the type of incident and the detection source. In conclusion, cellular phones are an important source of information for incident detection. However, at the current level of development in the technology, cellular phone reports are best used in conjunction with other sources and may be used to verify incidents reported by other AID methods.

Surveillance cameras are relied on heavily in many traffic management centers (TMCs) for maintaining surveillance of the roadway system. Similar to PP reports, an incident reported in the field of view of surveillance cameras can be visually detected and verified immediately. Moreover, properly trained TMC operators can adequately assess the severity of the incident as well as its impact on the current traffic conditions. However, high levels of misdetection and long detection mean times hinder the reliability of surveillance cameras. Also, the more complex the network to be monitored, the more inefficient and labor intensive is visual detection using surveillance cameras. Here again, the most efficient use of

this method of detection would be to complement other approaches where the cameras would automatically tilt/zoom/pan to the location of a reported incident to allow efficient incident management on the part of TMC operators.

Automatic incident detection has existed since the early 1970s and its importance is widely recognized among traffic agencies. The purpose of AID is to minimize the human requirements in the efficient and effective detection of incident events.

Since this study is based on data acquired from TransGuide, San Antonio's TMC, this chapter includes a description of the facility. It also summarizes the basic components of incident management:

- Data sensors,

- Detection algorithms, and

- Incident verification and response.

2.1 TRANSGUIDE

TransGuide can be described as one of the nation's most sophisticated Advanced Transportation Management Systems (ATMS). It is one of the four TMCs selected as part of the ITS Model Deployment Initiative aimed at showcasing various Intelligent Transportation (ITS) technologies for the Federal Highway Administration (FHWA). The goals of TransGuide are to provide:

- Incident detection within minutes,

- Traffic control changes within seconds,

- Police, fire, and paramedic dispatch,

- System reliability and expandability, and

- Support for transit dispatch operations (Southwest Research Institute 1995).

Designers made use of state of the art technology in an attempt to achieve real-time detection, assessment of and response to traffic incidents, as well as to deliver accurate traffic management information to reduce the resulting congestion and delays and deal with dangerous situations in a timely manner. The desirable time-to-detect (TTD) freeway incidents was set to 2 minutes after occurrence along with a 15-second requirement to initiate a preplanned response. To speed up the process, local police, emergency, and transportation agency representatives are all present in the TransGuide operation center.

The system is built on a complete digital communications network using the communication standard "SONET," a fully redundant fiber optic network, a fault tolerant computer system, software developed to "POSIX" standards, and field equipment consisting of changeable message signs, lane control signals, loop detectors, and surveillance cameras (ITS Joint Program Office 1998). The first phase of the project started in February of 1993

and consisted of monitoring 26 miles of highway concentrated in the downtown area for a total cost of \$32 million. The next two phases are intended to cover the rest of the 191 miles originally planned for instrumentation. Of the originally planned 78,000 vehicle tags, 58,500 have been distributed at no cost to the users until this date (Rodrigues 2000).

Currently, TransGuide makes use of a simple speed threshold algorithm as a basis for incident alarms. TransGuide also operates a number of courtesy patrol vehicles that help in detecting and verifying incidents as well as in helping stranded motorists.

The AVI system deployed in San Antonio serves as an important source of real-time traffic information to TransGuide's ATMS and Advanced Traveler Information System (ATIS) applications. Currently, AVI is used for the "Travel Tag Program" aimed at collecting travel times all around the city. The collected data is used to update a dynamic map posted on the TransGuide Web site showing travel times along major links. The use of the data generated by AVI for the purpose of incident detection is currently being investigated by a team of researchers at The University of Texas at Austin.

2.2 INCIDENT DETECTION

To differentiate it from recurrent congestion, incident-induced congestion is referred to as nonrecurrent congestion. Recurrent congestion occurs regularly when the demand on the road network exceeds its capacity. On the other hand, nonrecurrent congestion due to incidents is unpredictable and often causes similar effects on travel patterns. The extent to which an accident causes a decrease in capacity of a network and the incident's total duration directly affect the magnitude of incident-induced delays experienced by motorists (Gordon 1996). By definition, the duration of an incident is the elapsed time from when the incident occurs to when it is ultimately cleared. Incident duration can be subdivided into detection, response and clearance times. The primary goal of AID is to reduce the detection time of an incident i.e., the time elapsed between its occurrence and the moment it is brought to the attention of the TMC personnel. By focusing on the detection time, AID indirectly reduces the response and clearance times, thus further contributing to a quick return to normal conditions.

Throughout the United States, different TMCs have adopted diverse incident detection techniques or a combination of techniques. Table 2.1 details the type of incident detection techniques applied in major metropolitan areas (Picado et al. 1997).

As stated earlier, although continuous visual observation of a network using live video images leads to the shortest detection time, it is not usually feasible. As the network gets larger and more complex, continuous visual observation is nearly impossible. Therefore, to ensure that incidents are found as early as possible, most TMCs use various AID methods. An incident causes changes in the traffic flow that can be detected by monitoring continuous streams of traffic measurements, such as vehicle volume and speed, taken at various points along the roadway. As might be expected, serious incidents are likely to cause greater disruptions in traffic and therefore are easier to detect. At the heart of AID are the sensors used to continuously monitor traffic characteristics and the detection algorithms used to process the generated data and signal incidents. The following is a description of various

sensor technologies currently being used along with a discussion of incident detection algorithms.

Table 2.1 Metropolitan Incident Management Programs 1997 (Picado et al., 1997)

Location	Police Patrols	Other Patrols	Call Boxes	Cellular Phones	Commercial Traffic Reports	Automatic Detectors	AVI	CCTV	Video Imaging	Radar	Aerial Surveillance
Atlanta		√		√	√						
Boston	√	√	√	√	√	√		√		√	
Buffalo	√			√							√
Charlotte, NC	√	√		√	√						√
Chicago	√	√		√	√	√		√			
Columbia, SC	√		√	√							
Dallas	√	√	√	√	√	√		√		√	√
Denver	√	√		√	√	√		√			√
Des Moines, IA	√			√	√						√
Detroit	√	√		√	√	√		√			√
Fort Worth	√	√	√	√	√	√		√		√	√
Houston	√	√		√	√	√	√	√	√		
Las Vegas				√	√						√
Kansas City	√	√		√	√						
Los Angeles	√	√	√	√	√	√		√			
Lower Hudson Valley, NY	√	√		√	√	√					
Milwaukee	√			√		√		√	√		√
Minneapolis/ St.Paul	√	√	√	√	√	√		√			√
New Orleans	√		√	√				√			
NY City	√	√	√	√	√			√			
Portland	√			√	√		√				
Sacramento	√	√	√	√	√	√		√			√
Salt Lake City	√	√		√	√						√
San Francisco / Oakland	√	√	√	√	√	√		√			√
Seattle	√	√	√	√	√	√		√			√
St. Louis	√	√		√	√					√	
Washington, D.C.	√	√		√	√	√		√	√		√

2.2.1 Sensor Technologies

The effectiveness of an AID system depends largely on the quality, quantity, and type of traffic data that is available (Solomon, 1991). Although a large number of traffic measurements exist, research has shown that certain types of measurements are better indicator variables for determining road traffic conditions. These traffic measurements can be classified as either macroscopic or microscopic. Macroscopic measurements are easier to acquire and relate to a group of vehicles. Microscopic measurements relate to individual vehicles. The most significant macroscopic measurements for AID are density, occupancy, and volume, while the most significant microscopic measurements are vehicle speed and intervehicular headway. The type of detectors used will largely determine the kind and

accuracy of the data that can be obtained. Klein et al. (1994, 1996) conducted a comprehensive field test on the accuracy of emerging traffic detection methodologies in different locations between 1993 and 1994. Table 2.2, adopted from Klein, summarizes the qualitative advantages and disadvantages of these technologies. This section presents a discussion about currently used and promising types of detectors.

Table 2.2 Performance Comparison Among Existing Automatic Detection Technologies (Klein et al. 1996)

Type	Advantages	Disadvantages
Inductive loop detector	* Low per unit cost * Large experience base * Relative good performance	* Difficulty compatible w/use of bridge, overpass, viaducts, poor roadbeds * Traffic interrupted for repair and installation * Experiences significant downtime * Susceptible to damages by heavy vehicles, road repairs, and utilities
Micro-wave (Radar)	* Installation and repair do not require traffic disruption * Direct measurement of speed * Multilane operation * Compact size	* May have vehicle masking in multilane application * Resolution impacted by FCC-approved transmit frequency
Laser	* Can provide presence, speed, and length data * May be used along the road or in an across-the-road orientation w/a twin detector unit	* Affected by poor visibility and heavy precipitation where applicable * Relatively high cost
Infra-red	* Day/night operation * Does not cause traffic disruption * Better than visible wavelength sensors in fog * Compact size	* Sensors had unstable detection zone * May require cooled IR detector for high sensitivity * Susceptible to atmospheric obscurants and weather * One per lane required
Ultrasonic	* Can measure volume, speed, occupancy, presence, and queue length	* Subject to attenuation and distortion from a number of environmental factors * Difficult to detect snow covered vehicles
Magneto-meter	* Usually used instead of inductive loops in bridge decks and heavily reinforced concrete	* Limited application * Medium cost
AVI	* Provide section speed data * Does not cause traffic disruption * Direct travel time computations	* Performance depends on level of tagged vehicle market penetration * Lack of industry standards * Public privacy concerns
Video imaging (VIP)	* Imagery for rapid incident management * Multiple lanes observed * No traffic interruption for installation and repair * Vehicle tracking	* Different algorithms usually required for day and night use * Possible errors in traffic data transition period * Susceptible to atmospheric obscurants and adverse weather

    2.2.1.1 Loop Detectors Inductive Loop Detectors (ILDs) are by far the most widely used sensors in the United States and the rest of the world. Typical ILDs consist of several

turns of wire forming a rectangular area of approximately 6'x6' buried under the road and connected to a detector unit. Whenever a vehicle moves over an inductive loop in the road the current of the loop jumps, causing a change in the inductance of the loop. This phase shift can be measured as an analog signal that is used to generate simple binary data describing the presence or the absence of a vehicle. Therefore, ILDs can provide traffic volumes, measure time headways, and determine occupancy. Also, vehicle length and speed can be estimated fairly accurately by configuring two closely spaced ILDs into what is commonly known as a trap. It is also possible to get an estimate of a link's travel time from its length and the estimated speed, as well as to identify the vehicle's type from observing the generated analogue signal since it is the shape of the vehicle undercarriage that determines the shape of the waveform. The levels of accuracy in the measurements obtained from using ILD are generally very good. The major problem associated with the use of these types of detectors results from the fact that they have to be buried under the pavement, causing installation, operational, and maintenance problems. As an example of the frequency of breakdown of loop detectors, a study showed that 25 percent of New York State's 15,000 ILDs were not functioning properly at any given time (Bikowitz and Ross 1980). Also, an initial statistical analysis performed on loop data obtained from TransGuide operators showed that on average, loop detectors in the network are properly operating 85 percent of the time. Moreover, although ILD technology has matured, there are still a number of limitations associated with its use. ILDs provide "point" estimates of traffic speed, meaning that the measurement is representative of a specific site rather than a section of a roadway and since traffic performance can be different elsewhere in the section than at the detector's location, the resulting view of traffic performance might be skewed. The performance of ILD in representing actual traffic performance is largely dependent on the number of detectors installed and their spacing; the more detectors and the closer they are spaced, the better the results. However, installing and maintaining loops at high densities in a network is economically infeasible, thus reducing their ability to detect changes in roadway performance on sections where they are widely spaced. Also, loop detector estimates are less accurate in congestion detection since spot speed estimates are not necessarily reliable for describing conditions upstream or downstream of the loop itself. A road section might be experiencing significant congestion without significantly affecting the speeds over the loop detectors, especially if they are spaced more than half a mile apart. All these limitations along with requirements for new motorist information systems and vehicle guidance/routing systems are making TMCs look for more accurate data sources, especially to better represent sectional travel times.

2.2.1.2 Magnetic Detectors Magnetic detectors sense changes in a magnetic field and are contained in nonmetallic conduits tunneled beneath the road. This type of detector is relatively inexpensive and very rugged but is limited in use because it can only provide passage data as opposed to occupancy or presence data.

2.2.1.3 Magnetometer Magnetometers take the shape of a small probe and also sense changes in a magnetic field. They can provide very accurate vehicle counts and are

sometimes used when the pavement cannot be torn apart to install ILDs on places such as bridges.

2.2.1.4 Ultrasonic Sensors Ultrasonic sensors operate by emitting an ultrasonic beam and measuring the frequency of its reflection. The Doppler effect principle is used to determine the presence/movement of objects through the detection zone. They are installed above the roadway, thus eliminating problems associated with cutting the pavement. Recent ultrasonic sensors provide poor estimates of speed but excellent volume measurements.

2.2.1.5 Microwave Sensors When compared to inductive loops, it was found that the microwave-based monitors missed about 3 percent of the vehicles counted by inductive loops when fired sideways and the error margin was less than 1 percent when fired in the direction of traffic (Klein et al. 1994). Moreover, these detectors are cost effective and have vehicle classification capability. In 1994, the New York City Department of Transportation (NYCDOT) tested a microwave-based detector to perform the task assigned to the already existing loops in collecting traffic data (Saito and Patel 1994). Results showed that a vehicle count difference of 1 percent ± 6 percent existed between the two technologies. This shows that the accuracy of microwave sensors in collecting traffic data is comparable to that of ILDs. Other benefits of these detectors include their ability to be mounted on existing poles, to operate both day and night, and the fact that they permit direct measurement of speed if programmed to do so.

2.2.1.6 Infrared Sensors   Infrared sensors can be classified into two categories: passive and active. While passive sensors are capable of detecting only the passage of a moving vehicle, active sensors also have the ability to detect the presence of vehicles. This allows these sensors to perform the same tasks as ILDs with the advantages associated with being mounted above the roadway.

2.2.1.7 Video Cameras Typically video cameras have been employed at TMCs for surveillance purposes. The cameras can pan, tilt, and zoom (PTZ) as needed to provide TMC operators with real-time traffic views. The use of video image processing (VIP) for traffic surveillance and control started in the mid-1970s in the United States and abroad, most notably in Japan, Australia, England, and Belgium (Michalopoulos et al. 1990). The past decade has seen much research done to prove the feasibility and effectiveness of extracting traffic measurements, such as volume occupancy and speed, from video images. VIP has the ability to provide measurements that could not be collected using conventional ILDs such as queue length. A typical system consists of video cameras and a central computer. The cameras are mounted above the road and send video signals back to the central computer where the image processing is done. VIP does not require color cameras but does require camera stability. Therefore, cameras with PTZ control are usually used. Vehicles are detected by creating sum images and difference images. A sum image is obtained after averaging a series of frames. This results in an image of the road without vehicles because any given point is typically characterized by the absence, rather then the presence, of a vehicle. A difference image is obtained by spotting the differences between a series of consecutive

frames, resulting in an image that shows the paths followed by vehicles (Solomon 1991). The operators use software to draw "virtual detectors" on the roadway and the system will detect the passage of vehicles past this line. Since a single camera has the ability to detect traffic in multiple lanes, it can effectively serve the function of several ILDs. The accuracy of video detectors tends to be inferior to that of loop detectors. Some of the typical problems that affect the performance of VIP are congestion, shadows, and changes in lighting. These conditions cause the image processor difficulties in distinguishing cars from each other, from their shadows, and from the road. Michalopoulos developed one of the most advanced systems using image processing under the AUTOSCOPE project at the University of Minnesota. The accuracy of the system in measuring both volume and speed is close to 95 percent. It was also estimated that on an intersection basis, the installation and maintenance costs would be 30 and 35 percent lower respectively than for ILDs (Michalopoulos et al. 1990). In summary, video detection systems still need to be further developed before they can efficiently replace loop detectors in collecting traffic data.

2.2.1.8 AVI   Automatic vehicle identification (AVI) was introduced in the United States during the 1960s for railroad car applications and found its way during the 1970s to applications involving road vehicles. Since then interest grew significantly in this new domain due to the important role AVI plays in Intelligent Transportation Systems (ITS) and recent technological advances. Real-time data acquisition using vehicle probes traveling the street networks is an important part of many current ITS deployments throughout the United States (San Antonio, Houston, Bay Area, Orlando, etc.) and the world (e.g., ALI-SCOUT and EURO-SCOUT systems). AVI systems are designed to uniquely identify vehicles located at specified locations and during particular times. Such systems have diverse functional capabilities ranging from toll/revenue collection to access control, surveillance, and fleet control. Several transportation agencies such as the Oregon Department of Transportation are making use of AVI technology in commercial vehicle operations (CVO) to provide mainline preclearance for commercial vehicles. The "Oregon Green Light" project makes use of different technologies to electronically verify safety and weight information of commercial motor vehicles and carriers from fixed and mobile roadside sites at highway speeds (ITS 1999). Defined as such, AVI systems are an important source of real-time traffic data to be used mainly in ATMS and ATIS applications. This diversity in the possible applications of the technology allows its cost to be shared by the different users of the data, thus offsetting the high initial cost associated with the system.

The initial cost of an AVI site depends largely on the amount of infrastructure that needs to be installed. The total cost of the AVI reader sites installed in the San Antonio network amounts to $2.17 million with a minimum of $26,897/site, a maximum of $64,460/site, and an average value of $40,935/site.   Mouskos, Niver, Lee, Batz, and Dwyer (1999) compared the annual total cost of AVI to that of ILDs, Video Image Detection Systems (VIDS), and Microwave Radar Detection Systems(MRDS). The costs are based on a typical site on a six-lane highway and are reported in Table 2.3. The hardware cost was defined to include field components of a typical detection site in addition to the ancillary equipment. The system installation cost was defined to include the field installation of

hardware, cabinet and foundation, cables, etc. The maintenance costs include on-site hardware and software support and personnel overhead. Finally, operations costs represent the costs associated with leasing telephone lines and utilities expenses.

The results show that the annual cost of a typical AVI site is 56 percent lower than an ILD site, 81 percent lower than VIDS, and 37 percent lower than MRDS's (Mouskos et al. 1999).

Table 2.3 Comparative Costs per Detection Site for a Six Lane Highway (Mouskos et al., 1999)

Description	AVI	ILDS	VIDS	MRDS
Capital Cost:				
• Hardware	$14,700	$4,100	$24,500	$26,500
• Installation	$21,700	$50,560	$45,100	$25,200
Total Capital costs	**$36,400**	**$54,660**	**$69,600**	**$51,700**
Maintenance Costs/Year	$2,900	$7,950	$3,300	$2,900
Operation Costs/Year	$2,040	$2,040	$2,040	$2,040
Total Annual Cost	**$4,940**	**$9,990**	**$5,340**	**$4,940**
Total Cost for One Year	**$41,340**	**$64,650**	**$74,940**	**$56,640**
% Cost based on AVI	**100%**	**156%**	**181%**	**137%**

From a hardware point of view, AVI systems consist of two major elements, the in-vehicle unit (tag or transponder) and the roadside unit (reader or interrogator). Most systems require a communications link between these two elements, a host computer, and another communications link connecting the reader and the host. Information transmission in most of the existing systems is done in the form of visible light, infrared radiation, microwaves, or radio waves. The tags can be either internally powered (battery or the vehicle's electrical system) or they can be powered by the interrogation beam. The reader or antenna can be placed either along the side of the roadway or overhead. Most installed AVI systems are designed to deal with single lanes, however a single reader and antenna can be used for multiple lanes. AVI systems can be used to monitor point-to-point travel times providing the user with traffic delays that occur between two points. The importance of point-to-point data resides in the fact that it improves traffic predictions and, therefore, the performance of ATMS's and ATIS's. In addition, travel times can be used directly in incident detection algorithms and provide an estimate of space mean speeds.

Parkany and Bernstein (1995) conducted an investigation pertaining to the application of AVI for incident detection. The researchers assumed that 50 percent of the vehicles traveling the network are equipped with AVI transponders, with detectors 0.75 miles apart and medium traffic flow (1000 to 1400 veh/lane). The main conclusion was that AVI has great potential as a stand-alone sensor for incident detection. In another study performed by the Texas Transportation Institute (TTI) on AVI data obtained from Houston, detection rates

were lower and false alarm rates were higher than those reported from other fixed detectors' incident detection algorithms (Balke et al. 1996). The lack of agreement between the results of the two previously cited studies suggests that one of the potential uses of the data collected from AVI systems is to integrate it with data obtained from other detector types mounted on the same sections of roadway. This will also produce more data to be used in incident detection algorithms.

One of the major drawbacks of AVI-collected data is its incompleteness, as not all vehicles or all types of vehicles are equipped with transponders. This will be particularly crucial in light traffic conditions and results in unreliable data. Using vehicle probes as a source of real-time data requires a certain market penetration level so that there are at all times enough equipped vehicles traveling in the network to provide reliable traffic data measurements. AVI systems are more expensive to install than traditional detectors. In addition, the public is concerned with privacy issues due to the fact that each tag can be uniquely identified.

The AVI system deployed in San Antonio could serve as an important source of real-time traffic information to TransGuide's ATMS and ATIS applications. The systems 'objectives and goals were defined as follows (Southwest Research Institute 1997):

- Provide real-time traffic condition information,

- Provide data that can be used by traffic management personnel to manage traffic,

- Provide data that can be used by the traveling public,

- Be flexible in order to allow additional sensors in the future,

- Provide easy system diagnosis and configuration, and

- Process data in a timely manner to make the data available in a real-time fashion.

These requirements were set in an attempt to achieve TransGuide's targeted 2 minute mean TTD incidents. The system was designed by Southwest Research Institute and consists of three major components: the AVI Data Processing System, the AVI Reader Field Site System and the AVI tags. The hardware system components were chosen off the shelf in an attempt to minimize costs, whereas the software was custom made to fit TransGuide's requirements. The tags are passive read-only tags supplied along with the antennas by Amtech Systems Corporation. Originally, 78,000 tags were planned to be distributed at no cost to the user, but by December 2000 only 48,000 had been distributed. There are currently fifty-one operational AVI sites in the San Antonio network. Two plain old telephone system lines (POTS) connect the AVI Reader Field Site to the AVI master computer providing for two-way communications. AVI Reader Field Sites establish and maintain communication with the AVI Data Processing System. As the tagged vehicles pass by an AVI reader, the radio frequency (RF) signal emitted by the AVI Reader Field Site excites the tag's transponder. The excited transponder then emits a RF signal containing the unique AVI tag identifier that is in turn captured by the AVI Reader Field Site. The AVI antennas having read the signal, the system then sends the tag reads to the AVI Data Processing System

located at TransGuide's headquarters. Each site has a buffer that stores the tag reads. Once there is a predetermined number of reads or a specified period of time elapses without achieving this predetermined number, the site contacts the TMC and sends the reads to the AVI data processing system. If the system determines that another reader in the network reported the same tag, it processes the data and produces travel times, travel speeds, and equipment status reports that are made available to other systems within TransGuide. The AVI system architecture and the context diagram for the AVI Master Computer Software are presented in Figures 2.1 and 2.2, respectively (Southwest Research Institute 1997).

The primary objectives of a traffic management center consist of reducing congestion and delays, and dealing with dangerous situations in a timely manner. In order to achieve these objectives, real-time detection, assessment, and response to traffic incidents, as well as the delivery of accurate traffic management information, become of immeasurable importance. The limits on the TTD set by current TMCs impose tighter functional specifications on the system (2 minutes for TransGuide). Based on the available literature and on the observation of existing systems, some functional specifications for an efficient system will be developed and defined in terms of:

- Number of readers versus number of lanes for each site,

- Percentage penetration of tagged vehicles,

- Spacing of readers,

- Efficiency of site communications, and

- AVI tag reliability, and maintenance.
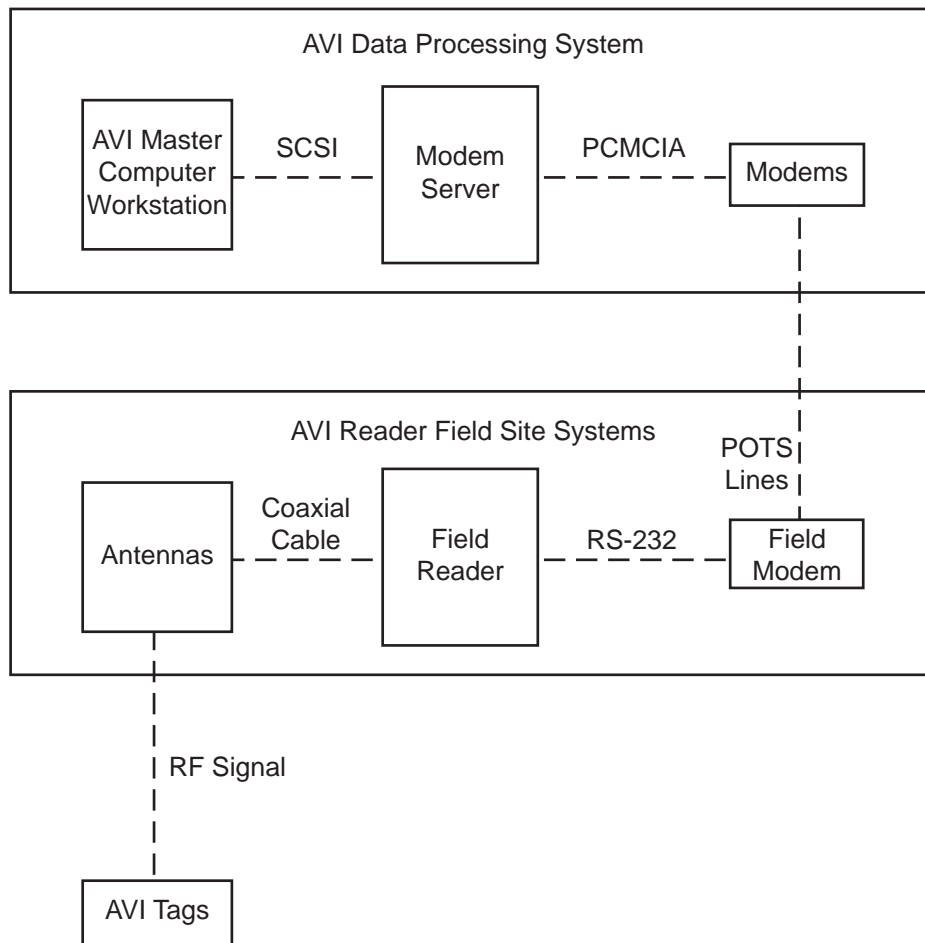
Figure 2.1 AVI System Architecture (Southwest Research Institute 1997)
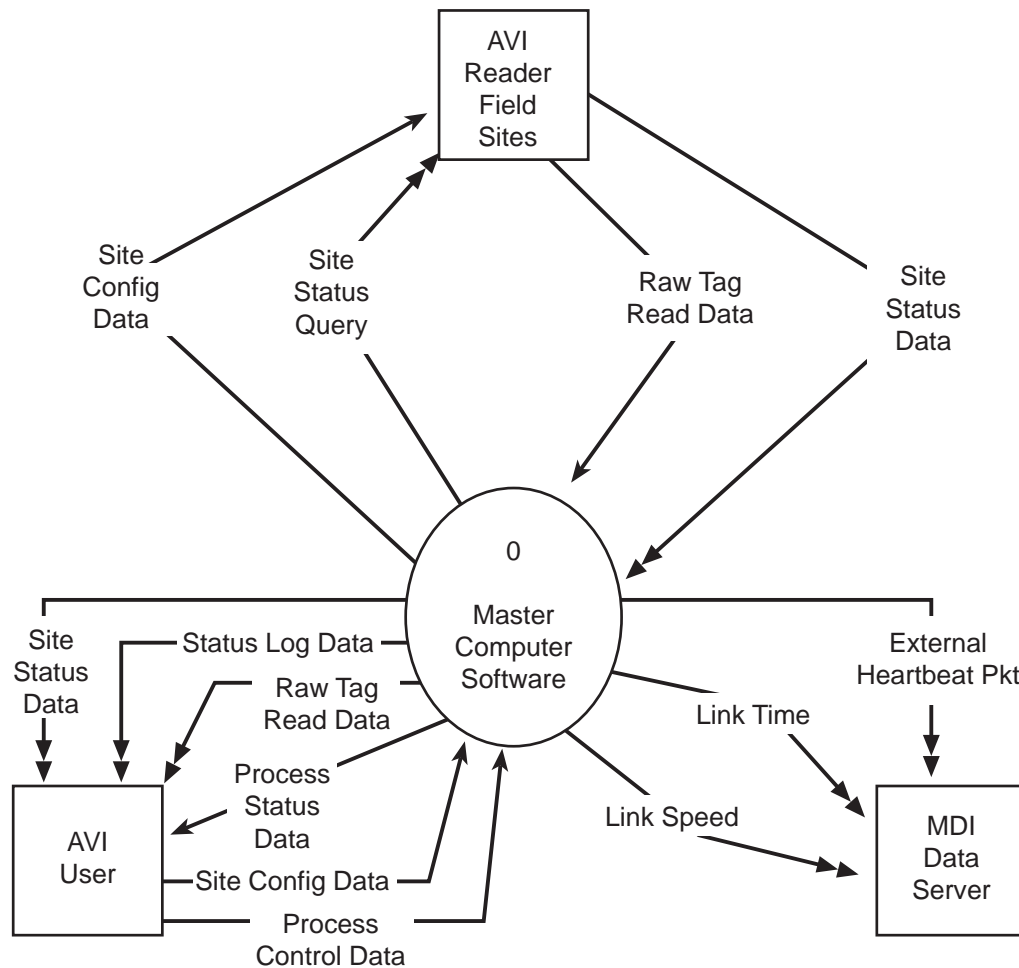
Figure 2.2 Context Diagram for the AVI Master Computer Software (Southwest Research Institute 1997)

Due to the high installation cost as well as operation and maintenance costs of AVI readers, some TMCs have decided to monitor only the innermost lanes of the freeway under consideration, rather than bearing the additional cost of covering all lanes. For the system installed on I-35 in San Antonio, different sites are equipped with different numbers of readers. At some locations, the two innermost lanes are monitored whereas at other locations all four lanes are monitored. Generally, every antenna is mounted above the centerline of the lane and tagged vehicles traveling in adjacent nonmonitored lanes are not picked up. In Houston, all lanes of the freeways are monitored with AVI readers. It is believed that the decision of whether to monitor the innermost or all lanes of a freeway depends to a great extent on the intended use of the data generated from the system and on the percentage of tagged vehicles traveling the network. If the collected data is intended to be used solely for link travel time determination for the purpose of public information, and if the market penetration of tagged vehicles is appreciable, monitoring only the innermost two lanes is

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adequate. However, if the data is intended to be used as input to an incident detection algorithm, monitoring all lanes will lead to better results and shorter TTD especially when incidents occur on the nonmonitored lanes.

Using vehicle probes as a consistent information source requires equipping a sufficient number of vehicles with tags so that at all times, there are enough probe vehicles actually traveling the network. Van Aerde et al. (1993) conducted research in an attempt to determine the level of market penetration of tagged vehicles that is necessary to provide adequate samples of travel times. The research was conducted on a small simulated network comprised of a single arterial street, a freeway and ramps connecting them. Van Aerde concluded that at a market penetration of 20 percent the actual link travel time experienced by the simulated vehicles fell within the 95 percent prediction intervals for each link determined by the travel time sample. Parkany and Bernstein (1995) conducted an investigation pertaining to the application of AVI for incident detection. The research group assumed that 50 percent of the vehicles traveling the network were equipped with AVI transponders, the detectors were 0.75 miles apart and there was medium traffic flow (1000 to 1400 veh/lane). The main conclusion was that AVI has great potential as a stand-alone sensor for incident detection. Hellinga and Knapp (1999) researched the performance of three AVI-based automatic incident detection algorithms using a network simulation of eight interchanges along a 12 km freeway section of Highway 401 in Toronto, Canada. The fact that a simulation model was used allowed for testing of the algorithms' performance for a range of market penetrations of AVI equipped vehicles. The most important trends observed are summarized as follows: the detection rate improves significantly as the level of market penetration increases from 1 percent to 5 percent, and there is an incremental small improvement when the level of market penetration goes up to 10 percent and it remains almost constant after that. It was also noted that as the level of market penetration increases, the false alarm rate also increases. Most importantly, the mean TTD decreases continuously with the increasing level of market penetration. The mean TTD decreases by about 35 percent with an increase in level of market penetration from 1 percent to 25 percent.

With these varying results, it is important to understand that all of the above-discussed experiments made use of simulated data due to the lack of real-time AVI data and due to the advantages that a simulator offers in terms of varying factors in the analysis. The level of market penetration that would be adequate should be evaluated in conjunction with whether AVI is going to be used as a stand-alone traffic conditions detector system or coupled with some other detector data such as inductive loops. Better incident detection can be achieved with increasing market penetration levels. Since the TTD varies inversely proportionally to the level of market penetration, an increasing level of market penetration is especially important in achieving the detection time goals set by TMCs. Attaining a market penetration of 20 percent or more should be adequate to achieve a reasonable TTD. For some markets such as Houston, such market penetration levels should not be difficult to achieve in the future, especially with the variety of AVI applications available, ranging from toll collection to access control. Additionally, tags from different cities can still be detected and act as a probe in the network.

No formal study was conducted to assess the effect of readers' spacing on the performance of AVI as a source of information for incident detection. In the studies performed on simulated networks, AVI readers were set at some constant intervals. To minimize cost, the location of the readers in existing AVI installations is determined to a large extent by the availability of supporting structures. When the San Antonio or the Houston networks are observed, it is obvious that readers were installed wherever bridges or message signs structures were already existent. It is believed that the spacing of the readers influences the performance of the system by the number of off-ramps between successive readers. The greater the number of off-ramps and on-ramps, the greater the chance of matching tagged vehicles traveling this particular segment of the network. This implies that the readers should be placed in such a way to reduce as much off-ramp interference as possible.

To ensure the shortest TTD, it is of primary importance that the communication means between every site and the control center be as consistent and timely as possible. Usually the AVI reader field sites are connected to the AVI master computer using POTS lines that provide for two-way communications. Radio-type connections were tested and found to perform much poorer than telephone communications (Mouskos et al. 1996). Cell phone lines may not be the most desirable, but the author is not aware if a thorough evaluation has been made of this option. The system installed in Houston differs from that of San Antonio in that as soon as a tag is read, the field site initiates a call in an attempt to transfer the tag read to the host rather than waiting for a prespecified time to elapse or for a prespecified number of tag reads. If during this time another tag is read, the system maintains communication and continues transferring data for up to a minute. After that, even if there are more tags detected, the system disconnects and tries to connect again to allow other sites to dial in. The modems used require an average of 15 seconds handshake duration. There are actually 160 operational sites in Houston along with 106 (POTS) lines to serve them. To ensure timely arrival of data at the TMC, continuous connection between the sites should be maintained along with an adequate number of phone lines to serve all the AVI sites of the network.

From a hardware point of view, AVI systems consist of two major elements, the in-vehicle unit (tag or transponder) and the roadside unit (reader or interrogator). Most systems require a communications link between these two elements, a host computer and another communications link connecting the reader and the host. Information transmission in most of the existing systems is done in the form of visible light, infrared radiation, microwaves, or radio waves. The tags can be either internally powered (battery or a vehicle's electrical system) or powered by the interrogation beam.

Although internally powered tags are more expensive and the battery has to be changed whenever dead (new tags have lithium batteries that can last up to 10 years), they are much less sensitive to the orientation of the antennas and require much lower powered transmissions than nonpowered tags. Therefore, they are the preferred choice from a reliability perspective. An economic analysis might yield a different preference.

Proper maintenance is as important as system design and installation. The system's operating agency should regularly check the sites to determine the ones with which

communication cannot be established. The TMC should have a specialized maintenance crew with the required skills to perform regular maintenance and to fix problems without inordinate delays. Furthermore, it is recommended that the direction of the antennas be checked regularly and be properly realigned, if needed, especially for the systems using nonpowered tags. It is also recommended that an agreement be reached with the local phone and power companies to ensure timely repairs of communication and power links.

The efficiency and timeliness of a TMC emergency response to highway incidents are largely dependent on the quality of the data available. Adequate performance is obtained whenever the location, type, severity, and scale of an incident are accurately and consistently reported. Each type of sensor has its associated strengths and weaknesses. It is expected that combining data from several sources might offset the weaknesses of a single source, thus leading to more accurate and complete information. The data obtained after sensor fusion has the potential to reduce delays and improve the overall incident detection performance of the system. Figure 2.3 represents the generic design for an incident detection system that makes use of fusion concepts.

AID systems using conventional sensors are useful tools for TMCs. However, the use of surveillance cameras and PP in providing visual confirmation is important. Finally, cellular phones are becoming an increasingly reliable source of information with their ever-increasing level of market penetration.
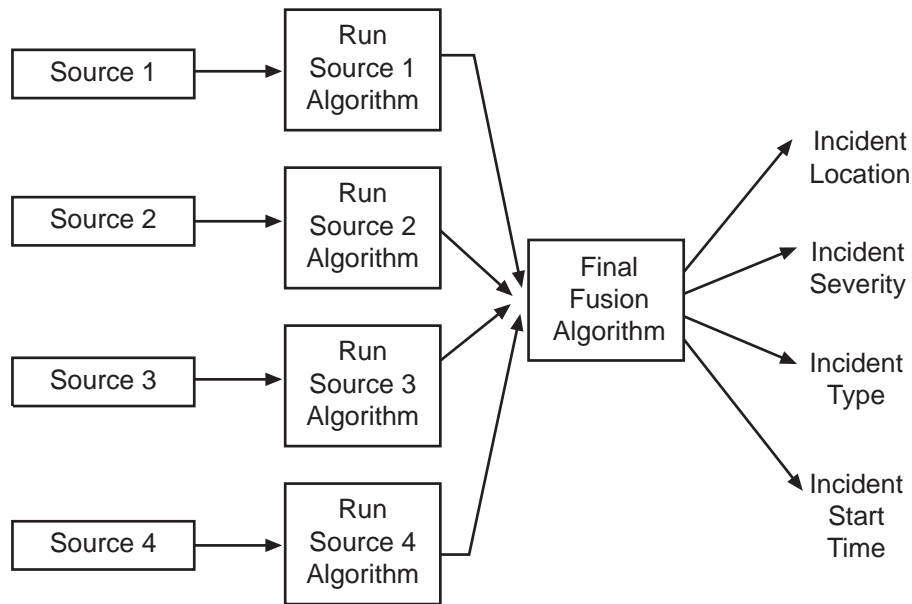
Figure 2.3 Generic Design of an Incident Detection System with Multiple Sources of Input

2.2.2 Algorithms

Incident detection algorithms are a key component of automated incident detection systems. The TTD an incident varies with the effectiveness of the detection algorithm

employed. The less effective the algorithm, the more substantial the delays that are incurred in responding to the incident and the less useful the AID system. Since the early 1970s, a variety of incident detection algorithms have been developed, catalyzed by a substantial national investment in ITS. At the heart of all incident detection algorithms is their reliance on disturbances or sudden changes in traffic conditions. It is the prevailing conditions i.e., traffic flow and speed, as well as the severity and location of the incident that determine the magnitude of these disturbances. Algorithms tend to perform differently depending on the traffic conditions they were intended to deal with. The performance of the different algorithms is affected also by the spacing of the detectors and by the resolution and aggregation of the data. Algorithms are most often based on either pattern recognition or forecasting principles (Solomon 1991).

Pattern recognition algorithms detect incidents by examining the collected data and finding values or combinations of values that are historically characteristic of incident conditions. Algorithms are developed to detect these conditions while dismissing patterns that do not correspond to incidents, such as recurrent congestion. The data collected at all detector stations is run through a decision tree logic which compares at each node a data measurement to a prespecified threshold value. The decision trees vary in complexity depending on the particular algorithm. Some are extremely simple, relying on just one measurement to determine whether or not an incident took place, while others use a much more complicated logic. Typically, algorithms using simple decision trees compare occupancy values to a threshold value.

Forecasting algorithms compare the collected measurements to forecasts obtained based on the most recent history of measurements. The difference among the different forecasting algorithms resides in the measurements employed and the forecasting techniques implemented. Unlike pattern recognition algorithms, forecasting algorithms monitor the rate at which traffic measurements change rather than the change in their absolute value.

It is important to note that most of the algorithms developed to date are meant to deal with freeway incident detection and are not adequate to be used with other more complicated types of roadways such as arterial streets. With the advent of cell phones, using AID for city streets is probably never going to be feasible. Also, algorithms are designed to operate at an optimal level when traffic volumes are between certain limits, thus a certain algorithm that works well under high volumes might perform poorly when low traffic flows are experienced. All algorithms require a steady stream of data and result in a binary output of incident or no incident with the exception of fuzzy algorithms. In the latter case, neural networks train themselves to look for and recognize incident patterns in traffic data and algorithms based on fuzzy logic give a "possibility" of incident occurrence.

It seems reasonable that combining the output of several algorithms, i.e., algorithm fusion, would lead to better results when compared to the use of a single algorithm. Algorithm fusion was explored in detail in a study conducted at The University of Texas at Austin (Zhou 2000). Fusing the outcome of several algorithms possessing complementary strengths combines the advantages that each algorithm possesses under different conditions. The associated incremental cost is minimal, especially since individual algorithms generally use similar data input.

2.2.3 Verification and Response

It is critical to stress the importance of incident verification and response compared to other objectives of incident management. Incident verification and response are as important as incident detection in ensuring an efficient incident management program. The program should also incorporate ways to inform motorists, so that they alter their travel plans in order to contribute to the reduction of the incident-induced congestion.

Verification is the first step that has to be undertaken once an incident pattern is detected by an algorithm. Once an alarm has been generated, surveillance cameras or mobile sources (cellular callers, highway patrol, etc.) are used to verify and characterize the incident and to drive the dispatch of any necessary emergency services. Surveillance cameras can be operated manually to observe the problematic area or this process can be speeded up by the use of software that activates the camera closest to the incident. At TransGuide, the software is designed to automatically zoom, pan, and tilt to the closest camera. Several operators, such as police and VIA Metropolitan Transit Authority dispatchers, as well as TxDOT operators, can access a view of the scene at the same time.

Once the incident is verified, the operator in charge decides on an appropriate response. The response is aimed at notifying emergency response agencies and motorists, as well as at implementing control measures. At TransGuide, the operator can choose from preprogrammed "scenarios" that act on lane control signals, dynamic message signs and traveler information systems. Although this research is focused on the incident detection phase of incident management, all other phases are of equal importance to a program aimed at optimizing safety.

Chapter 2 presented the technology deployed at TransGuide. Also, the chapter included a description of the components of incident management, i.e., sensor technology, algorithms, and, finally, detection and response.

The following chapter illustrates the logic behind several incident detection algorithms used with data collected from ILDs. Promising incident detection algorithms that make use of AVI-generated data are also described.

CHAPTER 3 AUTOMATIC INCIDENT DETECTION ALGORITHMS

Automatic Incident Detection (AID) relieves part of the stress incurred by Traffic Management Center (TMC) operators in managing complex networks, thus allowing for better incident management. Central to AID are the incident detection algorithms. The importance of AID algorithms has been increasing ever since TMCs started moving toward higher levels of automation. While algorithms making use of fixed detector data were subject to extensive research, the literature reviewed showed that there is still a lot to be done in the development of algorithms using probe vehicle data. This chapter starts by presenting measures of effectiveness to be used in evaluating the performance of the different algorithms, followed by an introduction to some of the most widely used fixed detector algorithms in TMCs. Also, promising probe vehicle algorithms are presented. It is to be noted, however, that the chapter is not intended to be an exhaustive review of all existing algorithms.

3.1 MEASURES OF EFFECTIVENESS

Whenever an incident detection algorithm tests for the occurrence of an incident, four outcomes are possible. The first type of outcome, characterized as a "correct non-incident classification," is one where no incident has actually occurred and where the algorithm has detected no incident. The second type of outcome, characterized as an "incorrect incident classification," is one where no incident has actually occurred and the algorithm has signaled the occurrence of an incident. This type of outcome is commonly referred to as a "false alarm." The third possible type of outcome, characterized as a "correct incident classification," is one where an incident has actually occurred and the algorithm has correctly detected its occurrence. The final possible type of outcome, characterized as an "incorrect non-incident classification," is one where an incident has actually occurred and the algorithm has detected no incident. This type of outcome is commonly referred to as a "missed incident." The implication of the different types of outcomes on the effectiveness of incident management differs with the worth being attributed to missed incidents. The most common measures of effectiveness for automatic incident detection algorithms are the False Alarm Rate (FAR), the Detection Rate (DR), and the Time-To-Detection (TTD). These measurements provide a consistent benchmark to compare the performance of the different algorithms considered in this research.

FAR is defined as the fraction of incorrect detections to the total number of algorithm applications. It is the probability that a type two outcome occurs, i.e., the algorithm detects an incident that did not occur. Most often FAR is expressed as a percentage, but may also be given as the number of false alarms per time period. FAR is largely influenced by the prevailing traffic conditions. If the algorithm is calibrated to detect only major accidents,

FAR should be relatively low. The more varied the traffic conditions experienced, the higher the FAR.

DR is defined as the ratio of number of detected incidents to the actual number of incidents that occur during a specified time period and is given as a percentage. It is the probability that a type three outcome occurs. The probability of a missed incident can be calculated by subtracting the DR expressed as a ratio from 1. Furthermore, an incident must be correctly detected in order to contribute to the DR. A correctly detected incident is one for which the algorithm outputs the correct date, time, and location.

The average TTD is defined as the average time needed by an algorithm to detect an incident. The TTD is measured as the time elapsed between the apparent time of occurrence of an incident and its detection by the algorithm. The average TTD is obtained by averaging the TTD values for all incidents detected over a certain time period. There is a distinction between apparent time of occurrence and actual time of occurrence of an incident. The latter is the exact time of occurrence of an incident and can be obtained only if that particular location is under constant surveillance, i.e., the location is being videotaped or observed manually. The more complex the network, the more labor intensive the task becomes. The apparent time of detection of an incident reflects the time reported in the incident log either by an operator or by the algorithm used at the TMC.

Based on these measures of effectiveness, three objectives are sought in the performance of an incident detection algorithm:

- Maximize the number of actual incidents detected by the algorithm,

- Minimize the number of times the algorithm reports an incident that has not occurred, and

- Minimize the time it takes the algorithm to detect an incident.

These objectives can be represented as an objective function in terms of the measures of effectiveness previously defined:

Maximize Z (DR, FAR, TTD) = α_1(DR) - α_2(FAR) - α_3(TTD)

The performance efficiency of an algorithm depends on the α factors of the objective function. In general, an algorithm that achieves the highest DR is not likely to achieve the lowest FAR and TTD. These measures of effectiveness are not independent and tend to be in conflict with one another, requiring trade-offs in algorithm performance. Algorithms tuned to detect a high percentage of incidents tend to result in a large number of false alarms. Along the same lines, an algorithm tuned to detect severe incidents produces fewer alarms at the expense of the number of incidents detected. Similarly, while a longer TTD allows an algorithm to analyze more data, thus increasing the DR and reducing FAR, it also has a

greater impact on traffic (Black 1997). These interrelationships suggest that each algorithm should be tuned for the specific application at hand.

Typically, an algorithm depends in its operation on a set of thresholds. Each set of thresholds corresponds to a different response in terms of DR, FAR, and TTD. Therefore, it can be said that there is not necessarily an optimal choice; rather, the chosen set of thresholds for a particular application should balance the DR, FAR, and TTD. Testing an algorithm with various sets of thresholds will typically result in performance curves as illustrated in Figure 3.1, when the DR and TTD are respectively plotted against FAR (Peterman 1999).
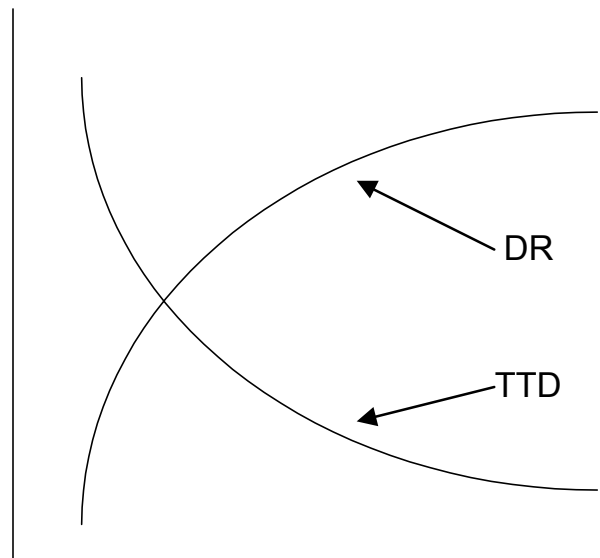
Figure 3.1 Typical Performance Curves for Incident Detection Algorithms

A set of thresholds is said to be "pareto-optimal" if there is no set of thresholds that will improve one attribute (DR, FAR, or TTD) without degrading at least one other attribute. The DR and TTD plotted against FAR represent the "efficient frontiers" of the algorithm or the set of thresholds that is "pareto-optimal." Since it is practically impossible to get the best performance from a single set of thresholds with respect to all three attributes, it is up to the system manager to decide on the relative importance of DR, FAR, and TTD to a particular application. Then the designer should choose the set of thresholds that maximizes the objective function by optimizing the attribute associated with the highest weight. With the basis for comparison defined, the algorithms are presented next.

3.2 FIXED DECTECTOR ALGORITHMS

Extensive research has gone into developing algorithms to be used with data collected from fixed detectors, namely Inductive Loop Detectors (ILD). Existing detection algorithms are organized in this study into five categories: comparative, statistical, time series, traffic model and theoretical, and finally, advanced incident detection techniques (Picado 1997). While comparative algorithms are based on pattern recognition principles, statistical, time series, and traffic model and theoretical are all based on forecasting principles.

3.2.1 Comparative Algorithms

Comparative or pattern recognition algorithms compare the current traffic flow conditions with those prevailing under normal conditions. The values of traffic parameters (volume, occupancy, or speed) are directly compared to predetermined thresholds. If the algorithm detects a substantial difference, an incident is flagged out and brought to the attention of the operator.

3.2.1.1 California Algorithms The California algorithms began in the late 1960s for use in the Los Angeles freeway surveillance control center (Black 1997). Although the logic is one of the first to be developed, these algorithms remain a benchmark against which new algorithms are compared. The logic assumes that an incident is likely to create congestion upstream and a relative absence of congestion downstream. The California algorithms compare occupancy data between adjacent detector stations. The occupancy data are manipulated in order to generate three additional traffic measurements as described in Table 3.1. The OCCDF and the OCCDRF variables are intended to capture the eventual significant change in occupancy upstream and downstream of an incident location. The DOCCTD is intended to differentiate incidents from recurring congestion by looking for short-term intense changes in occupancy values at the downstream section.

Table 3.1 "Features" of the California Algorithms (Payne 1976)

Measure	Description	Definition
OCC (i, t)	Occupancy at detector station i at time t	
DOCC (i, t)	Downstream occupancy	OCC (i+1,t)
OCCDF (i, t)	Spatial occupancy difference	OCC (i, t) - DOCC (i, t)
OCCRDF (i, t)	Relative spatial occupancy difference	$\dfrac{\text{OCCDF (i, t)}}{\text{OCC (i, t)}}$
DOCCTD (i, t)	Relative temporal downstream occupancy difference	$\dfrac{\text{DOCC(i,t-2) - DOCC(I,t)}}{\text{DOCC (i, t-2)}}$

The outcome of the algorithm is an ultimate state reached after running in sequence through a series of decision nodes. Algorithm #1, which was the original algorithm, differentiated between only two states characterizing incident conditions and non-incident conditions. The second version of the algorithm, i.e., algorithm #2, had the additional capability to determine the beginning and termination of an incident. These first versions of the algorithm were sensitive to compression waves and anomalous disturbances in traffic data. In 1973, Payne started developing modified versions of the California algorithms as part of a Federal Highway Administration (FHWA) sponsored study aimed at developing improved detection algorithms. Payne's research resulted in the development and testing of ten different algorithms. Of those ten, the California #7 and California #8 gave the best overall results. The current downstream occupancy replaced the spatial occupancy difference in California #7 to alleviate the high FAR experienced as a result of compression waves. Also, a persistence check was added to the later version of the algorithm. The persistence check required that the incident conditions remain for at least two iterations of the algorithm before signaling an incident. The California #8 differs from the rest of the series by delaying all incident detection for 5 minutes after a compression wave has been detected (Black 1997). The decision trees and state for the California algorithms #7 and #8 are presented in Figures 3.2 and 3.3, respectively.

Figure 3.2 Decision Tree for California Algorithm #7 (Payne et al. 1976)
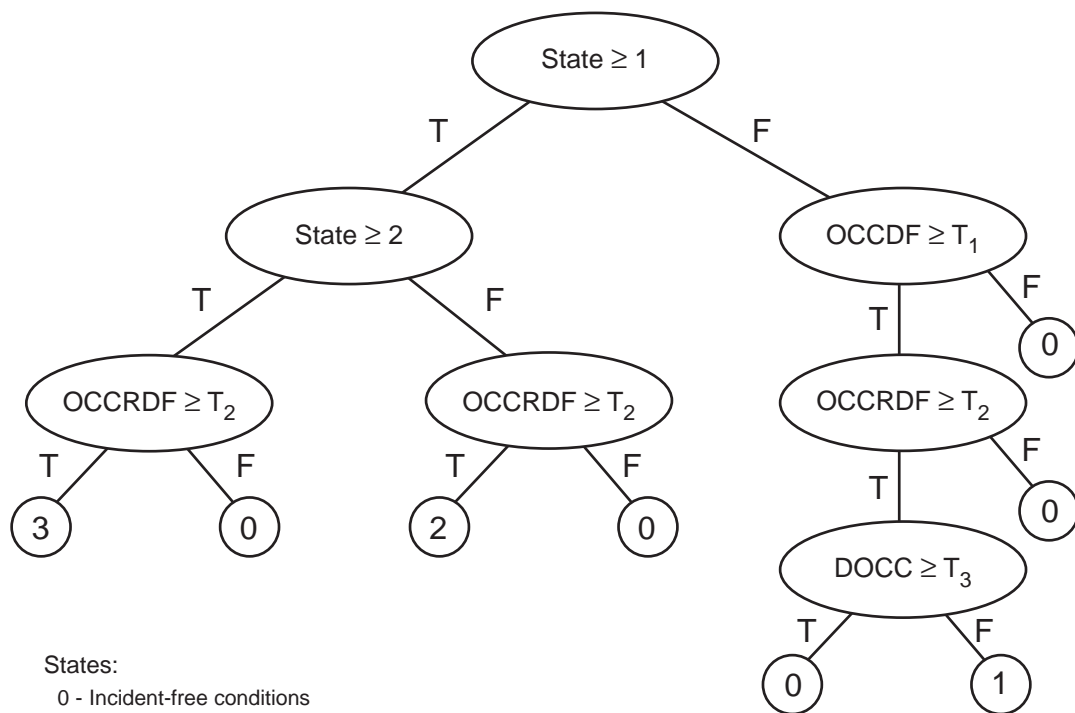
States:

0 - Incident-free conditions
1 - Tentative incident
2 - Incident confirmed
3 - Incident continuing

Variables:

OCC = Minute average occupancy
DOCC = Minute average occupancy measured at downstream detector
OCCDF = OCC - DOCC
OCCRDF = OCCDF/OCC

From H.J. Payne, D.N. Goodwin, and M.D Teaner,
"Evaluation of Existing Incidental Detection Algorithms."
Federal Highway Administration
Report No. FHWA-RD-75-39, Feb 1975

Figure: Decision Tree nodes (top to bottom, left to right):

State ≥ 6 — T → OCCDRF ≥ T_3; F → DOCC ≥ T_5

OCCDRF ≥ T_3 — T → State ≥ 7; F → DOCCTD ≥ T_2

State ≥ 7 — T → 8; F → 7

DOCCTD ≥ T_2 — T → 0; F → DOCC ≥ T_5

DOCC ≥ T_5 — F → 0; T → State ≥ 7

State ≥ 7 — T → 0; F → 1

DOCC ≥ T_5 — T → DOCCTD ≥ T_2; F → State ≥ 1

DOCCTD ≥ T_2 — T → State ≥ 1; F → 1

State ≥ 1 — T → State ≥ 2; F → 0

State ≥ 2 — T → State ≥ 3; F → 2

State ≥ 3 — T → State ≥ 4; F → 3

State ≥ 4 — T → State ≥ 5; F → 4

State ≥ 5 — T → 0; F → 5

State ≥ 1 — T → State ≥ 2; F → OCCDF ≥ T_1

State ≥ 2 — T → State ≥ 3; F → 2

State ≥ 3 — T → State ≥ 4; F → 3

State ≥ 4 — T → State ≥ 5; F → 4

State ≥ 5 — T → 0; F → 5

OCCDF ≥ T_1 — T → OCCDRF ≥ T_3; F → 0

OCCDRF ≥ T_3 — T → DOCC ≥ T_4; F → 0

DOCC ≥ T_4 — T → 0; F → 6

States:

0 - Incident-free conditions
1 - Compression wave this minute
2 - Compression wave 2 minutes ago
3 - Compression wave 3 minutes ago
4 - Compression wave 4 minutes ago
5 - Compression wave 5 minutes ago
6 - Tentative incident
7 - Incident confirmed
8 - Incident continuing

Figure 3.3 Decision Tree for California Algorithm #8 (Payne et al. 1976)

3.2.1.2 Texas Algorithm Developed by Texas Department of Transportation (TxDOT), the Texas algorithm is a simple comparative algorithm that weighs the speed at detector stations against a preset threshold using a 2-min. average (Peterman, 1999). The speed measurement is substituted for occupancy measurements on on-ramps and off-ramps. An alarm is triggered if the speed or occupancy value exceeds the threshold. To achieve better results, the algorithm could be calibrated at each detector station. The Texas algorithm is used in TMCs throughout the state of Texas, namely TransGuide in San Antonio, TranStar in Houston, and TransVision in Fort Worth.

3.2.1.3 High Occupancy Algorithm (HIOCC) Developed by the Transport and Road Research Laboratory in England (1979), the HIOCC inspects occupancy data from individual

loop detectors for the presence of stopped or slow-moving vehicles. The algorithm parses through the data looking for very high values of occupancy and compares them to the threshold value. Although the HIOCC resembles the TxDOT algorithm, the occupancy threshold is usually set at a much higher value.

3.2.1.4 All-Purpose Incident Detection (APID) Algorithm The APID algorithm was originally developed for use in the Toronto COMPASS advanced traffic management system (ATMS) and is designated as "all-purpose" since it was designed to perform under all traffic conditions. The logic behind the APID algorithm is similar to that of the California #8 with the addition of a speed measurement. The algorithm parameters, i.e., the set of thresholds, are automatically modified according to the prevailing volume conditions. The algorithm differentiates between "low," "medium," or "high" volumes and includes an incident termination routine, a test for compression waves, and a persistence check.

3.2.2 Statistical Algorithms

Statistical algorithms rely on detecting large differences between the actual value of a traffic variable and the corresponding statistically predicted or estimated value.

3.2.2.1 Standard Normal Deviate (SND) The Texas Transportation Institute (TTI) developed the Standard Normal Deviate (SND) algorithm to be used on Houston's Gulf Freeway (I-45). The algorithm examines the SND also known as Z-transform of a traffic variable (usually occupancy). The SND can be obtained as shown in Equation 3.1:

$$SND = \frac{x - \bar{x}}{s}$$
(Eq. 3.1)

Where x = traffic variable being considered,
$\bar{x}$ = mean of traffic variable over previous sampling periods, and
s = standard deviation of the traffic variable over previous sampling periods.

The logic is based on the assumption that a significant change in the traffic variable would be observed in case an incident happens leading to a high value of SND. The algorithm can be set to perform a persistence check before reporting an incident, i.e., two consecutive values of SND have to be critical to trigger an alarm. In 1974, Dudek studied the performance of an algorithm using occupancy values as input and computing moving averages over the previous 5 minutes. His algorithm required two consecutive critical SND values to trigger an alarm. The detection rate of Dudek's algorithm was close to 92 percent and FAR approached 1.3 percent (Dudek 1974).

3.2.2.2 Bayesian Algorithm Levin and Krause (1978) applied Baye statistical techniques to determine the probability of occurrence of an incident caused by downstream

lane blockage. Historical data on the occurrence of capacity-reducing events along the section of freeway under consideration is used to generate relative spatial occupancy differences. The latter value is used as the basis for determining incident probabilities. The spatial occupancy difference calculated is similar to the OCCRDF value described under the California algorithm, with the exception that the Bayesian algorithm computes conditional probabilities that the relative difference is caused by an incident. The algorithm requires large databases of traffic volume and occupancy during incident conditions, traffic volume and occupancy during incident-free conditions, and finally information about incidents such as their type and location. Furthermore, this approach requires complicated calibration at each station and usually results in high detection times.

3.2.3 Time Series Algorithms

Time series algorithms make use of statistical modeling of traffic behavior in determining short-term traffic forecasts based on recent values of a traffic variable. These algorithms employ large time windows to reduce short duration traffic disturbances.

3.2.3.1 ARIMA Algorithm The logic behind the ARIMA algorithm was developed by Box and Jenkins (1976) to recognize patterns in data and generate forecasts. The logic was applied later by Ahmed and Cook (1980) to incident detection. The researchers observed that an Auto-regressive Integrated Moving Average (ARIMA) time series model could represent traffic flow on a freeway. Used to develop short-term forecasts and confidence intervals, the ARIMA algorithm tries to predict the difference in the values of a traffic variable between the current time period and the preceding one. The prediction is based on averaging the errors between the predicted and the observed traffic variable from the previous three time periods. An incident is detected whenever the observed value of the traffic variable falls outside the confidence limit of the forecast.

3.2.3.2 Exponential Smoothing Algorithm Exponential smoothing algorithms predict future traffic conditions by assigning weights to past and current traffic variable values. These algorithms can be mathematically modeled by a single or double smoothing function associated with a smoothing constant that weighs past observations. Cook and Cleveland (1974) developed a double-exponential smoothing algorithm described by Equations 3.2 and 3.3.

$$S_1(t) = \alpha(X(t)) + (1-\alpha)S_1(t-1) \qquad\qquad (Eq.3.2)$$
$$S_2(t) = \alpha(S_1(t)) + (1-\alpha)S_2(t-1) \qquad\qquad (Eq.3.3)$$

Where $S_1(t)$ = single exponentially smoothed variable at time t,
$S_2(t)$ = double exponentially smoothed variable at time t,

$X(t) =$ state variable measured at time *t*, and

α = smoothing constant.

Cook and Cleveland examined speed, volume, occupancy, and ten other traffic variables. The algorithm relies on a tracking signal to detect incidents. The tracking signal is defined as the sum of all previous errors, i.e., the difference between the predicted and actual value of the traffic variable considered. During normal conditions, the predicted and actual values of the variable should be close, leading to an insignificant value of the tracking signal. During incident conditions, the predicted and actual values of the traffic variable are expected to vary significantly leading to higher values of the tracking signal. The best performing indicator variables examined were occupancy and volume.

3.2.3.3 Detector Logic with Smoothing Algorithms (DELOS) Stephanedes and Chassiokos (1993) extensively investigated the effects of temporal smoothing and exponential smoothing. Exponential smoothing resulted in better results than temporal smoothing using either the mean or median of a data window. The researchers put together the logic behind what is known as the DELOS algorithm or the Minnesota algorithm. The DELOS algorithm produces a smoothed moving average in an attempt to level the data. The algorithm eliminates peaks while allowing low frequency fluctuations to pass.

3.2.4 Traffic Model and Theoretical Algorithms

Traffic model and theoretical algorithms make use of complex traffic flow theories to describe and predict traffic behavior for the duration of an incident. The Dynamic algorithm and the McMaster algorithm are introduced next.

3.2.4.1 Dynamic Algorithm In 1955, Lighthill, Witham, and Richards introduced the first order continuum theory which was the base for the development of several traffic flow models using higher-order continuum formulations such as those proposed by Payne (1971). Willsky et al. (1980) investigated the application of Payne's macroscopic traffic model to describe the change in spatial-average traffic variables in order to capture the dynamic aspect of the traffic phenomena. The likelihood of occurrence of an incident is calculated using a Kalman filter that processes measured data to generate estimates for the underlying system variables. Two statistical hypothesis-testing procedures are used to study flow-density relationships in the traffic data: the Multiple Model (MM) and the Generalized Likelihood Ratio (GLR). The MM method is used to generate conditional probabilities serving as control measures for the detection of incidents. The GLR evaluates the likelihood that the observed flow-density pattern is typical of incident conditions.

Cremer (1981) investigated Kalman filtering for AID purposes on congested cross-country freeways in Europe. He concluded that with an appropriate traffic flow model, speed

and density measurements provide the input needed to calculate a "disturbance volume." The "disturbance volume" is defined as being a hypothetical follow intended to explain and measure reductions of roadway capacity. An incident is triggered in case the "disturbance volume" goes past a certain critical value.

Both the Willsky and Cremer approaches were not picked up extensively by practitioners because they require the calibration of traffic flow model and the fine-tuning of filter matrices. This limited the application and the testing of these approaches to a small number of simulated incident patterns.

3.2.4.2 McMaster Algorithm Researchers at McMaster University in Ontario, Canada, developed the McMaster algorithm. To detect incidents, the algorithm relies on the hypothesis that unlike speed, which changes sharply when traffic moves from a congested to an uncongested state, flow and occupancy change smoothly. The algorithm starts by identifying congested areas and then attempts to determine if a permanent bottleneck or an incident is responsible for the detected congestion. The algorithm develops a volume-occupancy template using historical flow-occupancy relationships during changes from congested to uncongested conditions. The traffic conditions at each detector station are classified into one of four areas corresponding to different states of traffic. These traffic states are shown in Figure 3.4 (Hall et al. 1989). In the case where congestion of type 2 or 3 is encountered, the algorithm examines the traffic state at the downstream section. The premise behind looking at the downstream station in this case is the hypothesis that recurring and incident congestion result in different downstream traffic patterns. An alarm is triggered if the downstream detector is in state 1 or 2. If a state 4 is detected at the downstream detector, the congestion is classified as recurring. If a state 3 is detected at the downstream detector, then the algorithm examines the next downstream detector using the same logic.
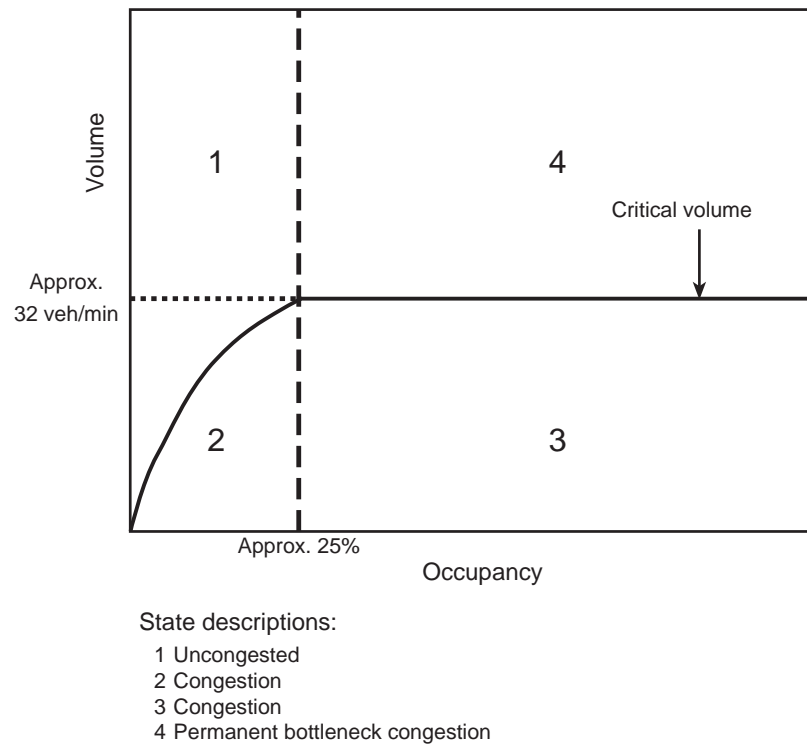
Figure 3.4 Original McMaster Template (Hall et al. 1989)

Later, the McMaster algorithm logic was refined to reduce the susceptibility of the algorithm to incident-related traffic patterns emanating from nonincident conditions, such as the disturbances in the traffic stream experienced at merge and diverge areas on freeways. The updated logic modified the original logic by adding states and by creating two separate templates to differentiate between detector stations, depending on their location with respect to recurring bottlenecks (Hall et al. 1993). Figures 3.5 and 3.6 respectively illustrate the template intended for normal stations and for stations under recurrent congestion.

Since volume-occupancy characteristics vary across stations, the McMaster algorithm requires calibration of the boundaries separating the four traffic conditions individually at each detector station.

Furthermore, it is important to note the similarity between the logic of the California algorithm and that of the McMaster algorithm. Both algorithms compare traffic state variables to predetermined thresholds at decision nodes and result in a final state based on the results of the decision nodes.
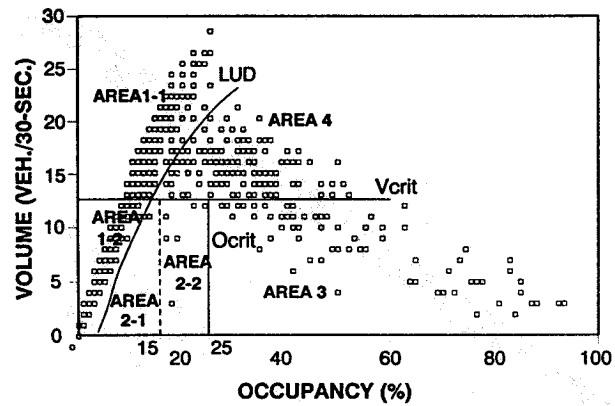
Figure 3.5 Template Showing Typical Parameters for a Normal Station (Hall et al. 1993)
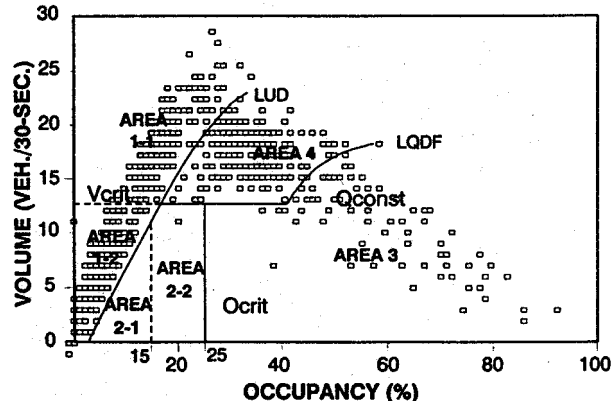
Figure 3.6 Template for a Typical Station Affected by Recurrent Congestion (Hall et al. 1993)

3.2.5 Advanced Incident Detection Techniques

3.2.5.1 Fuzzy Set Algorithms Fuzzy logic is appropriate to combine uncertain and incomplete measurements such as those provided by sensors. The possibility of an incident is determined using membership functions instead of sharp decision thresholds. Chang and Wang (1994) researched the application of fuzzy logic to the California #8 algorithm under high-volume conditions. Fuzzy theory has also been applied along with image processing techniques to try and detect incidents based on the abnormal behavior of a vehicle. Furthermore, fuzzy logic and adaptive resonance have been integrated to produce

FuzzyART, capable of charting a set of input patterns to a set of categories much like a neural network (Ishak and Al-Deek, 1998).

3.2.5.2 Neural Network Algorithms Much like the human brain, neural networks can be designed and trained to learn certain patterns. Neural networks have to be trained to recognize recurring/nonrecurring uncongested/congested conditions. A neural network is constituted by a multitude of simple processing elements each of which can receive inputs from many other processing elements. The input is weighted according to connection values and a processing element has the ability to rapidly communicate its outputs to many other processing elements. Typically, the processing elements are arranged in a multilayer, feed forward (MLF) structure as that shown in Figure 3.7 (Black, 1997).

Three layers characterize a multilayer feed forward neural network, the input layer, the intermediate layer, and the output layer. Also, varying numbers of processing elements can be contained in each layer. Typical input to an MLF include velocity and time-averaged volumes and occupancies at both upstream and downstream detectors. The network must be appropriately trained in order to determine suitable weights on the links between processing elements.

Recent developments in the application of neural networks to incident detection include Probabilistic Neural Networks (PNN) that integrate prior probabilities of occurrence, road conditions and the cost associated with misclassifying a serious incident (Abdulhai et al. 1997). The main difficulties associated with the use of neural networks are their extensive data requirements and training time.
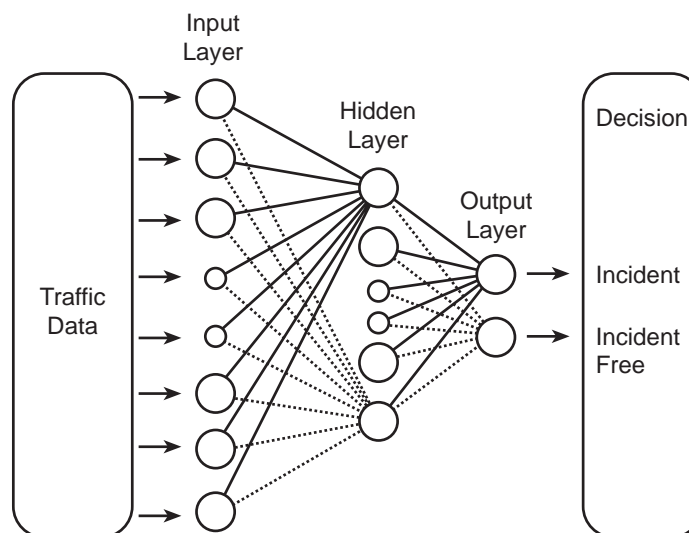
Figure 3.7 Part of a Multilayer Feed Forward (MLF) Neural Network (Black 1997)

3.2.6 Reported Performance

Black (1997) reviewed and summarized some of the available test results performed on the above-described algorithm. These results are presented in Table 3.2.

One must be careful interpreting these results due to the fact that each test is associated with a certain set of conditions. Some of the tests were performed using simulated data sets, while others were done either online or offline. It is to be expected that testing done online or offline should be a better indicator of the actual performance of an algorithm when compared to testing done on simulated data sets. Also, the geographic region, road geometry, and traffic incident database (i.e., the number, type and severity of reported incidents) are characteristic of each test. These heterogeneous conditions associated with the presented test results indicate that the actual performance of the algorithms may vary from the ones reported in Table 3.2.

Table 3.2 Summary of Algorithm Performance (Black 1997)

Algorithm		Detection Rate [%]	False Alarm Rate [%]	Average Detection Time [minutes]
California	Basic	82	1.73	0.85
	California #7	67	0.134	2.91
	California #8	68	0.177	3.04
	APID	86	0.05	2.5
Standard Normal Deviate		92	1.3	1.1
Bayesian		100	0	3.9
Time Series ARIMA		100	1.5	0.4
Exponential Smoothing		92	1.87	0.7
Low-Pass Filter		80	0.3	4.0
Modified McMaster		68	0.0018	2.2
Neural Networks	MLF	89	0.01	0.96
	PNN	89	0.012	0.9
Fuzzy Set		Good	Good	Up to 3 minutes quicker than conventional algorithms

3.3 PROBE VEHICLE ALGORITHMS

Automatic Vehicle Identification (AVI) holds the potential to be an important component of an integrated highway surveillance system. The majority of the reviewed types of sensors can only be used to count vehicles at a particular point and determine their instantaneous velocity at that point. The importance of AVI technology in the area of incident detection lies primarily in its ability to monitor point-to-point travel times. Point-to-point data can improve traffic predictions and hence improve the performance of Advanced Traveler Information System (ATIS) and ATMS. The literature reviewed showed very few

applications of AVI-generated data to freeway incident detection. Furthermore, most of the studies performed made use of simulated data (Hellinga et al. 1999). There are advantages associated with testing an algorithm using simulation-generated data, which provide the kind of controlled experimental conditions needed to evaluate the effect of different experimental factors, such as the level of market penetration of tagged vehicles traveling the network, the spacing of readers, incident start and end times, or simulating varying numbers of incidents of different types and magnitudes. However, the observed performance of the algorithm might not be readily transferable to actual conditions. The installations available at TransGuide made possible the evaluation of AVI algorithms using actual data collected from the network. The rest of the chapter will introduce the underlying logic of different AVI algorithms.

3.3.1 Hellinga and Knapp Algorithms

Hellinga and Knapp (1999) examined the performance of three AVI-based algorithms using data obtained by simulating a 12 km section of the collector facility of Highway 401 in Toronto, Canada. The network was divided into 1.2 km segments with AVI roadside antennas at both ends of the segments. The researchers simulated the network using the integration traffic simulation model (Van Aerde 1998). The simulation targeted the AM peak from 5:30 a.m. to 10:30 a.m. and resulted in a total of 101,142 vehicle trips. The simulation model provided link travel times for individual vehicles and a post processor was developed to combine individual link travel times for each vehicle and to produce travel times associated with each AVI-equipped segment. Furthermore, data was aggregated over 20-second intervals. Only matching tags, i.e., vehicles that have passed the upstream detector on a segment, were used in the analysis. A total of 120 incidents with varying locations, durations, times of day, and severity were simulated.

The three algorithms considered can be classified as statistical time-series models. The foundation for the logic of all three algorithms is that the travel time experienced by vehicles over a section of roadways increases more rapidly as a result of a change in capacity such as that resulting from an incident than it does as a result of a change in demand. Travel times collected before the occurrence of an incident can be thought of as belonging to one population while those prevailing after the occurrence of an incident as belonging to another population. The algorithms start by determining the mean and variance of the travel times experienced under normal conditions and attempt to assess if the currently reported travel times lie outside the confidence limits associated with the normal conditions.

3.3.1.1 Confidence Limit Algorithm The confidence limit algorithm computes the mean and variance of recently acquired travel times from the previous *N* intervals constituting the comparison window. The mathematical equations for calculating the mean AVI interval travel time, the mean travel time for the comparison window, and the interval

travel time variance for the comparison window are illustrated in Equations 3.4, 3.5, and 3.6 respectively (Hellinga et al. 1999).

$$\bar{\tau}_i = \frac{1}{n_i}\sum_{j=1}^{n_i}\tau_{ti} \qquad \text{(Eq. 3.4)}$$

$$\bar{\tau}_\delta = \frac{1}{n_\delta}\sum_{j=1}^{n_\delta}\bar{\tau}_i \qquad \text{(Eq. 3.5)}$$

$$\text{var}_\delta = \frac{1}{n_\delta - 1}\sum_{j=1}^{n_\delta}(\bar{\tau}_i - \bar{\tau}_\delta)^2 \qquad \text{(Eq. 3.6)}$$

Where i = aggregation interval,

j = segment reference,

t = time of the day,

τ_{ti} = segment travel time reported by an AVI-equipped vehicle at time t during interval i

n_i = number of AVI-equipped vehicle reports received during interval i,

δ = duration of the comparison window,

n_δ = number of intervals within comparison window of duration δ,

$\bar{\tau}_i$ = mean interval travel time for all AVI-equipped vehicles in interval I,

$\bar{\tau}_\delta$ = mean of all mean interval travel times $\bar{\tau}_i$ in comparison window, and

var_δ = variance of all mean interval travel times $\bar{\tau}_i$ in comparison window.

The algorithm makes the assumption that the individual mean interval travel times are log-normally distributed. An upper confidence limit for the mean segment travel time of the interval following the comparison window is obtained by computing the lognormal mean and the lognormal variance of the mean interval travel times contained within the comparison window. The mathematical equations for calculating the lognormal mean of the mean interval travel times contained in the comparison window, the lognormal variance of the mean interval travel times contained in the comparison window, and the upper confidence limit for the mean segment travel time of the interval following the comparison window are illustrated in Equations 3.7, 3.8, and 3.9, respectively (Hellinga et al. 1999).

$$\mu = \ln(\bar{\tau}_\delta) - 0.5\sigma_\delta^2 \qquad \text{(Eq. 3.7)}$$

$$\sigma_\delta^2 = \ln\left(1 + \frac{\text{var}_\delta}{\bar{\tau}_\delta^2}\right) \qquad \text{(Eq. 3.8)}$$

$$UL_i = e^{(\mu_\delta + z\sigma_\delta)} \qquad \text{(Eq. 3.9)}$$

Where σ_δ = lognormal variance of $\bar{\tau}_i$ in comparison window,

μ_δ = lognormal mean of $\bar{\tau}_i$ in comparison window,

z = value associated with the level of confidence, and

UL_i = upper confidence limit for the mean travel time for interval i.

The algorithm logic assumes that the underlying mean of the mean interval travel time distribution remains unchanged during the comparison window and the interval for which the confidence limit is being estimated. The probability that this assumption does not hold is proportional to the duration of the comparison window. It is assumed with a level of confidence with associated z that an incident has occurred if the mean interval travel time is greater than its corresponding upper limit. If added, a persistence check can help reducing the FAR by delaying an incident from being declared before a predefined number of consecutive intervals have a mean interval travel time greater than the corresponding upper confidence limit.

3.3.1.2 Speed and Confidence Limit Algorithm The Speed and Confidence Limit algorithm adds a speed check to the Confidence Limit algorithm. The algorithm calculates the mean speed of the AVI-equipped vehicles for each interval as well, as for the comparison window. The mathematical equations for calculating the mean AVI interval speed and the interval mean speed for the comparison window are illustrated in Equations 3.10 and 3.11.

$$\bar{u}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} u_{ti} \qquad \text{(Eq. 3.10)}$$

$$\bar{u}_\delta = \frac{1}{n_\delta} \sum_{j=1}^{n_\delta} \bar{u}_i \qquad \text{(Eq. 3.11)}$$

Where $\bar{u}_i$ = mean interval speed for all AVI-equipped vehicles in interval i,

u_{ti} = speed reported by an AVI-equipped vehicle at time t during interval i, and

$\bar{u}_\delta$ = mean of all mean interval travel times $\bar{\tau}_i$ in comparison window.

The decreased capacity observed when an incident occurs is expected to create congestion upstream of an incident and reduce the flow downstream of the incident. This reduction in the downstream flow causes an increase in the speed of the vehicles exiting the segment at the downstream detector station.

If the mean interval travel time is greater than the associated confidence limit and if the mean speed of the vehicles exiting the segment during the interval is greater than the mean vehicle speed for the comparison window, the Speed and Confidence Limit algorithm flags out an incident.

3.3.1.3 Dual Confidence Limit Algorithm Unlike the Confidence Limit algorithm, the Dual Confidence Limit algorithm seeks to compare mean interval travel times to a

confidence limit threshold and attempt to remove the values exceeding the confidence limit. The Confidence Limit algorithm always includes the last N intervals even if the mean interval travel time for the current interval is not statistically part of the comparison window population. Based on the data enclosed in the comparison window, the Dual Confidence Limit algorithm defines two confidence limits, the Window Limit and Alarm Limit. The algorithm starts by comparing mean interval travel times to the Window Limit. If a mean interval travel time is greater than the Window Limit, the value is considered part of another population. This results in the comparison window not being moved forward by one interval when testing for the next interval. If a mean travel time value is greater than the Window Limit, but smaller than the Alarm Limit, no incident is declared but the comparison window does not advance when evaluating the next interval. Hellinga and Knapp (1999) implemented the algorithm with a maximum stationary time of 8 intervals.

3.3.1.4 Reported Performance Different combinations of durations of the comparison windows, confidence levels, and number of persistence checks were investigated for varying levels of market penetrations. Six different levels of market penetration were investigated: 1 percent, 5 percent, 10 percent, 25 percent, 50 percent, and 100 percent. The researchers based the evaluation of the algorithms based on a maximum allowable FAR of 0.2 percent. The McMaster algorithm was evaluated using simulated loop data from the same network. The performance was used to provide a basis for comparison with the performance of the three AVI algorithms described.

Results of the simulation showed that the Speed and Confidence Limit algorithm performed best in terms of DR for all levels of market penetration investigated. Moreover, the DR and FAR obtained from the Speed and Confidence Limit algorithm are comparable to those obtained from the McMaster loop detector–based algorithm. It was also observed that the maximum DR was obtained for a level of market penetration of 10 percent while the TTD continued to decrease as the level of market penetration increased. Table 3.3 summarizes the detection rates, false alarm rates, and mean TTD as a function of the level of market penetration for all three algorithms (Hellinga et al. 1999).

3.3.2 TRANSMIT

The Transportation Operations Coordinating Committee's System for Managing Incidents and Traffic (TRANSMIT) makes use of Electronic Toll and Traffic Management equipment (ETTM) for traffic surveillance and incident detection in the New York City area. The equipment used is compatible with that of the EZ-Pass electronic toll collection system installed along the New York State Thruway (NYST) in addition to several other facilities in the New York City metropolitan area, New Jersey, and Connecticut. The AVI equipment was installed during the fall of 1995 and became fully operational in January 1996 with more than 1.5 million vehicles equipped with AVI tags.

Table 3.3 AID Results as a Result of the Level of Market Penetration (Hellinga et al. 1999)

	LMP (%)	DR (%)	MTTD (minutes)	Off-line FAR (%)	Off-line FAR (FA/Km/h)[a]
Confidence Limit	1	16	9.30	0.08	0.12
	5	28	4.94	0.13	0.20
	10	30	3.37	0.13	0.20
	25	25	2.99	0.19	0.29
	50	28	2.27	0.17	0.26
	100	29	2.44	0.19	0.29
Speed and Confidence Limit	1	43	7.12	0.18	0.27
	5	43	5.89	0.15	0.23
	10	51	4.82	0.18	0.27
	25	51	4.01	0.19	0.29
	50	48	4.07	0.20	0.30
	100	39	2.94	0.13	0.20
Dual Confidence Limit	1	24	8.70	0.19	0.29
	5	28	4.48	0.16	0.24
	10	32	4.14	0.17	0.26
	25	27	3.08	0.15	0.23
	50	30	2.93	0.20	0.30
	100	32	3.25	0.15	0.23
McMaster	N/A	37.3[b]	---[d]	0.02[b]	0.20[c]

[a] FAR presented as false alarm per km of highway per hour
[b] as reported by Rakha and Van Aerde, 1996
[c] calculated based on data from Rakha and Van Aerde, 1996
[d] Rakha and Van Aerde, 1996, do not report MTTD

In 1995, the FHWA appointed a team to evaluate TRANSMIT's capability to detect incidents reliably and accurately (Mouskos et al., 1999). Also, the evaluation team was assigned the task of evaluating the performance of the communication system in term of its transmission and detection rates. The lengths of the links between AVI readers in the network varied from 0.8 to 3.38 km (0.5 to 2 miles). The incident detection algorithm used by TRANSMIT is presented next along with the reported performance results.

3.3.2.1 The TRANSMIT Algorithm   PB Farradyne, Inc. developed the incident detection algorithm used to process the data collected from the Operations Information Center (OIC) at Jersey City, N.J, in real-time. The link travel times of the expected tagged vehicles are estimated using the probability distribution for specific time intervals. The algorithm's logic assumes that under free flow conditions, vehicle link travel times can be represented by a normal distribution. The probability that an incident occurred on a particular link is directly proportional to the link travel time, i.e., the probability of occurrence of an incident increases when a number of vehicles fail to arrive at the downstream detector at the estimated travel time. Furthermore, the probability of a false alarm decreases as vehicles

passing the upstream detector fail to pass the downstream detector. As the frequency of late arrivals at the downstream detector increases, the confidence level of the possible occurrence of an incident increases up to a point when it goes beyond the threshold value set by the user. Once the confidence limit exceeds the threshold, an alarm is triggered. The probabilities of an incident and that of a false alarm in a specific time interval are determined using Equations 3.12 and 3.13, respectively (Mouskos et al. 1999).

$$P(Inc) = P(FA_1) \times P(FA_2) \times P(FA_3) \times ... P(FA_n)$$ (Eq. 3.12)

Where $P(Inc)$ = probability that an incident has occurred on the link,
$P(FA_1)$ = probability of a false alarm determined for each vehicle i that arrives late, and
$P(Inc)$ = 0 if there are no late vehicles arriving at the downstream roadside reader.

$$P(FA_1) = P(E) \times P(NE) \times P(LT)$$ (Eq. 3.13)

Where $P(E)$ = probability that a vehicle exits the link before reaching the downstream roadside reader and this is not detected; this probability is calculated for each 15 min. time interval of the day for four different day types (weekday, Saturday, Sunday, or holiday),
$P(NE)$ = probability that a vehicle does not exit, $P(NE) = 1 – P(E)$, and
$P(LT)$ = probability that a vehicle arriving late at an RST is not delayed by an incident (decremented from 1 toward 0).

The system computes a travel time threshold for each link in the system by maintaining a 15 min. historical value of the link's mean travel times and the link travel time standard deviations. The link travel time threshold is determined using Equation 3.14 (Mouskos et al. 1999). The algorithm categorizes a probe vehicle as a late arrival if its travel time on link k is greater than the 15 min. link travel time threshold of a particular period of the day. The probability that a late vehicle was not involved in an incident is decreased from 1 to 0 over a number of standard deviations (steps) specified by the user.

$$T15 = HT15 + MSD \times HSD15$$ (Eq. 3.14)

Where $T15$ = 15 min. link travel time threshold for period i,
$HT15$ = historical link travel time for link j,
MSD = multiplier that is currently set to three standard deviations, and
$HSD15$ = historical link travel time standard deviation for link j.

3.3.2.2 Reported Performance The incident detection algorithm proposed by PB Farradyne, Inc. was tested using data collected from the New York State Thruway (NYST)

and the Garden State Parkway (GSP). The difference between the two facilities is the level of market penetration of tagged vehicles. GSP experiences lower volumes of tagged vehicles since the EZ-Pass system has not yet been implemented on this facility. Due to its higher level of market penetration, the algorithm performed better on the NYST where detection rates of up to 95 percent were obtained. Table 3.4 details the performance of the TRANSMIT algorithm as compared to fixed detector algorithms for both NYST and GSP.

**Table 3.4 Comparison of the TRANSMIT Algorithm with Various AID Algorithms
(Mouskos et al. 1999)**

ALGORITHM	DR	FAR	Mean TTD
Pattern Recognition Type			
California Algorithm	67%	0.134%	2.91min
All Purposes Incident Detection (APID)	66%	0.05% per stn.	2.55min
Statistical Type			
Standard Normal Deviate	92%	13%	1.1min
Bayesian Algorithm	100%	100% - 0%	3.9min
Time Series Type			
Box Jenkins ARIMA Model	100%	1.4% 2.6%	 0.39min
Smoothing Model	92%	1.87%	0.74min
Double Exponential Smoothing Model	82%	0.28%	5.05min
High Occupancy (HIOCC) Algorithm	96%		
Filtering Model	95%	1.5%	40sec
Dynamic Model		Prob. < 0.0002	Small
Catastrophe Theory Type	100%	0.043%	1.5min
Neural Network	97%	0.213%	170sec
Video Image Processing			
INVAID – TRISTAR System	>90%	1 every 3h (avg.)	20sec
TRANSMIT - NYST	72 – 95 %	(0.0022%: 1 in 124 h) (0.0127%: 1 in 22 h)	N/A
TRANSMIT - GSP	67 – 79%	(0.0%: ∞) (0.0034%:1 in 83 h)	N/A

The reported results show that at an appropriate level of market penetration, the TRANSMIT algorithm holds the promise of performing comparably to fixed detector algorithms. Also, the TRANSMIT algorithm outperformed the rest of the algorithms in terms of FAR.

The researchers omitted TTD estimates for lack of reliable data. Moreover, the initial assumption regarding the normality of the distribution of vehicles' link travel times was not verified.

3.3.3 Boyle and Ring Algorithms

Boyle and Ring studied the potential benefits of AVI systems for traffic monitoring and incident detection (Hallenbeck et al. 1992). Also, since major trucking companies are

using AVI technology for weigh in motion purposes, the project attempted to assess the extent to which the truck fleet tagged as part of the Heavy Vehicle Electronic License Plate (HELP) project, or even the entire truck population, is representative of actual traffic performance. Limited by the availability of field data, the researchers hypothesized that it is very unlikely for an AVI algorithm to be able to differentiate between recurrent congestion and incidents with the exception of major incidents. This hypothesis led to the conclusion that an AVI system would be better described as a congestion detection system rather than an incident detection system. The congestion patterns experienced as a result of an incident depend on the capacity reduction of the incident. Three cases are identified:

- Complete facility blockage,
- Significant blockage, and
- Minor blockage.

Since each one of these situations results in a different flow pattern, three different algorithm logics were developed.

3.3.3.1 Complete Lane Blockage Algorithm The complete lane blockage algorithm is intended for use with incidents causing the blocking of all lanes of traffic. The AVI system would be able to detect such an incident at either one of the downstream or upstream detectors. If the incident occurs close to the upstream detector station, congestion backs up quickly and no new-tagged vehicles would pass the upstream reader. The TTD stopped traffic at the upstream detector can be evaluated using Equation 3.15 (Hallenbeck et al. 1992).

$$DT = [(T)(-\ln(LevCon))] + \left[\frac{(L)(DB)}{(Vol)(VehLen)}\right] \qquad \text{(Eq. 3.15)}$$

Where *DT* = detection time,
   T = mean headway of tagged vehicles,
   LevCon = level of confidence desired by the user that this
   detection time will not be exceeded,
L = number of lanes (one direction),
DB = distance from the reader to the lane blockage,
Vol = total directional volume (all vehicles) at that time, and
VehLen = average length per vehicle in a queue when all vehicles are stopped due to a lane blockage.

The first term in Equation 3.15 represents the maximum expected time for a tagged vehicle to pass the upstream detector and the second term represents the time needed for the queue to grow to a length that would prevent more vehicles to pass the upstream detector. Estimates of the time headway of tagged vehicles control to a large extent the first term in the

equation and can be obtained from historical values, headway values recorded at upstream stations, or from values experienced by that particular station during some previous period of operation. The second term in Equation 3.15 depends on the volume of traffic, the number of lanes of the facility, and the distance between the incident and the reader. The second term in most cases will be much greater than the first term of the equation and also from the acceptable time limits for congestion or incident detection.

A faster way to detect incidents blocking all lanes would be to look at the downstream detector station. A lack of tagged vehicles crossing at the downstream detector station is indicative of congestion on the link. The TTD a total lane blockage by looking at the upstream detector can be evaluated using Equation 3.16 (Hallenbeck et al. 1992).

$$DT = [(T)(-\ln(LevCon))] + \left[\frac{(DR)}{(Vehspd)}\right]$$ (Eq. 3.16)

Where DR = distance from the blockage to the downstream reader, and
$Vehspd$ = speed of the last tagged vehicle traveling between the blockage and the downstream reader.

The first term in Equation 3.17 is similar to the one in Equation 3.16. The second term represents the travel time required by the last tagged vehicle to reach the end of the link from the accident location assuming worst-case scenario, i.e., the last vehicle is just in front of the tagged vehicle involved in the accident.

The weakness of the described approach resides in the fact that detection time is based on the distance between the incident location and the detector sites rather than on the distance between the readers. The distance between the blockage and the readers can be conservatively set to half the link length, but this would result in marginally high detection times especially for low levels of tagged vehicles' market penetration.

3.3.3.2 Significant Lane Blockage An incident resulting in a significant lane blockage would still allow the flow of vehicles between the upstream and the downstream detectors. If tagged vehicles are filtering through the incident area, the fastest way to detect the reduction in the capacity of the facility would be to investigate the change in the link travel times rather than the change in tagged vehicle headway. An algorithm that relies on the travel times of individual vehicles is proposed for use when the experienced level of tagged vehicles' market penetration is low. Equation 3.17 describes the logic behind the proposed algorithm (Hallenbeck et al. 1992).

$$Alarm = TT_e - TT_i - (z \times \sigma_{TT})$$ (Eq. 3.17)

Where *Alarm* = alarm variable. If this value is positive, the tested travel
time is great enough to warrant the incident or congestion alarm.
TT_i = travel time obtained from the AVI reader,

TT_e = mean of the distribution of expected travel time,

σ_{TT} = standard deviation of the expected travel times, and

z = the statistical level of confidence associated with the alarm.

Equation 3.17 is based on the assumption that the travel times experienced by tagged vehicles on the link considered are normally distributed.

If the level of market penetration of tagged vehicles traveling the network is appreciable, the mean travel time of tagged vehicles is considered for use, thus reducing the sensitivity of the algorithm to false alarms. Equation 3.18 describes the logic behind the refined algorithm (Hallenbeck et al. 1992).

$$t = \frac{(\overline{TT_i} - TT_e)}{(\frac{s}{\sqrt{n}})} \qquad \text{(Eq. 3.18)}$$

Where t = student's t-statistic,

$\overline{TT_i}$ = mean section travel time for the tested time period,

TT_e = expected travel time

s = standard deviation of TT_i, and

n = number of samples used to compute $\overline{TT_i}$.

In order to determine if an alarm should be sounded or not, the t value is weighted against values defined at different levels of statistical confidence.

A different algorithm has been proposed to keep track of traffic performance changes over time offsetting the problems associated with the use of an arbitrary static value for a particular link travel time. The current mean travel time is compared to historical values obtained from groups of vehicles traveling the network in a previous time period. Equation 3.19 mathematically describes this algorithm (Hallenbeck et al., 1992).

$$t = \frac{\left|(\overline{TT_1} - \overline{TT_2})\right| - DT_0}{s\sqrt{\frac{1}{n_1} - \frac{1}{n_2}}} \qquad \text{(Eq. 3.19)}$$

Where s = pooled estimate of the standard deviation for the two samples,

t = the student's t-statistic,

$\overline{TT_1}$ = travel time mean for the current interval,

$\overline{TT_2}$ = travel time mean for the previous period,

DT_0 = difference necessary to indicate a change large enough to require an alteration in control strategies, and

n_1, n_2 = number of travel times in the two samples.

If the value of t is used to assess whether the measured travel time differences are statistically significant at a predetermined level of confidence. The sensitivity of the

algorithm can be controlled by tuning either the required difference between the current and previous mean travel times or the statistical level of confidence required for that detection. The detection times possible with the described algorithm depend on the headway between tagged vehicles, the distance between stations, the speed of the vehicles, and the number of vehicles needed to measure changes with a given level of confidence.

3.3.3.3 Minor Lane Blockage Incidents causing minor lane blockages are harder to detect due to the similarity between their effect on traffic flow and that of recurrent congestion. The same algorithm used for significant lane blockages is proposed for use with minor lane blockages. However, more vehicles have to be detected in order to state with the desired level of statistical confidence that a change has actually occurred. The use of shorter detector spacing and market penetrations for higher tagged vehicles can help in solving the problem, but most are not economically feasible.

3.3.4 Promising Algorithms

The link travel times that can be inferred from AVI data constitute the advantage that this technology has over other sources of data for incident detection and, therefore, are at the core of the previously described approach. In addition to the above-described attempts at developing efficient probe vehicle algorithms;,several other ideas are worth looking at.

If extensive historical data is available from an implemented AVI system, one possible detection logic would be to compare currently observed link travel times to corresponding historical values. The travel time comparison should be based on day of the week and time of day. An incident would be reported if the current travel time for a particular link were greater than a threshold determined based on the historical mean. A similar logic could be applied to vehicle speeds or vehicle speeds could be used as a second check after the travel time comparisons.

In addition, flow values of tagged vehicles past a detector could be used as input to a comparative algorithm. Either historical flow values obtained from similar days of the week and times of the day or a window of past intervals can be used to determine threshold values above which an incident is reported. If the direction and the lane of travel are being reported and archived, the AVI data can be used with the same logic applied by lane of traffic.

In the case where extensive AVI data is available, travel times for each link could be expressed as a percentage of the travel times experienced on the following link. The computed percentages can be used to determine threshold values above which it could be stated with a certain level of confidence that an incident has occurred. The algorithm would proceed by computing for each link the current travel time as a percentage of the travel time at the downstream link and then comparing it to the threshold value.

Also, there is value in revisiting some of the logic intended for use with fixed detector data such as the Texas algorithm described earlier. Speed values obtained from AVI reads

can be compared to a predetermined threshold set by the TMC (30 mph in the case of TransGuide).

All of the above-described logics hold the promise of superior incident detection performance depending on the availability and the quality of the AVI data. Adding a persistence check can also complement the described logics. Checking travel times or speeds at downstream detectors can be employed to differentiate incidents from recurrent congestion. If the downstream detector is experiencing an appreciable increase in travel time as well, the increase in the link travel time is attributed to recurrent congestion and the algorithm would hold on reporting an incident.

Chapter 3 started with an introduction to the common measures of performance used to evaluate incident detection algorithms, i.e., DR, FAR, and TTD. The performance measures were followed by a description of the logic behind the best performing and most commonly used fixed detector algorithms. Finally, proposed and promising AVI incident detection algorithms were introduced.

The next chapter describes the loop, AVI, and incident data used in the study.

CHAPTER 4 AUTOMATIC VEHICLE IDENTIFICATION FOR INTELLIGENT TRANSPORTATION SYSTEM APPLICATIONS AND ADVANCED TRAVELER INFORMATION SYSTEM DATA REQUIREMENTS

Probe vehicle use for Intelligent Transportation System (ITS) applications is addressed in several previous studies as well as in ongoing research. Several studies highlight new uses for Automatic Vehicle Identification (AVI) as noted in Chapter 1. The intent of this study is to evaluate an on-line AVI system for Advanced Traveler Information System (ATIS) purposes. The work reviewed in this chapter seeks to identify current work related to probe vehicle implementation for traffic-monitoring purposes. The intent is to position the evaluation presented in Chapter 8 relative to existing research.

The following review of current literature is presented in four parts. The first outlines current probe vehicle techniques for ITS travel time data collection, and presents additional uses of probe vehicle data. The second section presents sample size criteria and efforts for determining the required number of probes for ITS applications. The third section discusses travel time estimation from AVI probe vehicles, in contrast to estimation from loop detector data. The strengths and weaknesses of the current body of work are addressed to highlight the contributions of the assessment of AVI for ATIS presented in Chapter 8. The final section presents ATIS data quality requirements.

4.1 PROBE VEHICLE BACKGROUND

An early effort at using probe vehicles for measuring traffic performance is presented by Hallenbeck, Boyle, and Ring (1992) for the Washington State Transportation Center (TRAC). The study assesses the possible benefits of using AVI systems for monitoring the performance of traffic and detecting incidents. The findings are based on part of the Heavy Vehicle Electronic License Plate (HELP) project.

The TRAC study identifies several advantages to using AVI-based vehicle detection. Provision of section speed data as opposed to point-based speed data is noted; however, the correct application of more accurate traffic flow theory principles to these data are not performed. The direct computation of travel time and delay information is identified as an advantage over other systems. Disadvantages identified include significant infrastructure modification, expense, standardization issues, and public resistance to a perceived invasion of privacy. The recommendations identify an urban toll facility using AVI tags for revenue collection as an ideal AVI-based performance-monitoring system. The data collected is best used for facility operation, motorist information, and planning analyses.

Hallenbeck, Boyle, and Ring (1992) find that the average speed obtained from an AVI system yields an excellent measure of the true performance of the roadway. The travel times and speed measures provide important input to motorist information systems and traffic control algorithms. The study did not suggest a distance among AVI readers, but noted that

the travel time estimate is better than estimates from conventional loop detector speed measurements at similar reader spacing.

The *Travel Time Data Collection Handbook* from the Federal Highway Administration (FHWA) (1998) presents several travel time data collection efforts. The handbook focuses on test vehicle techniques, license plate matching, probe vehicles, and other nontraditional techniques for travel time estimation. The goal of the study is to provide guidance in the collection, reduction and reporting of travel time data. The focus discussed here is on the probe vehicle section (Turner, Eisele, Benz, and Holdener 1998).

Table 4.1 Comparison of ITS Probe Vehicle Systems/Techniques (Turner et al. 1998)

Technique	Costs				Data Accuracy	Constraints	Driver Recruitment
	Capital	Installation	Data Collection [1]	Data Reduction			
Signpost-Based Automatic Vehicle Location (AVL)	High	High	Low	High	Low [2]	No. of signpost sites, transit routes, and probes	None - uses transit vehicles
Automatic Vehicle Identification (AVI)	High	High	Low	Low	High	No. of antenna sites and tag distribution	Required - but can use toll patrons
Ground-Based Radio Navigation	Low	Low	Low	Low	Moderate	No. of probes and size of service area	Required
Cellular Geolocation	High	High	Low	Moderate	Low	No. of cell users and cell towers	None - uses current cellular users
Global Positioning System (GPS)	Low	Low	Low	Moderate	High [2]	No. of probes	Required - but can also use currently instrumented vehicles

Notes: [1] Assumes that all data collection software development has been completed.
[2] Unless passenger vehicles are included in the study, samples are composed of transit or commercial vehicles.

The handbook identifies "passive" probe vehicles as vehicles that are already in the traffic stream and are equipped to gather travel time information. The contrasting "active" vehicle probes are test vehicles driven by researchers, typically referred to as a "floating" car data collection method. An AVI-equipped vehicle is a vehicle that is already in the traffic stream and is most often equipped voluntarily for toll collection or other purposes. License plate matching techniques for travel time estimation are often not automatic or are not applicable to a real-time system. The handbook study on probe vehicle techniques is directly related to the work presented here.

Several advantages of ITS probe vehicles systems for travel time data collection are identified in the *Travel Time Data Collection Handbook* (1998), with several probe vehicle systems presented. Low cost per unit of data and continuous automatic electronic data collection are identified as major strengths. The disadvantages to probe vehicle measurements are a high implementation cost, fixed infrastructure (not for cellular phone probes), and privacy issues. Table 4.1 compares the five ITS probe vehicle systems presented in the handbook.

The low rating for data accuracy for cellular geolocation was most likely identified prior to recent cellular E-911 mandates. An Automatic Vehicle Location (AVL) system lacks accuracy because the results are biased to transit vehicles, which typically do not travel on major highways or at the same speeds as passenger vehicles.

The Automatic Vehicle Identification (AVI) system discussed in the handbook is shown in Figure 4.1. The installation depicts the typical components of an AVI. Additional advantages such as the ability to collect vast amounts of data, the accuracy of data collection, and ability to gather lane-specific information are noted for AVI. The handbook also identifies the "clock drift problem" where loss of clock synchronization is identified as a disadvantage. Another disadvantage of an AVI system is that the number of probes is limited to the number of tags within the study area. The recommended number of tags or sensitivity of the data to clock synchronization is not presented in the handbook.
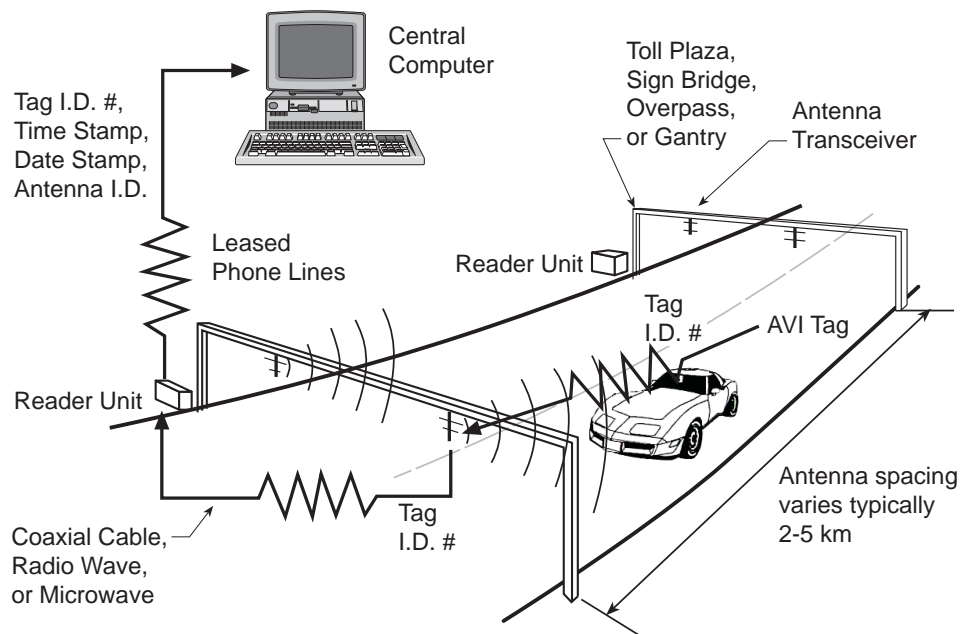
Figure 4.1 AVI Basic Components (Turner et al. 1998)

Rakha and Van Aerde (1995) investigated the accuracy of probe vehicle estimates of link travel times and instantaneous speed. The instantaneous speed measurements were obtained from standard loop detectors. Details about the route guidance system employed in the "probed" vehicle are not provided; however, a global positioning system (GPS) was utilized. The effort was an early attempt at estimating the usefulness of probe vehicle data for travel time data collection. The tests performed were limited in both scope and data availability. However, link travel time estimates based on speed estimates from loop detectors are compared to probe vehicle travel times and are found to statistically correlate.

Yermack, Gallagher, and Marshall (1995) apply electronic toll and traffic management strategies (ETTM) to incident detection, another ITS application. For a thorough investigation of AVI for incident detection, refer to Khoury (2000). Table 4.2 from Yermack et al. presents a comparison of the loop detectors to vehicle probe technology.

Table 4.2 Comparison of Traffic Monitoring Techniques (Yermack et al. 1995)

Technique	Advantages	Disadvantages
Conventional – **Loop detector or Video Monitoring** **(Spot mean detection)**	• Mature Technology • Samples near 100% of vehicle population	• Data is localized • Inferences required for incident detection
Vehicle Probes – **ETTM or other vehicle-monitoring technique** **(Space mean detection)**	• Provides data for roadway section • Travel time more relevant to the information needs of motorists	• Small sample • Inference required of traffic volume

The distinction between spot mean and space mean detection is made in Chapter 5. The current work in travel time estimation from probe vehicle data lacks in the quantity of data available from a full on-line AVI system. Current research also does not assess the quality of data for use with ATIS applications. The work presented in this study uses the extensive on-line system installed in San Antonio to evaluate the effectiveness of AVI data for ATIS. Attempts are made in Chapter 6 to quantify the effects of the clock synchronization problem identified in both the TRAC study and the handbook.

4.2 SAMPLE SIZE CRITERIA

Another major area of research related to AVI is determining the number of probe vehicle measurements required for a sufficiently reliable estimation of parameters for ITS applications. The probe vehicle sample size is determined by the availability of instrumented probe vehicles in the traffic stream. The fraction of equipped vehicles or penetration rate is desired when designing (e.g., how many tags should be distributed), evaluating, and analyzing data obtained from a probe vehicle system. The number of probe vehicles required will depend on the accuracy desired from the system. Several studies discussed in this section attempt to quantify the number of equipped vehicles required for a given application.

The TRAC study by Hallenbeck, Boyle, and Ring (1992) attempted to determine if the HELP fleet or even an entire population of trucks would provide an unbiased estimator of traffic performance. Incident detection or congestion detection was a primary consideration in the TRAC study. The results noted that in Tacoma, Washington, only 3 percent of the vehicles that use the highway during the peak period are trucks. If all of these trucks were

equipped, a 20-second headway between tagged vehicles would be realized, producing about 175 trucks per hour. A 20-second headway for readers spaced 1 mile apart will detect five vehicles reducing speeds from 60 miles per hour to 50 miles per hour in 2.3 minutes, according to the study.

Boyce, Krikson, and Schofer (1991) estimated sample size requirements for a dynamic route guidance model for the subsequently aborted ADVANCE project in suburban Chicago. The model was based on a static, user-optimal route choice traffic assignment analysis. The findings indicated that about 4,000 probe vehicles would be required for a 200-square-mile suburban road network. These findings are intended for a full-scale network, whereas the San Antonio analysis presented corresponds only to a corridor (as noted in Chapter 1). The findings by Boyce et al. assume that if a link is traversed by at least one vehicle, that vehicle reliably represents the travel time of all vehicles traversing the link. The study is applicable to the planning and development of an AVI system and is not effective for the purpose of comparative evaluation relative to other implemented systems.

Srinivasan and Jovanis (1996) present an algorithm for estimating the number of probe vehicles required for travel time estimation under various conditions. The results are based on simulation results of the Sacramento, California, network. The objective of the study was to determine the number of probe vehicles required in the given network so that a desired proportion of links are covered for a given measurement period and peak period length. The resulting implication of the study is that less than 5 percent of the vehicles during a 2-hour peak period are required to be probes for a 10-minute measurement interval with 80 percent of the links being reliably monitored. These results are directly applicable to the penetration rates estimated in San Antonio outlined in Chapter 5. A main goal of the Srinivasan and Jovanis study was to determine if the percentage of drivers on freeways or arterial streets that should be provided with information would also provide adequate probe coverage.

The work presented in Chapter 5 attempts to investigate the market penetration of the existing San Antonio on-line system. Previous work is designed to estimate the number of probes that are needed to achieve a desired level of confidence. These studies are easily tested in a simulator where a subset of vehicles is assigned as probes. Two factors not noted in existing literature include variation in tag penetration across different links and the positive effect additionally equipped vehicles (from other cities for example) could have on the local penetration rate.

4.3 TRAVEL TIME ESTIMATION

Accurate travel time estimation is an important input to the advanced traveler information system as users can directly relate to time measurements. The inductive loop detector (ILD) is the most pervasive traffic-monitoring device, however it is not necessarily able to directly provide travel time data as an AVI system can.

Coifman (2000) presents a method for estimating the travel time on a link from modified traditional loop detectors. The method relies on closely spaced dual loop detectors and the propagation of a signal through the array of detectors, which extrapolates the local information to a link. The limitation of the study is in the transition from congested to uncongested conditions. No information about the number or the spacing of the detectors is provided. The procedure relies on simple traffic flow theory; however, the interpretation and implementation may be beyond the current capability of traffic management centers (TMCs).

AVI systems provide an excellent method for estimating travel time and directly measuring space mean speeds. Most loop detection methods rely on properly calibrated dual loops or single loop detectors with a calibrated average vehicle length to derive spot mean speeds. Recent developments to estimate travel times from loop detectors are promising, however, they require upgrading existing technology and are not easy to understand.

4.4 AVI DATA QUALITY GUIDELINES

A major goal of this research is to evaluate AVI systems for use in ATIS's, therefore the data requirements for ATIS need to be defined. Recent documents by the Intelligent Transportation Society of America ATIS Committee, in collaboration with the United States Department of Transportation (USDOT), forms the basis of the discussion presented. Chapter 6 will apply these data guidelines to the investigated automatic vehicle identification data from San Antonio.

The Advanced Traveler Information Systems Data Collection Guidelines Workshop, held in Arizona in February 2000, provided a forum for discussion of ATIS data requirements. A document titled "Closing the Data Gap: Guidelines for Quality Advanced Traveler Information System (ATIS) Data" was released in September 2000 highlighting the findings.

Several challenges to the ATIS initiative include the collection of complete and timely data; transforming data into useful information; and, finally, packaging, marketing, and communicating the information to the traveling public. The growing complexity of the "commercial architecture" of ATIS makes this one of the more difficult areas of ITS to deploy. The wireless market is expanding and users are demanding more information from advanced telematics services. However, raw data required to support useful telematics services are not yet fully realized. Information service providers (ISPs) are interested in any and all data from transportation agencies. Often they are unsure of how delayed data affects their users, and the volume of data collection coverage necessary to support market activities. The focus of the ITS America Steering Committee was to establish guidelines for real-time or dynamic traffic information systems limited to highways and principal arterials.

This section focuses on the guidelines for ATIS data quality, including the market for ATIS data, the quality guidelines themselves, and opportunities to share data among different ITS's. The ITS America Steering Committee on data quality stresses that these are guidelines and are subject to review and modification. Other ATIS design findings from

other sources in the literature are noted to support the guidelines. The next section presents the market opportunities for ATIS data, followed by a section defining the guidelines. The last section outlines opportunities for data sharing among ITS component systems.

4.4.1 Market

The market opportunities for ATIS's largely define the levels of data quality required to support such systems. The customers of ATIS include both commercial vehicle operators and the traveling public; however, there are important characteristics that define different types of ATIS users within these broad categories. It is important to identify the issues of data quality around the different types of users. First, a definition of the ATIS user market is presented followed by an investigation of what these users demand. The discussion presented focuses primarily on commuters who demand traffic information, recognizing that there is a much larger ATIS market potential.

The ideal ATIS market is a major metropolitan area that is highly congested with frequent unpredictable traffic events and that has alternatives available to travelers. Traffic congestion at peak or other times should be excessive enough to induce demand for information, provided there are other options available that are in fact preferable. The information provided by an ATIS is not limited to traffic congestion levels; information can also include the status of other modes of transportation. Users will only find traveler information of use if there are viable alternatives that will make their trip more enjoyable.

The term "enjoyable" does not necessarily imply getting to the destination by the fastest route. As a personal example, when congestion builds enroute to a university with known limited parking facilities, provision of timely transit alternatives would be of value to traveling students. Students could then park just in time to catch a bus to complete their trip. A traveler may not be willing to change their plans until congestion builds up, at which time they will be more willing to consider alternative suggestions. Such suggestions could be alternative routes, alternative modes, or information about the location of commercial facilities that may be of interest to the traveler. Provision of information is more successful if alternatives to the current situation are available.

The quality of ATIS services defines the market from the standpoint of how frequently users will make an effort to consult such information, if at all. The current quality of ATIS data will continue to be expected of provisioning agencies and improvements in quality and scope of information are necessary for retaining ATIS users. The purpose of the trip and its characteristics also influence the demand for ATIS services. Factors such as travel time flexibility, modal choices, and route selection can affect demand for traveler information services. It is no surprise that commute trips are most likely to generate demand for ATIS, particularly for the return trip, when alternatives are typically greater. The most important factors are the values and attitudes of the traveler, including preference for timeliness, personal connectivity, and likelihood to request information.

4.4.1.1 Who are the ATIS users?   Lappin (2000a) identifies the attitudinal market segmentations for the ATIS market in a report titled "Who are ATIS Customers?" Much of the work is linked to the 1997 Puget Sound Regional Council (PSRC) Household Travel survey of approximately 2,000 individuals. The main segments identified include control seekers, Web heads, low-tech pre-trip information seekers, and "mellow techies." A user is defined as an individual who reported using ATIS services installed as part of the Seattle Metropolitan Model Deployment Initiative (MMDI).

Technologically equipped "control seekers" play a major role in the demand of ATIS products and services. Typically, these users come to expect always-on real-time access to the most accurate traffic data available. Control seekers are most enamored with the technological device and with the control it allows them in planning their time. A second group, termed "Web heads," consists of Internet-savvy users who demand accurate real-time traffic information to aid in pre-trip decision making. These users do not demand the level of accuracy required by the control seekers. Pre-trip users express dissatisfaction with radio reporting, and expect a higher level of service from Internet traffic sources and demand up-to-date information.

In contrast to the technologically equipped users, low-tech users are split into travelers who demand pre-trip information from conventional sources and others who may use technology but do not care about traveler information. Users in the lower technology category are more likely to use radio and television to make their own decisions. Interactive maps and specific speed or travel time data does not appeal to them; they prefer to see live video or hear about conditions and make their own judgments. The low-tech users represent a large and sustained base of ATIS users. Their needs should continue to be met, supplemented by new information sources.

Another major segment to consider are individuals who feel that their own experiences are the most reliable source of traffic information. Many feel that radio information is unreliable and that there is no alternative to traffic congestion and little value to ATIS. However, expectations for traffic information are generally high due in large part to a conditioning from an Internet culture for faster, cheaper, and more reliable information services (Lappin 2000a).

4.4.1.2 What do ATIS users want?   Lappin identifies the current context for ATIS services in a January 2000 report titled "What Do ATIS Customers Want?" (Lappin 2000b). As with the previous report concerning who ATIS customers are, the report builds on the evaluations for the MMDI study of Seattle, as well as other MMDI studies including San Antonio. The study presents findings from a Web-based survey from the Washington State Department of Transportation (WSDOT) traffic Web site. The findings are broken down into two groups based on their expectation of ATIS data quality, a low expectation group and an advanced group already familiar with ATIS data services.

A significant limitation to both the Lappin study and current literature is that the findings are only for ATIS traffic needs. It is noted that there are few ATIS deployed for transit travelers. The results and guidelines are biased toward the information currently available as travelers can relate to the information they are already able to receive, particularly in the Puget Sound region.

Of significant benefit to travelers is reducing the uncertainty of their travel time. It is well understood that drivers prefer a route where they can rely on a consistent travel time, to a route that has a higher potential to vary. The most important aspects of traveler information are accuracy, timeliness, and reliability. Secondary factors include cost, personalization, and convenience of access, as well as speed and safety of operation of enroute systems (Lappin 2000b).

Customers want information about incident locations, time, and type. Direct measures of speed for each highway segment and travel times between selected origin and destination pairs are very important. Ideally a service would provide both speed and travel time data–users place a high value on speed and graphical representation of speed and volume on Web maps or television maps. The coverage requested is all major freeways and arterials in the region. Some markets require better coverage of local streets and analysis of local driving patterns is necessary for prioritizing the coverage by market demand. As was noted earlier, these results are biased to what is currently available. Users cannot prefer something that they do not yet have available to them.

One of the greater demands of ATIS is for enroute information, as pre-trip information is often outdated by the time a driver reaches a potential route decision. Driver safety while accessing information is a concern to the traveling public. The division between users who have access and users who cannot access data can segregate the traveling public. Providing as much information as possible to society at large is important for fair access to data collected from public funds. TransGuide in San Antonio, Texas, is able to provide travel time information via a large array of dynamic message signs.

Lappin (2000b) identifies ATIS requirements for so-called "advanced" users of ATIS for insight into what customers may demand in the near future or be willing to pay more for. Experienced ATIS users focus on predictive or trend data. Travelers will check conditions over a period of 15 to 30 minutes suggesting that a measure of the evolution of conditions over time would be beneficial. For example, a Web-based map could allow cycling through the last few maps to make a decision about congestion buildup. Advanced users also recommended that ATIS employ historical data in conjunction with real-time data to make near-term predictions for route conditions. Such fusion would allow users to make more effective pre-trip choices. Lappin (2000b) notes that "advanced" ATIS users identify some periods where relatively open travel exists, even within the peak hour. These users would like to see these "windows" identified, although the likelihood of consistently identifying such short and transient events is low. The travelers note that often various entrances to

highways have lower queues at different times. Identification of these gaps in the congestion and location of better-flowing ramps would be beneficial to travelers.

Several studies address the ATIS design vision and present findings on the data needs of ATIS users. A COMSIS Corporation report (1995) presents extensive background on the driving task, decision-making, and information display methods. Pagan, Mahmassani, and Kraan (2000) present trip-planning behavior of tourists in San Antonio to attempt to determine how advanced technology can help unfamiliar travelers plan and execute trips. The findings of the study are limited to tourist travel, which often varies considerably from traditional traffic information services. The final implementation of an ATIS system should address the needs of all potential users.
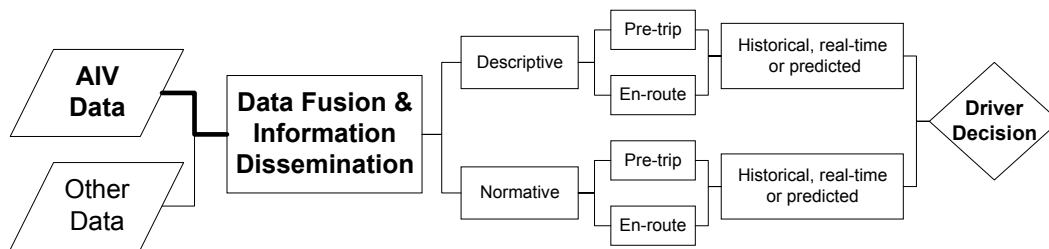
Figure 4.2 ATIS Information Process

Categories of user information are identified in a COMSIS Corporation report (1995) to understand driver behavior in response to information. The categories identified include descriptive or normative information; pre-trip versus en route; and historical, real-time, or predicted information. Descriptive information provides current conditions and allows users to make their own decisions, while normative information provides route guidance instructions to achieve systemwide objectives. Figure 4.3 outlines the ATIS process and categories of information dissemination.

Data from the field or other ITS sources is processed and prepared for information dissemination. The information is either presented to the user as descriptive or normative, and then is accessed either pre-trip or enroute. In all cases, the data is either based on historical, real-time, or predicted data, or a combination of the three.

The guidelines presented in Section 4.4.2 focus on the data quality of detector data (such as an AVI system) to support the fusion and information dissemination component of ATIS (noted by a thick line in Figure 4.3). For more information on ATIS design to support traveler decision making, refer to Kaysi (1997) for an organization of traveler information needs and considerations.

4.4.2 Data Quality Guidelines

The ITS America ATIS-Data Collection Steering Committee outlines several quality guidelines and attributes for collection of data necessary to support ATIS applications. This section addresses specific guidelines that relate to AVI data collection. Chapter 8 applies the guidelines to evaluate current practices with the San Antonio AVI and provides suggestions for effective use in ATIS applications.

To understand ATIS data quality guidelines, a few definitions are needed. In this context, data refers to "real-time/dynamic road-related information to support traveler information services within the next five years." Quality consists of the metrics and attributes that evaluate the data. Finally, guidelines are meant to serve as tools to assist in the consistent deployment of data collection for ATIS-related applications.

For highway ATIS applications, four primary types of data are available to a TMC including, traffic sensor data, incident reports, road and environmental data, and images. Each of these types has a specific set of attributes associated with defining the quality of such data. Table 4.4 outlines these attributes and the next sections identify the metrics for levels of quality.

Table 4.3 Data Attributes for Quality Analysis (ITS America 2000)

Data Type	Data Attributes
Traffic Sensor Data	Nature
	Accuracy
	Confidence
	Delay
	Availability
	Breadth of Coverage
	Depth of Coverage
Incident and Event Reports	Nature
	Detail
	Timeliness
	Accuracy
	Confidence
	Breadth of Coverage

The following guidelines from the ITS America Data Quality Steering Committee (2000) operate on a simple hierarchy of quality levels. The hierarchy was developed to identify "good," "better," and "best" properties of each attribute. A "good" quality rating is necessary for the minimum level of quality for each attribute. As consumer expectations

increase, the "better" and "best" levels will be demanded. The steering committee is deficient in quantifiable data to support category distinctions. As ATIS systems are implemented and on-line assessments of data quality are made, the quality levels can be better quantified.

4.4.2.1 Nature The nature of ATIS input data refers to the type of data collected. As noted earlier, the four primary traffic parameters of use to ATIS applications are travel time, speed, volume, and percent occupancy. The nature of data also refers to the classification of point-based or segment-based data. For example, travel times can be computed based on spot-measured speeds or measured across a segment of a facility depending on the nature of the system. Table 4.5 outlines the data quality levels for limited access highways.

Table 4.4 Nature of Data Quality Guidelines (ITS America 2000)

Good	*Aggregated Point Data* – Data collected at a point. Data from individual sensors can be aggregated (across time or lanes), but data from general purpose lanes should not be mixed with High Occupancy Vehicle (HOV) lane data
Better	*Discrete Point Data* – Data collected at a point. Data from individual lanes are provided without aggregation. or *Aggregated Section Data* – Data collected over a section or segment of roadway. Data from discrete link measures can be aggregated, but data from general purpose lanes should not be mixed with HOV lane data.
Best	*Discrete Section Data* – Data collected over a section or segment of roadway. Discrete link measures, such as the travel times for all vehicles detected, are provided. Note that discrete data should not be associated with a vehicle or person to preserve privacy.

4.4.2.2 Accuracy The accuracy of traffic sensor data refers to how closely collected data matches the actual conditions. Accuracy refers to the physical ability to determine the traffic state parameters. Some technologies such as video, radar and acoustics are subject to interference, weather conditions, and occlusion (where one vehicle shadows another and "hides" it from the sensor). Some systems cannot count vehicles in the process of changing lanes resulting in either a missed count or double count. Table 4.6 provides the benchmarks for the assessment of the accuracy of a technology. The percentages provided are not defined adequately in the ITS America documentation, though they are most likely intended as

average quantities taken over a meaningful operating period. The accuracy benchmarks for a system will vary based on the measurement attributes of the system. More research is necessary to quantify levels of accuracy for other systems.

Table 4.5 Accuracy of Data Quality Guidelines (ITS America 2000)

Good	10-15% error
Better	5-10% error
Best	<5% error

4.4.2.3 Confidence The confidence, or trustworthiness, of the data collected relates to the ability of the system to determine anomalous data before processing it further. An example related to AVI data collection consists of a vehicle that may report an extremely long travel time because it left the highway for fuel and subsequently reentered the facility between the sensors (tag readers) defining the measurement segment. The vehicle would result in a very high, and meaningless, travel time. Table 4.7 displays the guidelines for ATIS data quality as it relates to sensor confidence. Only two categories are presented: "good" relates to a qualitative description, while a quantitative description of the confidence of data is noted as "better."

Table 4.6 Confidence Data Quality Guidelines (ITS America 2000)

Good	Qualitative Description – Tiered Confidence Description – e.g., "good," "suspicious," "bad"
Better	Quantitative Description – % Confidence Factor −e.g., 95% confident
Best	N/A

4.4.2.4 Delay Traffic sensor delay is the amount of time that elapses before the data collected is made available for use in ATIS applications. The total delay accounts for the time the technology takes to read raw data, package the data for transmission to the TMC, transmit the data, and finally the time required to process and interpret the data. Table 4.8 outlines the guideline recommendations of the ITS America Steering Committee for delay. The guidelines provided are subjective, reflecting the professional judgment of the ITS America Steering Committee participants, and not based on comprehensive performance versus cost tradeoff analysis. Further investigation is required to quantify the benefits of more timely data.

Table 4.7 Delay Data Quality Guidelines (ITS America 2000)

Good	2-5 minutes
Better	1-2 minutes
Best	<1 minute

4.4.2.5 Availability The availability of traffic sensor data refers to the periods during which the sensor system is able to provide data to users. Most systems are designed to operate continuously. However, access to data will inevitably be lost due to system outages. For example, if a system reports average conditions every 15 minutes, four data points are generated each hour. The system should produce 35,040 data points in a year; if 700 data points are unavailable, the availability would be 98 percent. A higher-quality data collection system would be indicative of continuous data availability, characterized by better design, operation and maintenance. Table 4.9 outlines the data quality guidelines for classifying data traffic sensor data availability. The percentages are the average probabilities that a specific data element will be operational and send data. Again, the guidelines are subjective and do not provide a time frame for which the availability percentage should be based.

Table 4.8 Availability Data Quality Guidelines (ITS America 2000)

Good	90-95%
Better	95-99%
Best	> 99%

4.4.2.6 Breadth of Coverage The fraction of roadways in a metropolitan region where sensor technology is installed defines the breadth of coverage. Typically, this is reported in the total number of lane miles or in a metropolitan area where a given technology is operational, often as a percentage of the total lane miles for a defined metropolitan region. It is important to distinguish the breadth of coverage by sensor technology type, as often the attributes of existing and state-of-the-art systems are quite different. For example, loop detectors measuring spot speeds may cover some highways, while another area may be covered by AVI where speeds are reported for link segments. The attributes of each are quite different and should be noted and correctly interpreted. Table 4.10 contains the extent of coverage data quality guidelines from the ITS Steering Committee.

Table 4.9 Breadth of Coverage Data Quality Guidelines (ITS America 2000)

	Limited Access Highways
Good	Major Limited Access Roadways
Better	All Limited Access Roadways
Best	N/A

4.4.2.7 Depth of Coverage The density of a traffic sensor technology along the facility is the depth of coverage. The depth of coverage refers to sensor spacing. For segment data, the section length is the primary attribute. Closer detector spacing or shorter section lengths provide higher-quality data. Table 4.11 outlines the metrics for determining the quality of traffic sensor data related to the depth of coverage.

Table 4.10 Depth of Coverage Data Quality Guidelines (ITS America 2000)

	Point Data	**Section Data**
Good	Between Major Interchanges	Between Major Interchanges
Better	Between Every Interchange	Between Every Interchange
Best	Maximum 0.5 mile spacing with at least one sensor site between every interchange	N/A

4.4.3 Data Sharing

A major issue with collection of data for ATIS purposes is identifying the agencies that collect data and the agencies or distribution channels that need data. Identification of the key players should be determined from both a public and private perspective, as well identifying the key ITS components that need raw traffic data. Often a public entity, such as a department of transportation or metropolitan planning organization, has the data and a private entity has the opportunity to utilize the data. Many information service providers argue that the data needed to support commercial ATIS applications are not made available. Other ITS functions, such as freight mobility services for commercial vehicle operations, could benefit from sharing data collected for ATIS purposes. It is important to maintain a wide scope when evaluating the collection of data for a particular purpose, as there may be several other applications for which the collected data could be useful.

4.4.3.1 Public/Private Partnerships A primary distribution channel of ATIS services is through private entities, while the primary data collection agent is often the public sector. The relationship between the public and private sector is essential to fostering an effective ATIS system. The three basic questions presented when public and private agencies form business relationships are "who performs, who pays, and who provides" (Gilroy, Puentes, and Schuman 1998).

Complex business relationships are forming between data collectors (typically the public sector) and information providers (typically the private sector). Some models include, in order of increasing private sector involvement: public-centered operations, contracted operations, contract fusion with asset management, franchise operations, and private competitive operations. The division between public and private responsibility in data collection, fusion, and dissemination is not well delineated and the usability of the data collected relies on efficient partnerships between agencies with data and businesses providing information. (Gilroy, Puentes, and Schuman 1998)

For example, a local toll authority may be charged with the responsibility of toll collection independent of the TMC. If automatic vehicle identification technology is employed to facilitate the collection of tolls, cooperation between the private toll authority and the public TMC would be necessary to use the AVI-equipped toll road users as probes for the regional system. Likewise, if a public entity collects traffic performance data and provides the data to an information service provider the limitations and quality of the data must be understood for effective information distribution.

4.4.3.2 Relationship to Other Functional ITS Areas ITS's consist of many entities that are collecting data or desire additional data for individual ITS components. The role of ATIS data needs to be positioned within the context of other data needs. A truly integrated ITS coordinates existing data collection with other areas and systems. Strategy developers should consider the needs of the various ITS component systems as well as existing data collected. The ITS architecture provides a framework to guide deployment of ITS's (USDOT 2000).

Typically, advanced traffic management systems (ATMS) represent the majority of the ITS data collection effort. ITS system integrators should assess available ATMS data and the goals of ATIS to efficiently use all data available to the TMC. Advanced public transportation systems often employ automatic vehicle location technology to track transit vehicles. Real-time bus tracking could be an additional input into the ATIS data collection effort. Again, an assessment of the type and quality of the data provided from the transit fleet needs to be considered with the goals of the ATIS implementation. (ITS America 2000)

Commercial vehicle operations (CVO) applications stand to benefit substantially from the data collection efforts undertaken in conjunction with other ITS applications. Existing CVO data collection applications can be enhanced to facilitate collection of data for ATIS purposes. Similar technologies are used for AVI for both truck weigh station applications and traffic management purposes. Integrating the two systems would be natural within the ITS framework.

Data collected for ATIS purposes can also be used for planning purposes. Planning activities usually require historical traffic volumes for calibration of forecasting models. Planning results can assist in selection of corridors that would be best for ATIS data collection. The National ITS Architecture recently provided for an Archived Data User Service (ADUS) to set standards for storing historical traffic data. Local metropolitan

planning organizations (MPOs) can benefit from the origin and destination patterns of a sample of the population. Traffic assignment models require calibration with actual Origin-Destination demand data, which is often difficult to ascertain, but may be available from ATIS data collection efforts. (ITS America 2000)

4.5 CONCLUSION

Application of the ATIS guidelines requires maintaining a long-term goal and vision of the ATIS strategy. The guidelines provided by the ITS America Steering Committee can be adjusted to suit regional ATIS needs and issues. Currently, these data quality guidelines are the best practice for assessing the data needs and implementation of ATIS systems. Identification of the goals of the ATIS largely defines the application of the data quality guidelines. Before the guidelines can be applied to the AVI data, the raw data must be properly processed to compute traffic state parameters according to proper definitions. The level of market penetration should also be ascertained to place the quality of AVI data within a context of the number of tags in the traffic stream. The next chapter focuses on data analysis of the raw AVI tag data and processing of the loop data for comparison purposes. Chapter 7 will focus on market penetration estimation, and Chapter 9 will apply the guidelines outlined here to the data from San Antonio.

CHAPTER 5 DATA ANALYSIS

In order to best determine the useful properties of Automatic Vehicle Identification (AVI) data for use in Advanced Traveler Information Systems (ATIS), the properties of the data and the process by which raw data is transformed into useful information must be reviewed. The study area outlined Section 5.1 provides a unique opportunity to examine both AVI and loop detectors for the same segment. This chapter discusses the data acquisition issues for both AVI and loop detectors for the San Antonio study segment. AVI data from Houston, Texas, will also be discussed, although the focus will remain on the San Antonio system. Section 5.4 applies traffic flow theory principles to both the AVI and loop data.

5.1 STUDY AREA

At present few cities employ ATIS's for traffic management purposes. The state of Texas is fortunate to have two of the premier operational AVI systems in the country. The data is readily available or easily provided by the agencies collecting the data. The work presented will focus on two cities in Texas, San Antonio and Houston; both study corridors are described in the following two sections.

5.1.1 San Antonio

The San Antonio, Texas, metropolitan area went on-line with a traffic management center in 1995, along 26 miles of roadway. Later in the fall of 1996, the metropolitan area was identified as one of four model deployment initiative (MDI) cities. The other cities included Seattle, Washington, Miami, Florida, and the New York/New Jersey metropolitan area. The cities were identified to showcase installations of intelligent transportation systems (ITS). The initiative called for a public and private partnership to develop and integrate ITS technology to reduce travel times, improve emergency response, and provide travel information to the public (FHWA 1998).

An AVI System was installed in San Antonio in 1997. The Texas Department of Transportation (TxDOT) purchased 78,000 tags for the AVI deployment in San Antonio. Of these, 58,500 have been distributed anonymously to San Antonio drivers as of October 2000 (Rodrigues, 2000). Residents voluntarily pick up tags at the TransGuide center or at other civic functions. There are fifty-two reader sites monitoring 193 lanes throughout the metropolitan region.

The study area, shown in Figure 5.1, is a 10-mile segment of Interstate 35 north of downtown San Antonio. The corridor stretches from New Braunfels Avenue to Randolph Boulevard (at the IH-410 interchange). There are numerous access locations along the facility, as the area is urban. There are five AVI locations along the facility, providing eight primary study links (four northbound and four southbound). Recently installed inductive loop detectors (ILDs) are provided on six of the links, allowing for a comparison of

measurement technologies. The study area was selected by the TxDOT, as the corridor provides a unique opportunity to compare the two technologies.
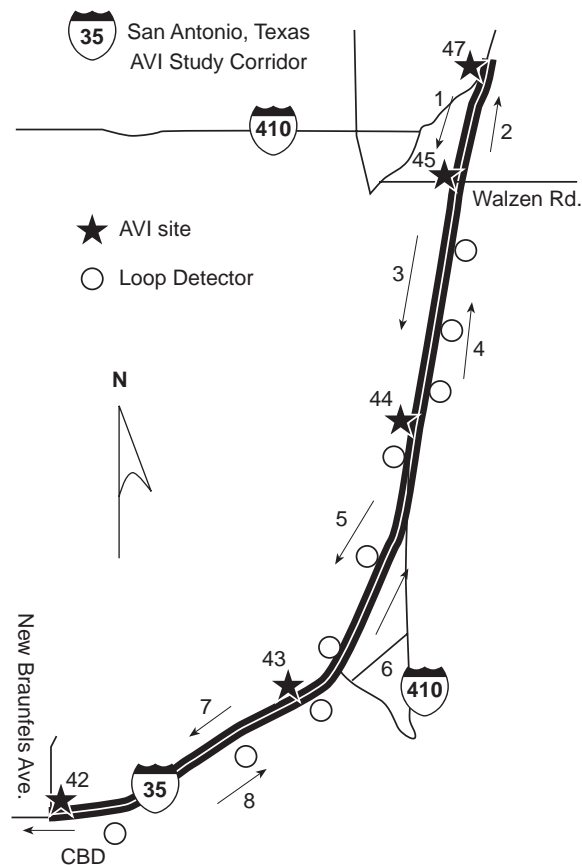
Figure 5.1 San Antonio Study Corridor

5.1.2 Houston

The Harris County Toll Road Authority maintains and operates two toll facilities within the Houston metropolitan region. The TxDOT installed AVI detectors along their facilities to gather traffic data from the vehicles tagged for toll collection. According to the Harris County Toll Road Authority, as of November 2000, 644,031 tags have been distributed. The Houston AVI study corridor is shown in Figure 5.2.
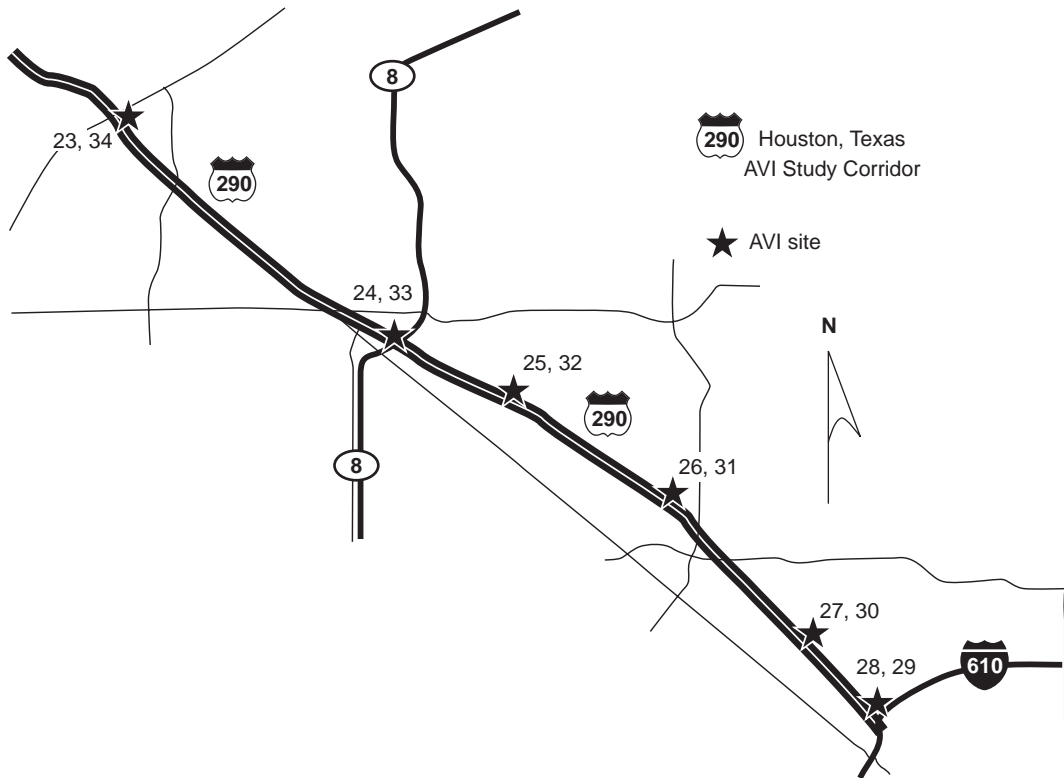
Figure 5.2 Houston Study Corridor

Limited data was provided by the Texas Transportation Institute (TTI), the agency that manages the Houston AVI project for TxDOT. The 14-mile AVI system along US 290 can provide a basis for comparison to the San Antonio installation.

5.2 SOURCE AND NATURE OF THE DATA

AVI and ILD data is obtained from TransGuide via an anonymous FTP site (www.transguide.dot.state.tx.us) and is extracted and converted to ASCII format. The daily files are processed individually and converted to standard spreadsheet files for further analysis. The following sections outline the basic properties of the data.

The San Antonio study period focuses on the last 2 weeks in June and 3 weeks in September. Installation of Austin Local Controller Units (LCUs) in June 2000 along the study corridor improved the quality of loop data. The Austin LCUs are provided by the Austin TxDOT District, and are different from the original LCUs implemented in the TransGuide system. AVI data was not affected by the installation of new LCUs. Data from Houston was provided for 3 weeks beginning on March 6, 2000. Valid loop data was not available from the Houston installation. The team did not have continuous access to Houston AVI data, and therefore limited analysis was performed on the data.

5.2.1 AVI Data

AVI data consists of two parts. The first is static information including the distances between the readers and reader configurations. For reader configurations, it is important to understand the format of direction information, if such information is provided. Accurate distances between site locations and synchronized clocks are essential for the proper computation of speed from travel times. The second component is the dynamic tag read data. The important elements of the tag data are a consistent tag identifier (at the very least daily consistency must be maintained), station identification, and an accurate time stamp. If direction information is provided, it can either be within the station identification or as an additional field.

5.2.1.1 San Antonio AVI Data The AVI data provided by San Antonio is raw tag read data, with scrambled tag identifiers. For security reasons the tags are scrambled with the UNIX crypt function using the date as a seed value. This is to dissuade any users of the data from tracking the anonymously assigned tags. The tags are scrambled with the same seed value for the duration of the day, so one can match the tag data and compute travel times and resulting speeds. San Antonio system integrators placed anonymity as a top priority and not only are the tags handed out at random and with no records maintained, the tag reads are also strongly encrypted. Figure 5.3 contains a sample of raw AVI tag data from June 14, 2000.

```
137 Sde9z8PKhuYHAnWcFNrvGwq6WYN437.o2&07:01:00.86 06/14/00%2C-1-04-1
112 yifEy.N2DK.rhMR1bex13ge8.A/UDe2/.&06:58:59.87 06/14/00%5E-0-0A-0
141 XAJLLGb8PU2C8ucfTZGj1Iq6WYN437.o2&07:02:17.75 06/14/00%32-0-02-0
123 EvrGROk8IZoWUFeQtUtHowq6WYN437.o2&07:02:15.76 06/14/00%46-1-0E-1
123 XAJLLGb8PU2swB8X093AVEq6WYN437.o2&07:02:17.43 06/14/00%46-1-04-1
119 EvrGROk8IZoZlb8W6hrEmQq6WYN437.o2&07:01:53.12 06/14/00%57-0-07-0
147 rUDUMNCIvrE8JOym6etOu2ZnMtIcX06bY&07:00:11.99 06/14/00%21-0-05-0
147 rUDUMNCIvrE8JOym6etOu2ZnMtIcX06bY&07:00:11.99 06/14/00%21-0-05-0
145 XAJLLGb8PU2Wv8zg8NhoJYq6WYN437.o2&07:00:49.13 06/14/00%1C-1-09-1
142 1o9fGHXn/MMD90nnN/ICNIq6WYN437.o2&06:59:01.37 06/14/00%16-0-06-0
145 EvrGROk8IZoC.JwXRo9B9.q6WYN437.o2&07:00:52.65 06/14/00%1D-1-02-1
142 9AJBA5t.e4IhyDjCeT0K1Yq6WYN437.o2&06:59:25.43 06/14/00%16-1-01-1
145 Q8s6g8nitRMkSGxLBoICm6q6WYN437.o2&07:00:58.72 06/14/00%1B-1-06-1
142 Sde9z8PKhuYRyyfjmhJS/Uq6WYN437.o2&07:00:00.89 06/14/00%16-1-07-1
145 I/HAlD3tAokrOsFLuZi1Rge8.A/UDe2/.&07:01:12.46 06/14/00%1E-1-0B-1
```

Figure 5.3 Raw San Antonio AVI Data

The first field is the station identification, followed by the scrambled tag identifier. For our purposes, the station identifiers are all reduced by 100 as they are all in the hundreds (that is, site 147 will be referred to as simply 47). The time and date are recorded after the tag identification. A TransCore (formerly Amtech) representative informed the author that the two digits following the percent sign represent the strength of the read in hexadecimal; the units are not known to the author. The last binary field indicates the lane and will be

discussed in Section 3.2.2. Note that at 07:00:11.99, site 47 returned a duplicate entry, which will be removed prior to analysis.

The analysis will focus on 5 weeks of San Antonio data including the last 2 weeks of June, and the last 3 weeks of September 2000. New loop detector equipment installed in the middle of June precludes the use of earlier June data to maintain consistency. Both AVI and loop data were not available on September 21, 2000. A gap in the data will be noted in the subsequent analysis, but this will not influence the statistical results. Weekdays are the focus of investigation; however, AVI data is obtained on the weekends and can provide valuable information to travelers.

5.2.1.2 Houston AVI Data The Houston AVI data for the network described in Section 1.4.2 were obtained via a temporary FTP agreement with the TTI, at the North Post Oak Road facility in Houston, Texas. Three weeks of weekday data, and static link information were provided to the research team. The data is provided in ASCII format and is processed by the same program, written by the author. Figure 5.4 shows a sample of Houston data from March 7, 2000.

```
0MCA00317931 2004    22   8:09:38    3/07/00
0MCA00159904 2060    28   8:09:49    3/07/00
0MCA00349488 2009    34   8:10:33    3/07/00
0MCA00324270 2000    35   8:09:40    3/07/00
0MCA00266778 2055    27   8:10:01    3/07/00
0MCA00400229 2045    26   8:09:53    3/07/00
0MCA00055121 2028    32   8:09:51    3/07/00
0MCA00467036 2059    29   8:09:51    3/07/00
0MCA00057965 2000    35   8:09:42    3/07/00
0MCA00489489 2009    34   8:10:38    3/07/00
0MCA00048615 2045    26   8:10:01    3/07/00
0MCA00268745 2054    27   8:10:04    3/07/00
0MCA00366546 2034    25   8:09:52    3/07/00
```

Figure 5.4 Raw Houston AVI Data

The first field contains the scrambled tag identifier. The second field represents the antenna number. It is important to note that this does not correspond to the lane, as most antennae span multiple lanes in the Houston installation. It is primarily used as a maintenance check measure (Vickich 2000). The third field is the station identifier, followed by the time and date of the tag read. The station identifier inherently defines direction, and is defined by the static data provided by the Houston division of the TTI. The tags are scrambled the same way everyday, using the same algorithm. Most of the Houston tag reads are from toll tags distributed for the Sam Houston Tollway and Hardy Toll Road, operated by the Harris County Toll Road Authority.

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5.2.2 Loop Data

The loop data are provided in a similar structure to the AVI data for the San Antonio study corridor. Averages are computed in the field and transmitted to TransGuide. The data prior to June 14, 2000, (that is, prior to the installation of the Austin LCUs) are not reported using a consistent average time window. From June 14, 2000, forward, data are provided on a 20-second average basis. Not all loop sites report data at exactly the same time; however, the rolling averages are maintained within each site. Some minor fluctuations do occur and some averaging windows are not exactly 20 seconds. It is not within the scope of this research to investigate the errors in the loop data from installation, hardware, or data collection software errors. The focus is on using this data in its current format for the express purpose of comparison with AVI data.

Figure 5.5 is a sample of San Antonio loop data for September 19, 2000.

```
09/19/2000 00:07:17   EN1-0410E-026.371 Speed=-1  Vol=000  Occ=000
09/19/2000 00:07:17   EX1-0410W-026.475 Speed=-1  Vol=000  Occ=000
09/19/2000 00:07:17   L1-0410W-026.515  Speed=71  Vol=002  Occ=002
09/19/2000 00:07:17   L2-0410E-026.515  Speed=61  Vol=000  Occ=000
09/19/2000 00:07:17   L2-0410W-026.515  Speed=68  Vol=002  Occ=002
09/19/2000 00:07:17   L3-0410E-026.515  Speed=66  Vol=001  Occ=001
09/19/2000 00:07:24   EN1-0035S-160.768 Speed=-1  Vol=000  Occ=000
09/19/2000 00:07:24   L1-0035N-160.892  Speed=61  Vol=002  Occ=002
09/19/2000 00:07:24   L2-0035N-160.892  Speed=57  Vol=002  Occ=002
09/19/2000 00:07:24   L2-0035S-160.892  Speed=61  Vol=000  Occ=000
09/19/2000 00:07:25   L2-0035N-162.899  Speed=71  Vol=000  Occ=000
09/19/2000 00:07:25   L3-0035N-162.899  Speed=71  Vol=001  Occ=001
...
09/19/2000 00:07:57   L1-0410W-026.515  Speed=68  Vol=002  Occ=002
09/19/2000 00:07:57   L2-0410W-026.515  Speed=64  Vol=002  Occ=002
09/19/2000 00:07:57   L3-0410E-026.515  Speed=66  Vol=000  Occ=000
09/19/2000 00:07:57   L3-0410W-026.515  Speed=66  Vol=002  Occ=001
09/19/2000 00:07:57   L4-0410E-026.515  Speed=79  Vol=000  Occ=000
09/19/2000 00:08:04   EN1-0035S-160.768 Speed=-1  Vol=000  Occ=000
09/19/2000 00:08:04   L1-0035N-160.892  Speed=64  Vol=001  Occ=001
09/19/2000 00:08:04   L2-0035N-160.892  Speed=62  Vol=001  Occ=001
09/19/2000 00:08:04   L3-0035N-160.892  Speed=57  Vol=002  Occ=002
```

Figure 5.5 Raw San Antonio Loop Data

The first field is the date followed by the 24-hour time. The third field is the location of the loop. This research only needs the main lane loops indicated by an "L#" where # represents the lane of the loop (Lane 1 is the innermost lane of travel, closest to the median). The milepost uniquely identifies each loop location as the distance north of the start of Interstate 35 in Laredo, Texas. The average speed in miles per hour, total volume over the average window, and percent occupancy follow the location information.

Loop data were provided from Houston for 3 days in March. The data are not useable, because most of the loop sites are not operational. There is not enough continuous data to work with from any given loop detector.

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5.2.2.1 Loop Time Errors Time errors observed in the loop data are defined as gaps in the database. Given that the loop detectors in their current configuration are designed to produce reads every 20 seconds, successive records in the database should be separated by 20-second intervals. However, this is not always the case. Although most of the loop readings occur at 20-second intervals, other interval lengths were observed. Figure 5.6 presents a plot of the time interval between successive reads against the time of day for a typical detector.
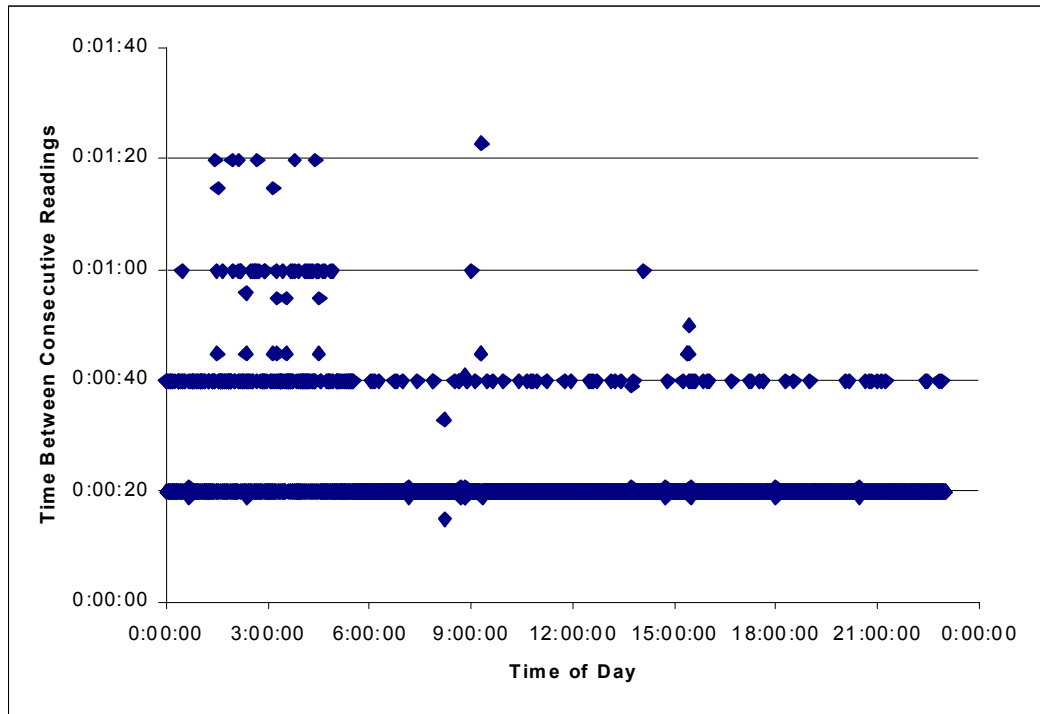
Figure 5.6 Graphical Representation of Time Between Consecutive Readings

The observed time gaps between consecutive reads for this particular reader vary from 20 seconds to 83 seconds with the bulk of the reads made at 20-second intervals.

The time error problem negatively impacts incident detection algorithms that take input from two successive detector stations. If the time stamps of the reads that the algorithm is comparing do not coincide, there is a possibility that the traffic characteristics represented by the reads are significantly different. In order to solve the problem, the data has to be either processed before serving as input to the algorithm or additional logic should be added to the algorithm itself.

There exist a number of missing value techniques aimed at filling the gaps by considering spatial and temporal readings from adjacent detectors. Missing values are generated either from previous reads of the same detector, from concurrent reads of adjacent detectors, or from a combination of the two. Since the likelihood of encountering missing data in a particular lane is much higher than that of missing data in all lanes of travel, some

fixed detector algorithms try to remedy the problem by taking as input roadway section averages.

For the purposes of this research, the data was processed prior to its use with AID algorithms in such a way to ignore missing values and to fill the gaps with records having the missing time stamps but no speed, volume, or occupancy values. An example of time error in the data and the corresponding solution are presented in Figures 5.7 and 5.8, respectively.

6/30/2000
0:11:38
L3-0035N-162.899
Speed=64
Vol=001
Occ=004

6/30/2000
0:12:18
L3-0035N-162.899
Speed=00
Vol=000
Occ=000

6/30/2000
0:12:38
L3-0035N-162.899
Speed=53
Vol=003
Occ=003

Figure 5.7 Example of Time Error

6/30/2000
0:11:38
L3-0035N-162.899
Speed=64
Vol=001
Occ=004

6/30/2000
0:11:58
L3-0035N-162.899

6/30/2000
0:12:18
L3-0035N-162.899
Speed=00
Vol=000
Occ=000

6/30/2000
0:12:38
L3-0035N-162.899
Speed=53
Vol=003
Occ=003

Figure 5.8 Example of Time Error Fix

5.2.2.2 Loop Data Errors If one of the traffic variables reported by the loop detectors (speed, volume, and occupancy) has a null value, then the other two must have a null value as well. Data errors are defined as a violation of the above-described rule and were identified in the loop data in addition to time errors.

The data used was preprocessed to eliminate data errors. A program was written to identify those errors and enter blank values for the corresponding time stamp. The preprocessed data was then used as input for the fixed detector algorithms.

5.2.3 Incident Data

In order to assess and compare the performance of AID algorithms, a substantial incident database containing a precise report of the time, nature, and location of each incident is required.

Incidents are detected automatically at TransGuide using the Texas algorithm introduced in the previous chapter, or manually by visual inspection using the CCTV cameras. When an operator detects an incident manually, the operator has to enter the alarm location causing the system to automatically generate the date and time. The system detects incidents automatically by comparing the mean speed on a particular segment to a threshold. If the mean speed is below the threshold, the closest CCTV camera to that location is automatically activated and the incident is brought to the attention of the floor manager, who in turn assigns the alarm to an operator. Control scenarios were developed and stored in a database at TransGuide to help operators manage incidents in the most efficient manner. The system matches the incident characteristics with the stored scenarios and gives the operator a list of prespecified control options appropriate for the incident at hand. For the system-generated alarms, the alarm location, time, and date are entered automatically and it is left up to the operator to complete the documentation of the incident. Ideally, the incident documentation consists of the type of incident, a field indicating if the capacity of the facility has been exceeded or not, the lanes affected, and the name of the incident manager.

Incident data at TransGuide is archived every day for the whole network along with information regarding the Changeable Message Signs (CMS's), and Lane Control Units (LCUs). Each incident detected is given a unique identification number (ID). If an incident is manually detected, the operator assigns to that incident an ID > 2500. Alternatively, if the incident is detected by the system, it is automatically assigned an ID < 2500. A program was developed to extract the incident-related information of importance to the study; i.e., incident information corresponding to the study corridor. Table 5.3 presents an example of the processed output format.

Table 5.1 Sample Incident Data

ID	Start Date	Start Time	End Time	Address	Type	Lanes Affected	Capacity Exceeded
170	6/29/00	16:56:50	16:57:35	SECT-0U35S-156.684	2	10000000	TRUE
185	6/29/00	17:19:43	17:20:55	SECT-0281N-145.124	2	10000000	FALSE

It is up to the operator to decide on the incident type based on the classification adopted by TransGuide and reported in Table 5.2. A major accident is defined as one whose expected duration exceeds 15 minutes. All other accidents are classified as minor. Incidents which are not accidents are classified based on a subjective decision by the operator.

The lanes affected by the incident are represented using eight-digit binary numbers as shown in Table 5.1. The lanes of the facility are represented from left to right with respect to the direction of travel i.e., the leftmost digit represents the left shoulder. If the digit representing a particular lane has a value of 1, then the lane in question is blocked as a result of the incident. On the other hand, if the value of the digit is 0, then the lane is not affected by the incident.

Table 5.2 Incident Type Classification

Incident Type	Identifier
Major Accident	0
Minor Accident	1
Congestion	2
Debris	3
Construction/Maintenance	4
Weather Condition	5
Stalled Vehicle	6

The breakdown of the incident database by incident type is presented in Table 5.3 and can be better visualized by looking at Figure 5.9. It should be noted that the incident database comprises only incidents that occurred during weekday peak periods. The bulk of the reported incidents are labeled as congestion (65 percent) that compares well to the 61 percent figure reported by Peterman (1999). No construction incidents were reported since construction is more likely to be done in off-peak periods. Also, no weather incidents were reported, which was to be expected for the period of the year considered in the study.

Table 5.3 Incidents According to Type

ID	Incident Type	Count	Percent Total
0	Major Accident	14	19%
1	Minor Accident	9	12%
2	Congestion	47	65%
3	Debris	1	1%
4	Construction	0	0%
5	Weather	0	0%
6	Stalls	2	3%
	Total	**73**	
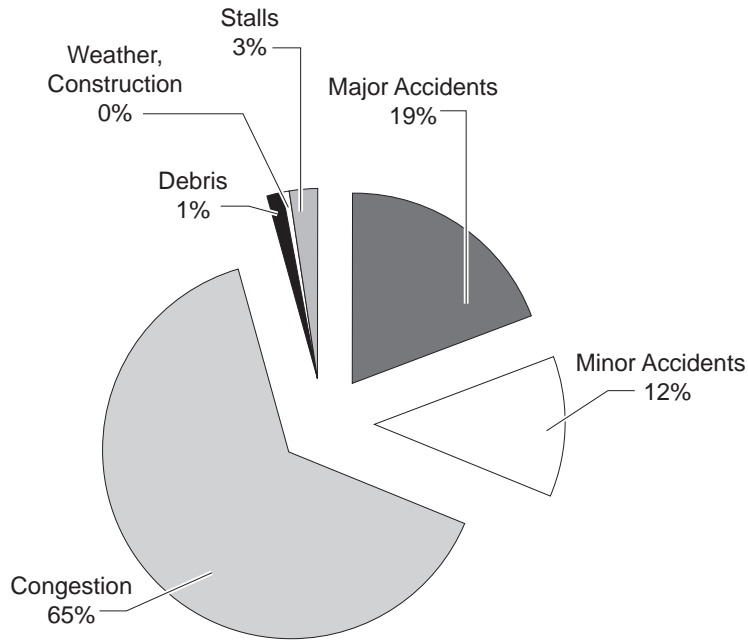
Figure 5.9 Incident Database Breakdown According to Type

Upon processing the incident data, several errors were identified. As mentioned earlier, the AID algorithm in place at TransGuide relies on a predetermined speed threshold to detect the occurrence of incidents. If the speed on a particular link falls below the threshold, the system generates an incident alarm with an ID less than 2500. The adopted logic is straightforward but may lead to a high false alarm rate. Therefore, in the absence of visual inspection, only those incident entries recorded manually by an operator were considered in this research.

In addition, multiple incident alarms were detected. Multiple incident alarms are defined as entries having the same incident ID, date, and location. The incident start and end times were either identical or consecutive. It is believed that multiple entries occur as a result of congestion-generated incidents. When encountered, the multiple alarm problem was resolved by creating a single entry for the incident with the earliest incident start time and the latest incident end times of the multiple entries.

Furthermore, upon comparing the incident start time and end time for all entries in the database, entries with similar start and end times or with an end time occurring before the start time were encountered. Such entries result in zero or negative incident durations and were entirely removed from the database.

5.3 DATA PROCESSING AND EXPLORATION

Initial efforts to characterize the quality of AVI data focused on the AVI data itself and its variation across the day and across multiple weekdays. Early work identified some system problems, which were brought to the attention of the staff at TransGuide. Initial work focused on the system as a whole, however most of the effort focused on the study corridor.

5.3.1 Unique Tag Reads and Duplicates Removed

One of the more important metrics for an AVI system is the number of unique tags read in a given day. The tagged vehicles represent only a sample of the actual vehicle population. The number of unique tags read coupled with an actual estimate of the number of vehicles can allow for a simple estimation of market penetration. The San Antonio tags are scrambled differently each day, therefore the number of unique tags read across days can not be ascertained. It would be beneficial to determine the number of tags read consistently across days, weeks or months to estimate the number of tags that can be relied on as active probes in the system.

In the early stages of analysis during the fall of 1999, duplicate entries were noted in the data set and it was desired to determine the cause of these repeat entries. A duplicate is a tag record that is exactly the same as the previous record in tag ID, station ID, and time. In November 1999, the number of duplicates dramatically increased. It was later determined that the cause was an invalid time-reporting problem at the AVI field sites. The time reporting problem was corrected by early May 2000. Duplicate entries are still observed in the data and are often due to reporting errors at the AVI field sites or with the processing data at the TransGuide center. The cause of duplicate entries in the data is not known; however, they can be filtered out and do not affect the analysis. A sharp rise in duplicates should concern operators that some aspect of the system is malfunctioning.

The chart in Figure 5.10 depicts the total unique tag reads per day for weekdays during the study period for the entire San Antonio AVI system.
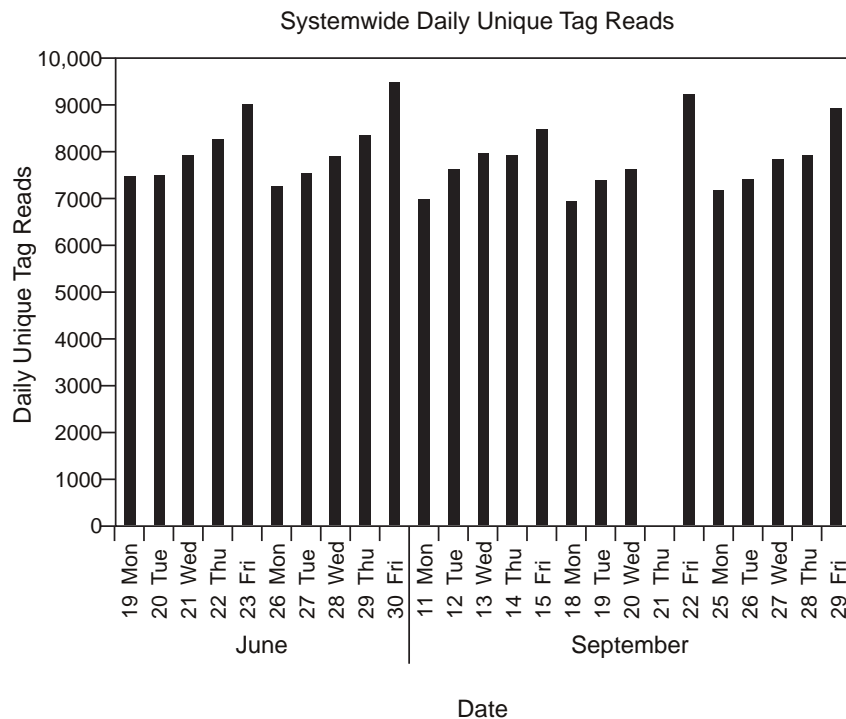
Figure 5.10 San Antonio System Daily Unique Tag Reads

It is clear that there is an increase in tag reads as the week progresses, often with a higher jump in reads for Friday. The most logical reason for the Friday increase is a rise in through travel, such as Houston or Dallas travelers (with toll tags installed in their vehicles). The hypothesis cannot be tested because the tag identification is encrypted, the first four characters in the tag ID defines the agency of the tag provider. No increase in the number of unique tag reads from June to September is apparent. It does not appear that tag penetration increased between June and September in the San Antonio system.

5.3.2 Peak Period Determination

In order to determine the best interval for peak period analysis, a count of the tag reads by time of day was made. Figure 5.11 shows the average number of tag reads by site for the month of June. Note that this average includes all weekdays in June. In this case, only the AVI sites in the 10-mile study corridor are considered.
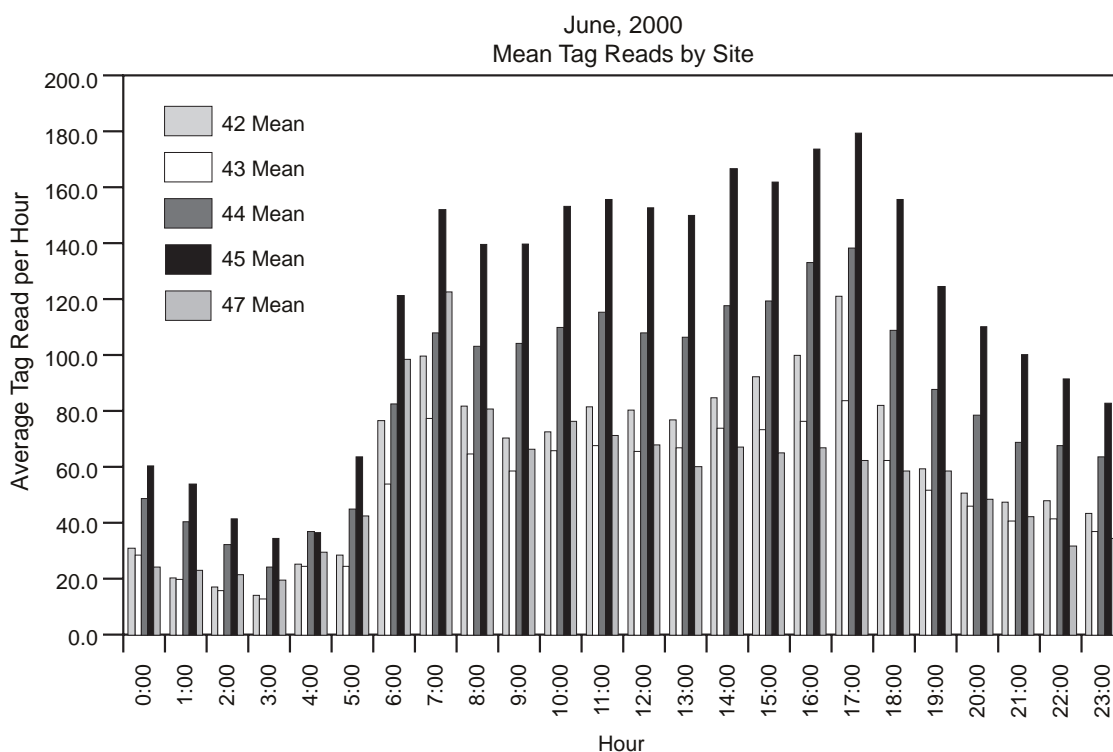
Figure 5.11 Mean Tag Reads by Site

It is clear that sites 45 and 44 read many more tags per day than the other sites. Sites 45 and 47 monitor all eight lanes of the facility (four northbound and four southbound). Site 44 is just north of the Interstate 410 interchange. The morning peak is clearly centered on 07:00 and the afternoon peak around 17:00. The exact time varies across the days of the week. Figure 5.5 is a monthly average and, therefore, most of these effects have been smoothed out.

The standard deviations of the average number of tag reads by hour across all weekdays in June 2000 are shown in Figure 5.12. The mid-day tag reads of site 44 vary substantially across the weekdays of June more than at the other locations. This is most likely due to the proximity to the Interstate 410 interchange (refer to Figure 5.1 for a map of the study area). There is a higher level of merging and diverging traffic at this location.
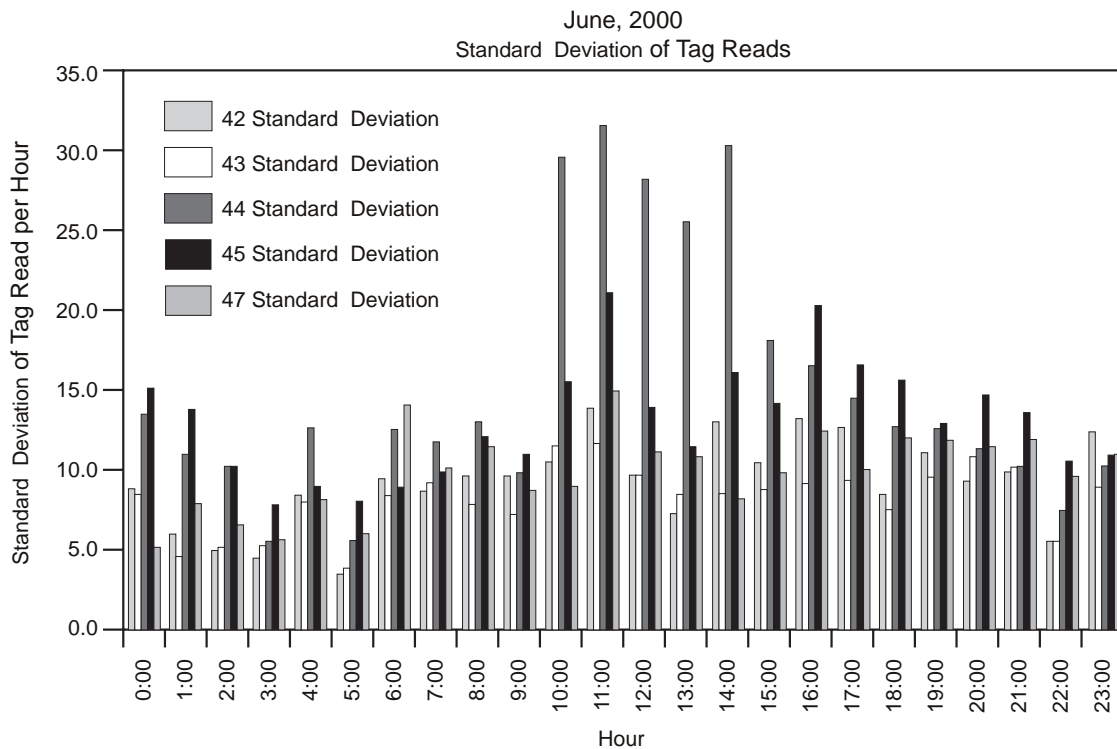
Figure 5.12 Standard Deviation of Tag Reads

The peak period selected for the analysis is 06:00 to 08:45 for the morning peak and 15:30 to 18:15 for the afternoon peak.

5.3.3 "Direction" Field

As noted earlier, the last field in the data represents lane position. The binary field was originally believed to indicate direction, zero for southbound and one for northbound. After some investigation, the "direction" field credibility was questioned. Analysis was performed to determine that the field certainly does not indicate direction. TransGuide and TransCore personnel were consulted.

Every AVI site has an address, such as 145 or 245. For each pair of antennae, a reader card resides in the cabinet. The first of these has the same address as the site itself and the antennas that monitor the two inside northbound lanes are wired to this card. The others

are 2XX, 3XX, or 4XX, continuing with the next northbound lanes followed by the inner southbound lanes. The system identifies the inner lane of an antenna pair with a zero and the outer lane of a pair of antennas as one. For a site that monitors all four lanes, such as site 145, Figure 5.13 describes the configuration.
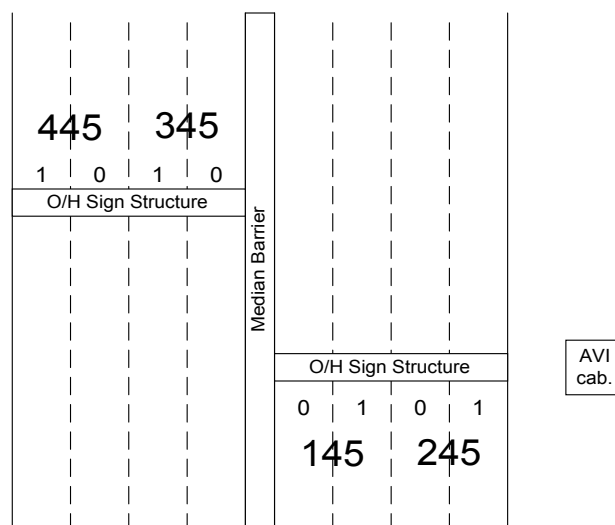
Figure 5.13 Lane Assignment at AVI Installation Site

It is not a valid assumption that 2XX is always northbound. Often identifier "2" represents southbound if the system is only monitoring the two inner lanes in each direction. The field sites do transmit the reader card identifier (which can be related to direction as described above). Unfortunately, these data are not captured or archived by the TransGuide system software.

The only method to obtain directional data with the current installation is to match the tag reads with downstream detectors. Relying on matched data to discern the direction of a vehicle limits the directional volume measurements that could otherwise be captured at a point. Often a vehicle may exit before a downstream detector can match the vehicle, the system fails downstream, or the vehicle changes lanes and is not detected by the downstream detector. The process of matching tag reads is also important for the calculation of travel times and the subsequent calculation of speeds based on the distance between detectors. The next section describes the match tag process.

5.3.4 Match Results

The central objective of an AVI system is to construct travel times for the links between the reader sites. With accurate distances between the reader sites, average vehicle speeds can be obtained. For the San Antonio system, matching the data is the only viable means to determine directional volumes of tagged (or in this case matched) vehicles. With

properly matched data, accurate speed, volume, and density of tagged vehicles can be made, as discussed in Section 5.4.

TransGuide provided the distances between the AVI sites. The distances were reported to the thousandth of a mile or to an accuracy of about 5 feet. It is imperative that these distances be measured and reported accurately. Inaccurate distance data can cause erroneous, higher, or lower average speeds. Such an error would be systematic across all results. Link identification numbers are assigned to the eight links between the AVI reader sites for the study corridor. The link identifications are depicted in Figure 5.1.

In some cases a vehicle misses a reader site but is identified by the next downstream detector. In order to capture vehicles that may not be read by the next subsequent downstream reader site, twelve additional composite links were generated. Shown in Figure 5.14 are the twenty possible link combinations from the array of five study AVI sites. The matching procedure searches for a match in link order. Matches are first made between adjacent sites (first order links) and then matches between nonadjacent sites are made.
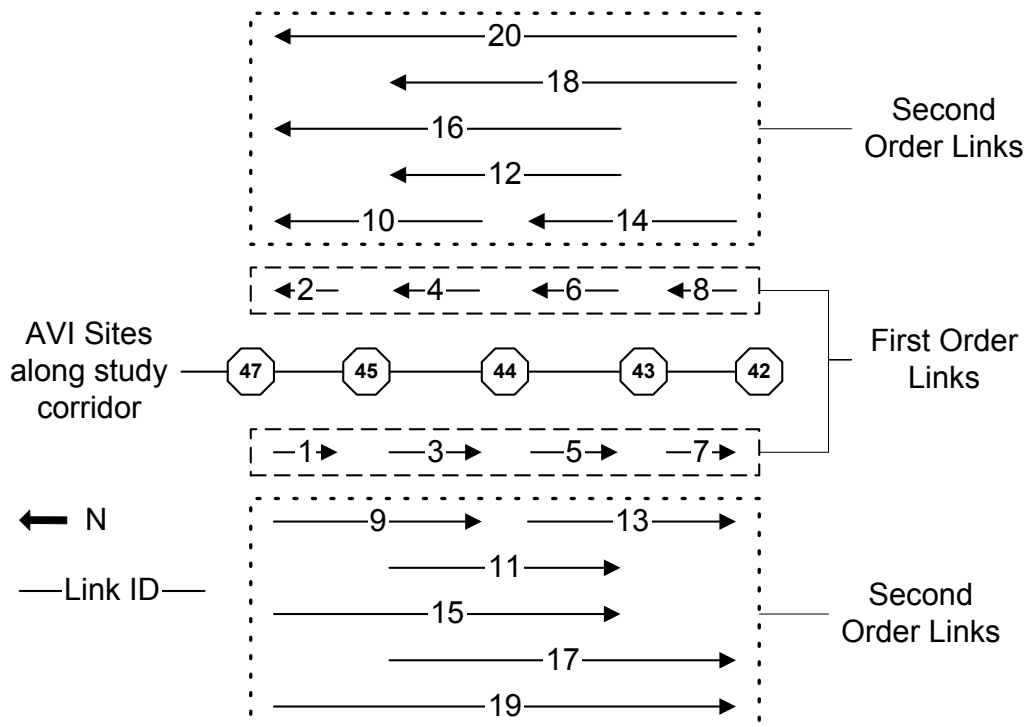
Figure 5.14 AVI Link Combinations

After the raw tag data are read and duplicate entries are removed, the tag reads are matched. The tag array is sorted using a simple insertion sort algorithm in ascending order by time of tag read. The first tag identifier is read and the rest of the array is searched for that tag. If the tag is located, the travel time is computed and link traversed identified, as

noted above. Using the known distance from the static distance data, a speed is computed for the vehicle and the results are stored in the match array.

Tags are matched for a given period of the day. In the following case, the period from 06:00 to 08:45 was selected to capture the 07:00 peak. The match is checked for reasonableness before the speed is actually computed. A match is considered invalid if the match is between two of the same sites (e.g., a vehicle that exits and turns around). If the resulting speed is less than 1 mile per hour the match is considered invalid as that often represents a vehicle that may have exited the facility and reentered after some time. Other checks for reasonableness should also be considered as there are times when the travel time is greater than three standard deviations away from the average travel time. For the purpose of ATIS, matches below 10 miles per hour are often invalid and are also removed. Matches with speeds below 10 miles per hour are more effective for incident detection purposes. The ATIS system would rely on an incident detection system to provide incident information. All match results would be necessary for incident detection conditions, as slow matches are indicative of incident conditions. However, periods with no incidents may have random slow-tagged vehicles that would not be indicative of the traffic stream for ATIS applications.

Figure 5.15 shows the average number of matches by day for the peak hour defined above (06:00 to 08:45) for the study period. On average, the total valid matches are 96.7 percent of the actual matches. Equipment failures may have caused the decrease in matches on June 7, 2000, and September 11, 2000.
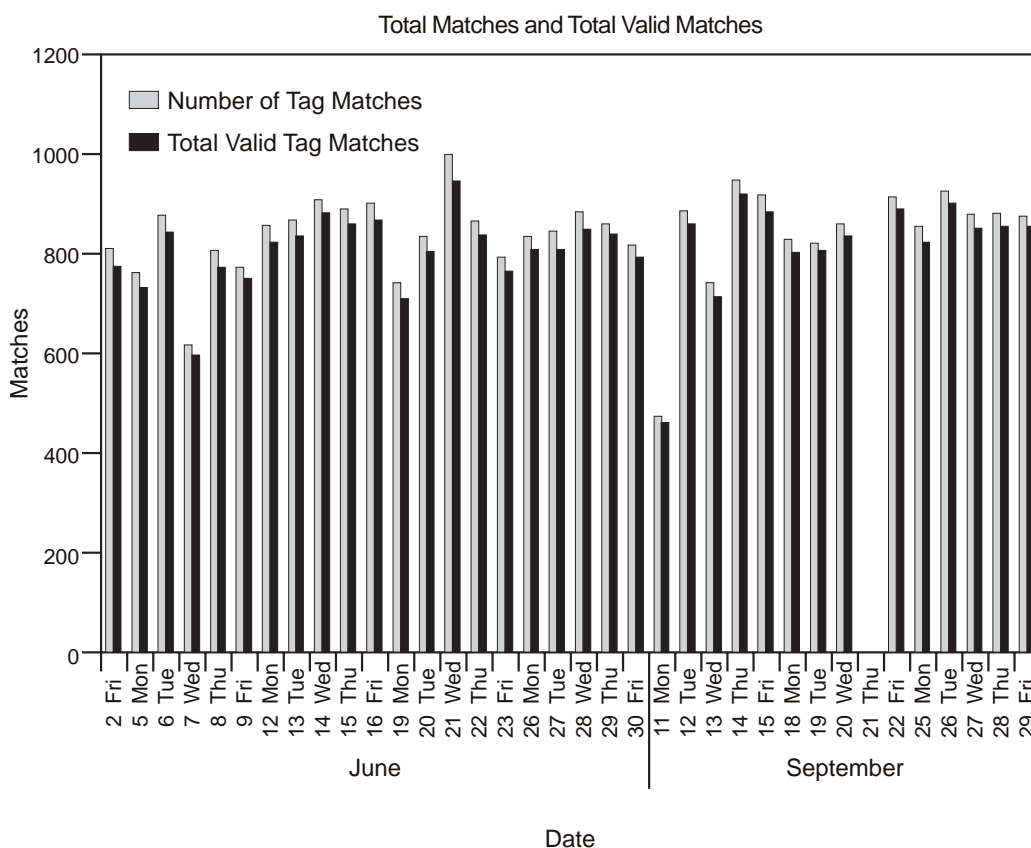
Figure 5.15 Total Matches and Total Valid Matches

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The matched data and individual vehicle speeds are used to estimate the traffic state descriptors as discussed in the following section. At this point, matches with speeds less than 10 miles per hour are not considered, as they are often erroneous and can skew the state descriptor estimates.

5.4 CALCULATION OF TRAFFIC STATE DESCRIPTORS

The major goal of gathering traffic data is to estimate the state of the system efficiently and accurately. Data from the automatic vehicle identification system provides additional flexibility and allowing for easier computation of properly defined traffic state descriptors. Proper definition of the traffic state descriptors is essential for correct interpretation and comparison across technologies.

The matched tag data are processed for the given time period within a specified averaging time window. The averaging time window is specified by the user and is most often 5, 10 or 15 minutes in duration. The matched data are averaged within the window beginning with the start of the specified peak hour. In order to obtain matches that may already exist in the network, the tag data are processed for a period of two time windows in advance of the specified peak hour. Loop data are similarly averaged over the same time window from the 40-second polled data. Details of the AVI implementation are presented in Section 5.4.2. Definitions of the traffic state descriptors are discussed in Section 5.4.1.

5.4.1 AVI Definitions

Several works discuss and debate the fundamental relation between average vehicle speed, flow, and density, and how these quantities are measured. The goal of this work is to implement a method for computing the state descriptors to evaluate the effectiveness of AVI. The classic definitions introduced by Edie (1965) and applied by Cassidy and Coifman (1997) to loop data are utilized. Edie's generalized definitions (1965) are used to compute the average flow, density, and speed on a given link monitored with AVI and loop detectors. Other measures, such as the standard deviation of space mean speeds, are computed by applying the usual definitions.

5.4.1.1 Density, Flow, and Speed Edie describes methods to define the average speed ($\bar{u}_{SMS}$), flow (q), and density (k) for any region in space and time. A rectangular region in space and time is shown in Figure 5.16, where there are n vehicle trajectories and each jth trajectory spends time t_j while traveling a distance x_j. The distance between two reader sites defines the spatial length (L) of the area. The temporal duration (T) of the area is defined as the specified averaging time window.
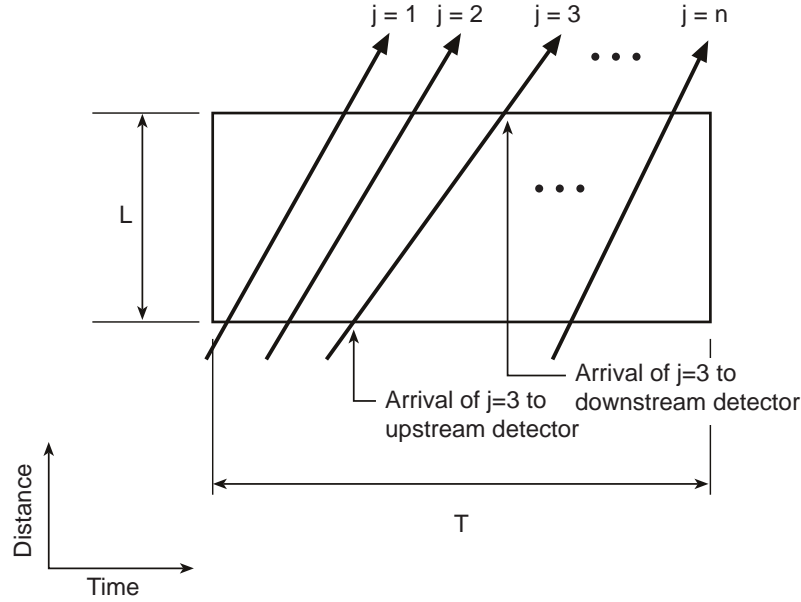
Figure 5.16 Rectangular Region with n Trajectories
(Cassidy and Coifman 1997)

Density for a given region LT is given by $k = \dfrac{\sum\limits_{j=1}^{n} t_j}{LT}$. Density is the sum of the individual travel times for each jth trajectory during a given time segment, divided by the area (LT) of the study period. Likewise, flow is computed as: $q = \dfrac{\sum\limits_{j=1}^{n} x_j}{LT}$, where the numerator is the summation of all distances traversed by each jth trajectory during the study period. Average speed can be computed as $\bar{u}_{SMS} = \dfrac{\sum\limits_{j=1}^{n} x_j}{\sum\limits_{j=1}^{n} t_j} = \dfrac{q}{k}$, from first principles (total distance divided by total time) or by manipulation of the fundamental $q = uk$ relationship. The speed computed from AVI data is a space mean speed; this is discussed further in Section 5.4.5.1 (Cassidy and Coifman 1997).

5.4.1.2 Standard Deviation of Space Mean Speeds   Space mean speeds are not the simple arithmetic mean of speed measurements. It is necessary to define the standard deviation of space mean speed measurements carefully. The standard deviation of the space mean speeds is computed as:

$$S_{SMS} = \sqrt{\frac{\sum\limits_{i=1}^{N}(\mu_i - \overline{\mu}_{SMS})^2}{N-1}}$$

Where μ_i is the speed of vehicle i, $\overline{\mu}_{SMS}$ is the sample space mean speed in the time-space region, as described in Section 5.4.1.1. N is the total number of speed observations, or vehicles, that contribute to the space-mean speed (May 1990).

5.4.2 AVI Implementation

The formulation outlined requires precise tracking of all vehicles for each individual link. As previously mentioned, the program analyzes data from a given set of detectors for a specified period of time. Figure 5.17 outlines the AVI implementation procedure on a theoretical time-space diagram. The heavy dashed line represents the time and space period of analysis, typically the morning or afternoon peak period. The thin solid diagonal lines represent vehicle trajectories. The facility is multilane, therefore the vehicle trajectories can intersect as one vehicle passes another. The analysis time period typically consists of eleven individual time windows; the selection of eleven time windows was arbitrary.

During each time window, every match is checked to determine if it is within the study link. If a match is representative of a vehicle on the link in the time window, the vehicle is moved according to its computed speed on that link. The speed is known because the tag data is already matched; the computation of space mean speed, flow, and density is a postmatching process. The sum of the individual travel times and distances traveled by all vehicles on the link is computed. If a vehicle traverses past the end of the link, it is tagged out of the link and only the portion traveled on the link during the current time window is considered. Likewise, if a vehicle is still on the link at the conclusion of the time window, the location is stored and the vehicle will resume from the stored location for the next time window.
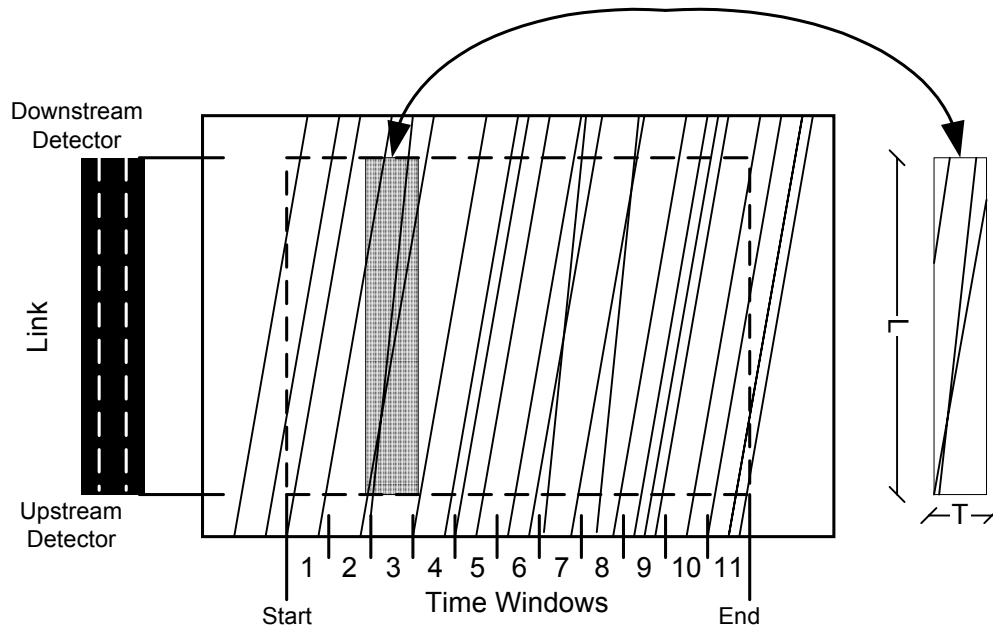
Figure 5.17 AVI Process Implementation Time-Space Diagram

The algorithm then computes the density, flow, and speed according to the definitions outlined in Section 5.4.1.1. The standard deviation of the speeds is computed and the number of vehicles on the link recorded. Output is displayed in a spreadsheet package for easy graphical interpretation and comparison with loop detector data.

It is important to note that the implementation described here would be limited for real-time implementation. The process presented must know the speed of the vehicle to properly "move" the vehicle during the time period of interest. The downstream detector must already detect and match the vehicle and compute the speed of the vehicle; the time necessary for this process to complete depends on the length of the link and the level of congestion. A rolling-average implementation where the state characteristics are updated with each new match as they are made would be more suited for a real-time implementation.

The procedures of the AVI analysis program were tested manually with segments of the raw data in a spreadsheet. Specifically, the raw data were tested to ensure that the proper tags for our study network and time period are extracted. The tag-matching procedure was tested for correct matches and computation of speeds from tag data. Finally, the flow, volume, and density computations were tested to guarantee proper calculation according to the definitions defined by Edie, outlined in Section 5.4.1.1. Successful implementation of the fundamental definitions is achieved when each vehicle is accounted for and properly moved on every link for each time step.

5.4.3 Proof That Edie Definitions Hold

After defining and implementing the Edie traffic state definitions, it is important to ensure that the definitions are applied correctly. Figure 5.18 confirms that the $q = kv$ relationship holds for AVI data when the measurements are properly defined. The ratio of flow to speed is plotted against density for the morning peak period of June 19, 2000, and shown to produce a perfect linear relationship. The algorithm, therefore, is computing correctly defined speed, flow, and density data.

q/v versus k for AVI Data
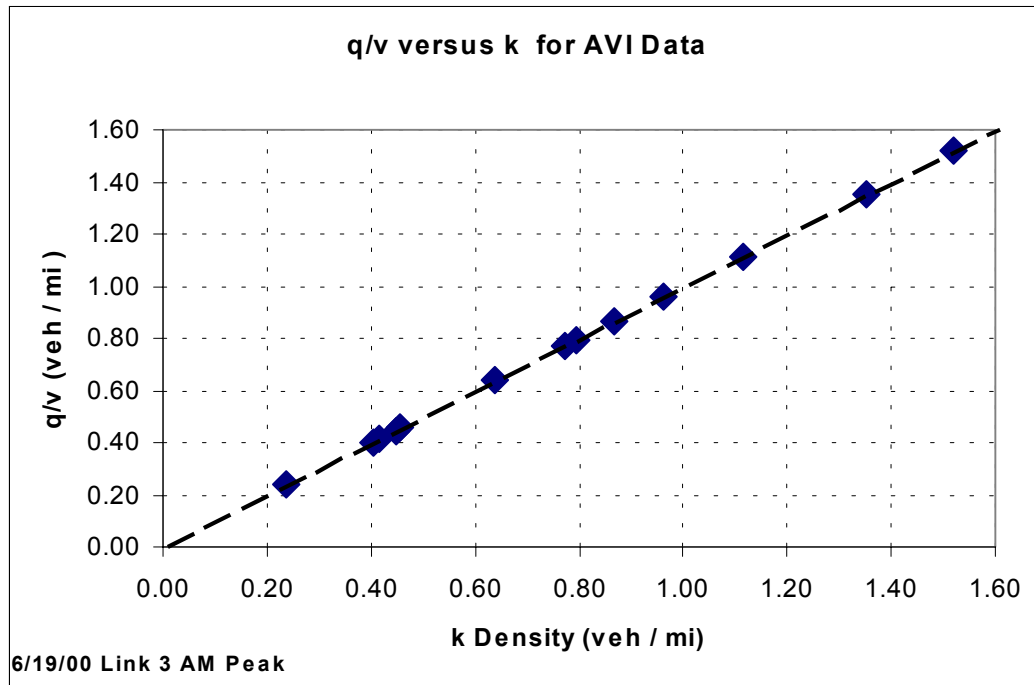
Figure 5.18 Edie Relationship Check

The Edie relationship could not be applied with the available loop data because of the inability to track individual vehicles and obtain updated position information about individual vehicles. AVI is a powerful technology that facilitates proper definition and averaging of traffic state parameters.

5.4.4 Loop Definitions

As noted in Figure 5.1 there are three loop detectors installed for every first order link. As currently implemented, the loop detectors do not have the ability to track vehicles and compute space mean speed measurements directly, as outlined in Section 5.4.1.1, for the AVI system. Difficulty arises comparing the instantaneous spot speed measurements from loops to the inherent space mean measurement from the AVI system. A system of three loop detectors comprising a single AVI study segment is shown in Figure 5.19. The dashed rectangles represent "effective" detection zones or lengths over which the speed obtained

from a loop detector is assumed to prevail. The length of an AVI detection zone is fixed as the system directly measures speed over a length. The focus of this section is to outline the definitions necessary to obtain a reasonable space mean speed estimate from loop detectors.
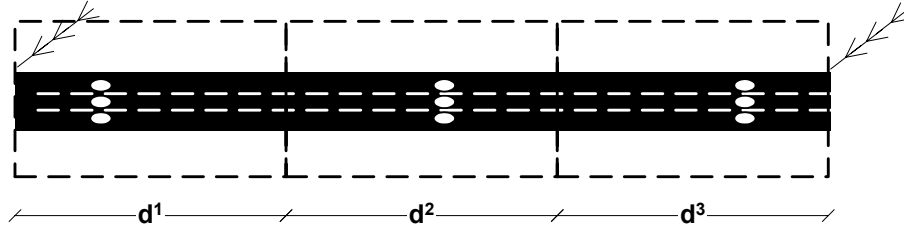
Figure 5.19 Loop Detection Zones

The average space between loop detectors is 0.5 mile and is assumed to be the "effective" detection length for all individual loop detectors. The San Antonio loop detectors in the study corridor are consistently located at 0.5 increments. The instantaneous speed obtained from a loop detector is assumed to be the speed of the vehicle for the entire 0.5 mile "effective" zone shown as dashed rectangles in Figure 5.19. The Edie formulation outlined in Section 5.4.1.1 is applied approximately, as all vehicles are not tracked and assumed to traverse the entire "effective" zone when detected.

A space mean speed comparable to the AVI-derived value could be obtained from loop data if an effective length over which the instantaneous speed obtained from the loop detector is assumed to prevail. The fundamental definition of speed is total distance D over total time T. In the equation below, d_i is the distance an individual vehicle i travels with time t_i.

$$\bar{u}_{SMS} = \frac{D}{T} = \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} t_i} = \frac{n_1 d^1 + n_2 d^2 + n_3 d^3}{\sum_{i=1}^{n} t_i}$$

The individual vehicles cannot be tracked; therefore, one must assume that in each time window a detected vehicle traverses the entire length of the detection zone, d^x, $x = 1,2,3$. There are three loop detection zones (x) for a single AVI segment, as shown in Figure 5.13. n^x is the number of vehicles that are detected by detector x, $x = 1,2,3$. Because all the detection zones are assumed equal, the equation simplifies to

$$\bar{u}_{SMS} = \frac{d\left(n^1 + n^2 + n^3\right)}{\sum_{i=1}^{n} t_i}$$

where d is the average detection zone of 0.5 mile.

The time a vehicle traverses the detection zone is not directly measured by the loop detection system. The travel time can be computed as $t_i = \dfrac{d}{v_i^x}$, where v_i^x is the instantaneous speed obtained of vehicle i from detector x. The relationship for space mean speed becomes

$$\bar{u}_{SMS} = \frac{d\left(n^1 + n^2 + n^3\right)}{d\left(\displaystyle\sum_{i=1}^{n}\frac{1}{v_i^x}\right)} = \frac{\displaystyle\sum_{x=1}^{3} n^x}{\displaystyle\sum_{i=1}^{n}\frac{1}{v_i^x}}$$

The above equation is the harmonic mean of the individual speeds obtained from the three loop detectors. The harmonic mean of the instantaneous spot speeds, given the assumption that each vehicle progresses at the detected speed over the entire length of the "effective" detection zone, is the space mean speed. If the distances between the detectors vary, the individual "effective" distances can weight the harmonic mean; however, this is beyond the scope of this work.

The loop density is computed using a procedure described in May (1990):

$$k = \frac{52.8}{\bar{L}_V + L_D}(\%OCC)$$

$\bar{L}_V$ is the average vehicle length in feet, and L_D is the distance between the two trap loop detectors in feet. The average vehicle length was assumed to be 18 feet and the detection zone as 6 feet. These parameters could also be calibrated from other data sources.

5.4.5 Loop Implementation

The procedure outlined in Section 5.4.4 was applied to the San Antonio loop data to obtain space mean speeds comparable to the AVI space mean speeds. The peak period and time window are consistent with the AVI implementation outlined in Section 5.3.2. The harmonic mean of the 20-second average field data is obtained. The San Antonio data is limited to a 20-second aggregation; individual speed measurements cannot be obtained. The number of 20-second measurement periods within the time window is obtained. Typically a loop detector in one of the three lanes is not operational for one or more 20-second reporting periods. The volume counts are summed for all lanes and percent occupancies are averaged.

The loop data is directed to a spreadsheet for side-by-side comparison with AVI data. The harmonic mean of the 20-second arithmetic average data for each loop detector is plotted with the AVI data. A single space mean average from the three loop detectors is obtained as follows:

$$\bar{u}_{Link} = \frac{\displaystyle\sum_{x=1}^{3} N^x}{\displaystyle\sum_{x=1}^{3}\frac{N^x}{\bar{u}_{harmonic}^x}}$$

where $\bar{u}^x_{harmonic}$ are the harmonic means of the 20-second aggregate data at loop x and N^x is the number of 20-second periods included in the computation of the harmonic mean. The $\bar{u}_{Link}$ estimation from loop data is the best single number available for comparison to the direct space mean speed measurement from the AVI system. The $\bar{u}_{Link}$ value is subject to the limitation that one arithmetic average (time mean) speed measurement is obtained for a 20-second period from the individual spot speed measurements. This speed is assumed to be the prevailing speed over an "effective" detection zone for the loop detector.

5.4.6 Results and Discussion

The AVI system determines the space mean speed of the probe vehicles across a fixed length by tracking the movements of individual vehicles. A loop detection system determines the arithmetic time mean average of instantaneous vehicle speed measurements at a fixed location. The AVI system has the uncommon ability to compute the average space mean speed for a group of vehicle trajectories, as outlined in Section 5.4.2. The arithmetic mean of the spot speeds is the time mean speed from the loop detector data. The harmonic mean of the spot speeds from the loop detector is the space mean speed from the vehicles passing the fixed location of the loop detector given the assumptions presented in Section 5.4.5.

Figure 5.20 presents results of the comparison of AVI and loop space mean speed results for Link 7 on September 25, 2000. The morning peak period was studied using a 15-minute average window, as described in Section 5.4.2.
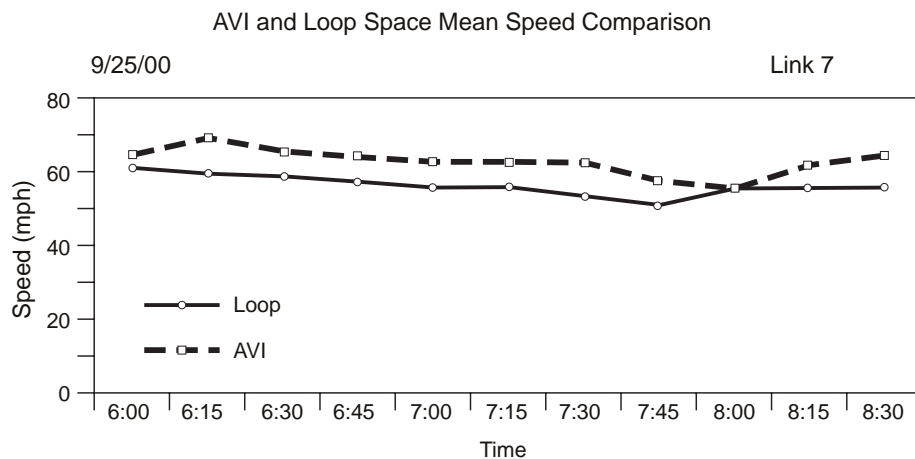
Figure 5.20 AVI and Loop Space Mean Speed Comparison

It is important to keep the context and assumptions in mind when comparing the two speed measurements. The speed measurements obtained from the loop detectors are based on space mean estimates from point data. The AVI speed was obtained as the direct computation of the space mean speed, based on Edie's definitions, from a fraction of the population that is tagged. Therefore, it is possible that the space mean speed from the AVI

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system can be greater than the loop space mean speed estimate. The probe vehicles are only a small fraction of the total vehicles that are used for the loop detector speed estimate.

The definitions presented by Edie are relatively easy to apply to the AVI data; the nature of the detection system is natural for measuring space mean speeds. Proper definitions are applied to the loop data for approximating space mean speed measurements given some limitations. The application of Edie's definitions to the loop data is more difficult considering the 20-second aggregation of the field data from San Antonio local control units. Additional study of how probe-based and link-based measurements can be properly compared is necessary. The procedure outlined in this work is suitable for a basic comparison and assessment of the AVI speed data for use in ATIS applications.

5.5 DATA ANALYSIS AND QUALITY CONCLUSIONS

In the preceding chapter, the source and nature of the raw San Antonio data were identified. A comparison of the raw data structure was made with data from Houston, Texas. The methods used to process the raw data into useable matched data were introduced, as well as some of the limitations of the San Antonio AVI data. The traffic state descriptors were defined and implemented for both AVI and loop data analysis. The limitations and implementation of the methods for computing speed data from the two detection systems were presented. The evaluation of the San Antonio AVI system uses the results from this analysis to assess the quality of AVI data for use in ATIS applications. Chapter 8 contributes to this effort by investigating the tagged vehicle penetration.

CHAPTER 6 INCIDENT DETECTION METHODOLOGY

Having described the study corridor and the data available in the previous chapter, this chapter introduces the methodology followed in conducting the experiments for this study. The standard steps developed to prepare the traffic and incident data, calibrate the chosen algorithms, and, finally, test the algorithms are presented hereafter.

Section 6.1 presents the algorithms chosen for calibration and testing. Section 6.2 describes the traffic and incident data sets used to calibrate and test the algorithms respectively. Section 6.3 describes the methodology followed in testing the algorithms. Finally, Section 6.4 describes the methodology implemented to conduct the calibration of the loop and Automatic Vehicle Identification (AVI) algorithms.

6.1 ALGORITHM SELECTION

The literature reviewed showed that extensive research went into the development and refinement of Automatic Incident Detection (AID) algorithms taking loop detector data as input. Although some AVI algorithms have been proposed, they are still in their early phases of development. Moreover, very little testing has been reported using actual, not simulated, AVI data. It is not within the scope of this research to evaluate the performance of all the detection logics presented in Chapter 3. A representative subset was selected for calibration and testing with data collected from TransGuide. The most important requirement considered in selecting an algorithm was the ability to implement the detection logic in real-time as data is received by the Traffic Management Center (TMC). Also, the detection logic had to be published and preferably tested.

6.1.1 Loop Algorithms

Two fixed detector algorithms were selected for calibration and testing, the California #8 algorithm and the Texas algorithm.

6.1.1.1 California #8 Peterman (1999) studied the performance of different loop AID algorithms using data collected from the San Antonio network. The study was intended to compare the relative performance of the California #8 algorithm, the McMaster algorithm, the Minnesota DELOS algorithm, and the Texas algorithm. Results showed that the California #8 algorithm was able to detect more incidents than the other algorithms considered, regardless of incident type. Although the described research made use of data collected from a previous time period and from other sections of the San Antonio network than the segment considered in this research, it is interesting to examine the transferability of the California #8 algorithm across time and space. Furthermore, the California #8 algorithm is used in various traffic management centers across the nation and often times constitutes a benchmark against which the performance of many other algorithms is measured. The algorithm logic described in detail in Section 3.2.1.1 is essentially a decision tree examining traffic measurements (OCC[i,t], DOCC[i,t], OCCDF[i,t], DOCCTD[i,t]) determined after

manipulating the occupancy values reported from Inductive Loop Detectors (ILDs). These traffic measurements were defined in Table 3.1.

The California #8 algorithm makes use of five different threshold values referred to as T1 through T6. The T1 threshold corresponds to a maximum value of the spatial occupancy difference (OCCDF) variable under normal conditions. The T2 threshold corresponds to a maximum value of the temporal difference in downstream occupancy (DOCCTD) variable under normal conditions. The T3 threshold corresponds to a maximum value of the relative spatial difference in occupancy (OCCDRF) variable under normal conditions. The T4 threshold corresponds to a maximum value of the downstream occupancy (DOCC) variable and is used to signal a tentative incident. Like the T4 threshold, the T5 threshold corresponds to a maximum value of the downstream occupancy (DOCC) variable but is used to detect compression waves.

As reported in Chapter 3, Payne (1976) developed a total of ten refined versions of the original California algorithm, the most efficient of which was the California #8 algorithm. Payne reported obtaining the best performance using a combination of five threshold sets presented in Table 6.1.

Table 6.1 Optimal Threshold Set for California #8 Algorithm (Payne et al. 1976)

T1	T2	T3	T4	T5	DR (%)	FAR (%)
10.2	-0.433	0.312	28.8	30	61	0.177
13.1	-0.296	0.309	16.9	30	51	0.038
18.1	-0.310	0.356	18.5	30	41	0.024
6.2	-0.401	0.590	27.9	30	31	0.010
24.4	-0.392	0.579	13.0	30	20	0.003

6.1.1.2 The Texas Algorithm The incident detection logic adopted in the Texas algorithm is straightforward and was detailed in Section 3.2.1.2. If the value of a traffic variable falls below a predetermined threshold value, an incident is detected. Usually, occupancy values are used and the threshold is set to a value near 37 percent (Peterman 1999). Unlike the California #8 algorithm that uses data from a pair of upstream and downstream detectors, the Texas algorithm uses data from a single detector.

The Texas algorithm is implemented considering mean occupancy values aggregated over a 3-minute rolling window. The algorithm starts by averaging the 20-second averages received at the TMC over 1-minute periods and then 3-minute averages are produced using three values of the 1-minute averages. Usually the Texas algorithm is implemented using section averages; however, this research will consider data collected from individual lanes.

6.1.2 AVI Algorithms

Two probe vehicle algorithms were selected for calibration and testing, the Confidence Limit algorithm proposed by Hellinga and Knapp (1999) and the Texas

algorithm. However, these algorithms were refined in such a way as to optimize their performance when applied to the network under consideration.

6.1.2.1 The Confidence Limit Algorithm   The Confidence Limit algorithm was presented in detail under Section 3.3.1.1 of Chapter 3. The algorithm logic calls for maintaining a temporally rolling average of travel times for each segment. The rolling window was divided into aggregation intervals and a mean travel time was determined for each segment by averaging individual vehicle's travel times over the aggregation intervals and then averaging the aggregation intervals' mean travel times over the comparison window. However, in the implemented algorithm, averaging was done based on the occurrence of a number of events (*n*) rather than on a time interval basis. An event is defined as a tagged vehicle detected at a link's upstream and downstream detectors. This decision was made due to the low level of tagged vehicles' market penetration experienced in the San Antonio network. By averaging the mean interval travel times of the aggregation intervals, one would be assigning an equal weight to the mean travel time of all aggregation intervals within the rolling window, irrespective of the number of events experienced during each aggregation interval. Using the logic developed by Hellinga and Knapp, an aggregation interval for which one travel time value was generated would be assigned an equal weight as an aggregation interval for which many values were generated, thus destabilizing the resulting rolling window mean travel time.

Each time a tagged vehicle is matched at the upstream and downstream detectors of a link, a travel time value is generated and included along with that link's last (*n - 1*) travel time values in the calculation of the link rolling window average travel time. Travel time values are obtained by subtracting the time a tagged vehicle passes the downstream detector of a link from the time that same tagged vehicle passed the upstream detector of that same link. Mean travel times for the comparison window are generated using Equation 6.1.

$$\bar{\tau}_i = \frac{1}{n} \sum_{j=1}^{n} \tau_j \qquad\qquad (Eq.6.1)$$

Where i = segment reference,
j = event reference,
$\qquad n$ = number of events considered for the rolling average, and
τ_j = segment travel time generated from event j.

The original Confidence Limit algorithm attempts to determine an upper confidence limit for the mean segment travel time of the interval following the comparison window by computing the lognormal mean and the lognormal variance of the mean interval travel times contained within the comparison window, thus assuming that the mean interval travel times are lognormally distributed. The implemented algorithm attempts to determine an upper confidence limit for the expected value of a segment travel time following the events included in the comparison window. This modification of the original logic causes the algorithm to execute each time an event occurs rather than executing at the end of an

aggregation time interval. This is perfectly feasible with the tagged-vehicle headways experienced on the network under the current levels of market penetration.

In order to determine expected link travel times, link travel time data was processed to determine the statistical distribution that describes it best. Figure 6.1 shows typical a.m. travel times experienced on Link 1.
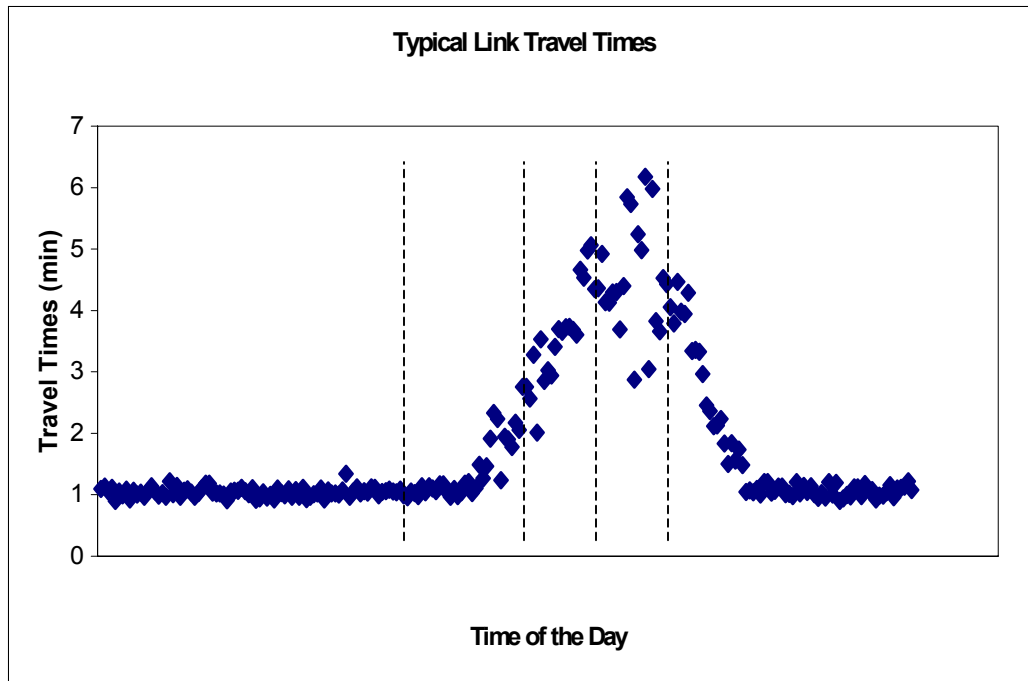
Figure 6.1 Typical A.M. Travel Times Experienced on Link 1

The data plot reveals two different regimes during the a.m. peak period: normal conditions (phase 1 in Figure 6.1) and congested conditions (phase 2 through 4 in Figure 6.1). Before and after congestion, the travel time values on Link 1, are close to 1 minute. Travel time values increase up to a value of 6.2 minutes at the peak of the congestion. When trying to fit a statistical distribution to all the a.m. link travel times recorded, it was found that no statistical distribution was adequate to represent the data due to the qualitative difference in travel times exhibited between normal and congested conditions. Therefore, attention was turned into investigating each phase separately. Six different distributions were investigated for each phase: gamma, lognormal, negative exponential, normal, shifted negative exponential, and uniform. For the uncongested regime, the gamma distribution performed best followed by the lognormal distribution. Both distributions are depicted against the observed travel times in Figure 6.2.
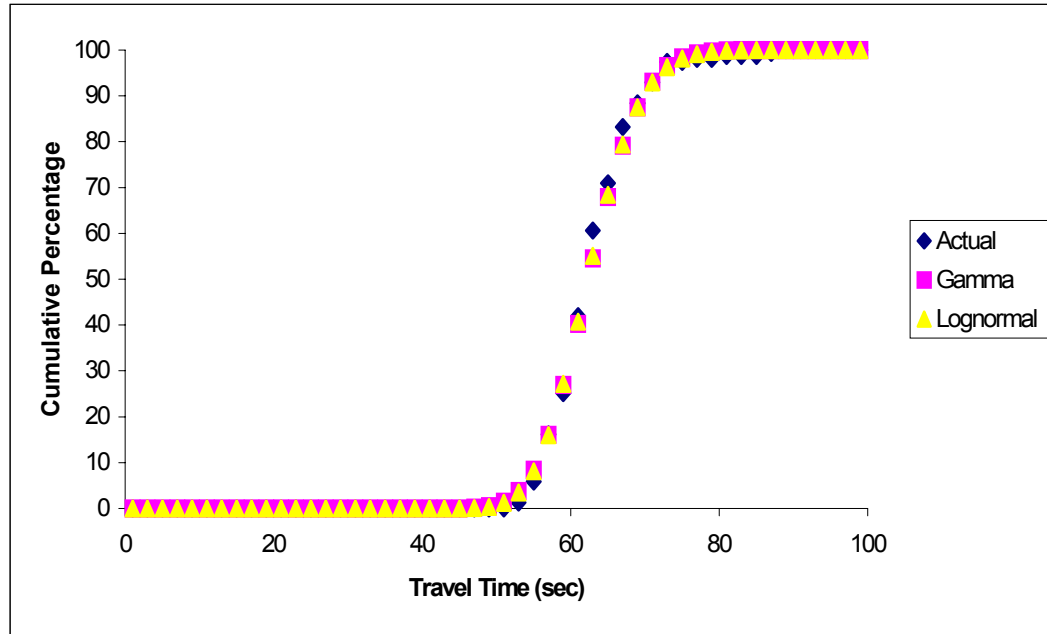
Figure 6.2 Link 1 Uncongested: Actual versus Gamma and Lognormal

The congested regime has been further subdivided into three phases: congestion buildup (2), congestion peak (3), and recovery (4). For the congestion buildup phase, the normal distribution performed best followed by the lognormal and the gamma distributions. When considering the peak of the congestion phase, the lognormal distribution gave the closest representation of the actual travel times. The gamma distribution was second best. Finally, for the recovery phase, the lognormal distribution performed best followed by the gamma distribution. Figures 6.3 through 6.5 present a plot of the best-performing distributions versus actual travel time data for the congestion builtup, congestion peak, and recovery phases respectively.
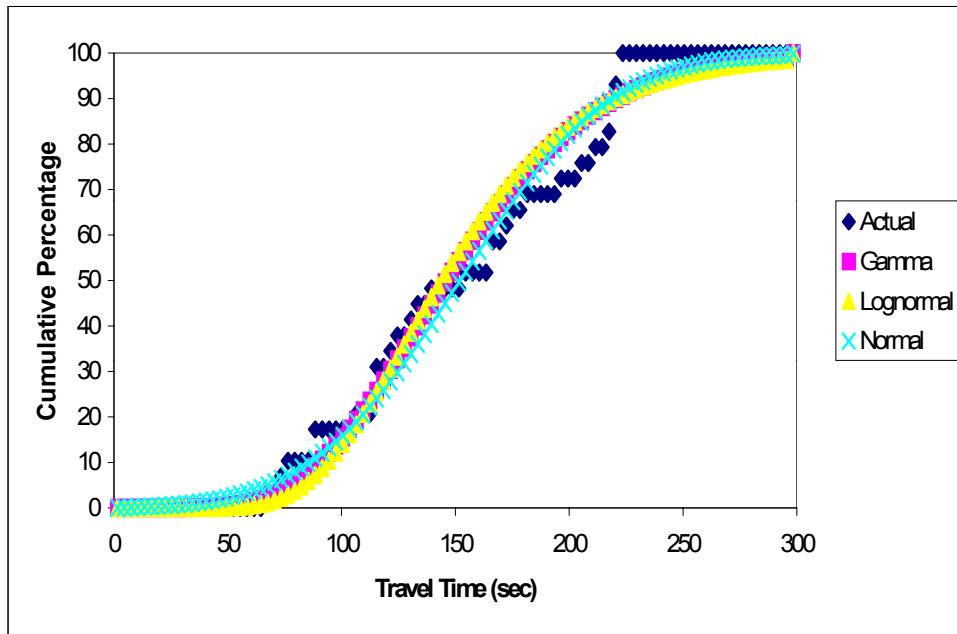
Figure 6.3 Link 1 Congestion Buildup: Actual versus Gamma and Lognormal
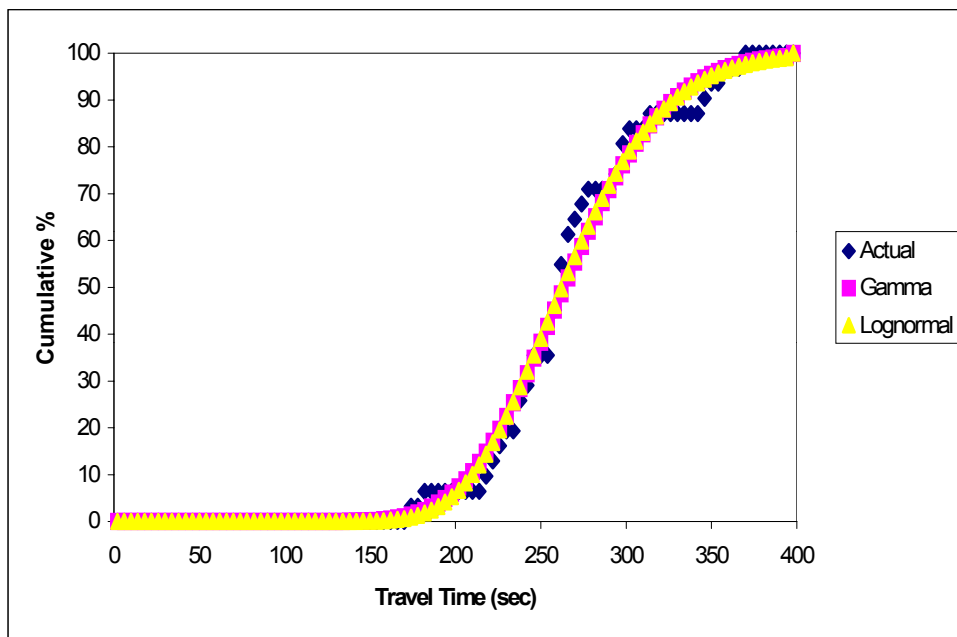
Figure 6.4 Link 1 Congestion Peak: Actual versus Gamma and Lognormal

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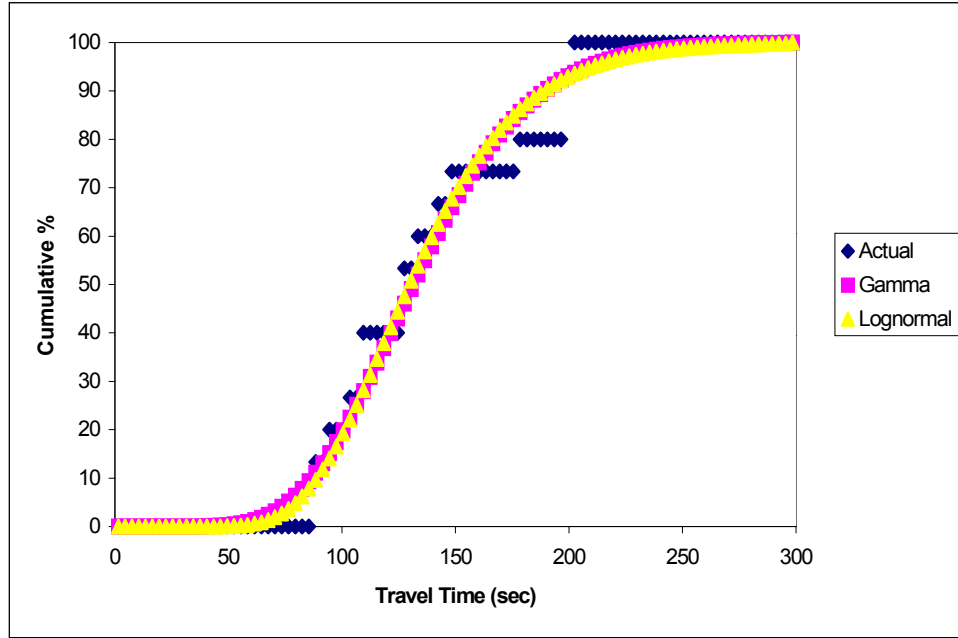
Figure 6.5 Link 1 Recovery Phase A.M. Travel Times: Actual versus. Gamma and
Lognormal

Results show that although the lognormal distribution did not perform best for all of
the described phases, it adequately represents actual travel times experienced. Having
verified Hellinga's assumption that the link travel times can be satisfactorily represented by a
lognormal distribution, the lognormal mean and variance of each link travel time are
calculated using the lognormal mean and variance equations presented in Chapter 3. The
upper confidence limit for each link's travel time is determined next using Equation 6.2.

$$UL = e^{(\mu+z\sigma)} \qquad\qquad \text{(Eq. 6.2)}$$

where μ = lognormal mean of the link's travel time,
z = level of confidence, and
σ = lognormal variance of the link's travel time.

The value of the travel time generated from the event following the (n) events
contained within the comparison window is compared to the computed upper confidence
limit for the link's travel time. If the current travel time exceeds the upper confidence limit,
an incident alarm is generated.

6.1.2.2 The Texas Algorithm   A variant of the Texas algorithm is currently being
applied at TransGuide and provides a benchmark against which the performance of other
AVI algorithms can be evaluated. When used with AVI-generated data, probe vehicle speeds
are used as input to the algorithm. The speed of each tagged vehicle traversing a link is
compared to a fixed speed threshold. If the speed of the tagged vehicle falls below the
threshold value, an incident alarm is generated.

6.2 CALIBRATION AND TESTING DATA SETS

Different data sets are required to calibrate and test the algorithms. While the calibration data set is intended to determine optimal thresholds, the testing data set is intended to evaluate the optimal thresholds determined from the calibration phase and test their transferability from one situation to the other.

The initial incident data set consisted of 73 incidents, the majority of which were labeled as congestion. Refer to Table 4.3 for a breakdown of incidents according to type.

For seven of the congestion incidents in the database, loop data from the relevant detector pairs was not available. Therefore, these incidents were not considered in calibrating and testing the loop algorithms. Of the remaining sixty-five incidents in the database, twenty-one were selected for calibration. The sample consisted of four major accidents, three minor accidents, and fourteen congestion incidents. The remaining forty-four incidents in the database were used to test the loop algorithms. The testing sample consisted of seven major accidents, six minor accidents, twenty-nine congestion incidents, and two stalls.

The same incident sample used to calibrate the loop algorithms was used to calibrate the AVI algorithms. However, the seven incidents that were not considered in the testing of the loop detectors for lack of traffic data were included in the testing of the AVI algorithms, raising the total number of incidents in the AVI algorithm-testing database to fifty-one. Out of the fifty-one incidents, ten were labeled as major accidents, six as minor accidents, thirty-two as congestion, and three as stalls.

For calibration purposes, traffic data included only those locations and peak periods of days where incidents occurred. However, when testing the algorithms, traffic data included both the a.m. and p.m. peak periods from everyday of the time span considered for the research except those considered for calibration. This was necessary in order to determine false alarm rate (FAR) and time to detect (TTD).

6.3 TESTING METHODOLOGY

The steps followed in testing an algorithm and evaluating its performance are illustrated in Figure 6.6. In order to execute, an algorithm requires traffic data and a threshold combination as input. The algorithm generates incident alarms associated with the threshold combination used. Also, the algorithm maintains a count of the number of tests it performs on the traffic data. Those algorithm-generated incident alarms are used in conjunction with entries in the incident database as input to the evaluation algorithm. The evaluation algorithm loops through all the incidents in the incident database comparing the algorithm-generated alarms for a given set of thresholds to each entry in the incident database. If the algorithm-generated alarm corresponds to an entry in the incident database, the evaluation algorithm increments accordingly the counter for the number of incidents properly detected of that type or the number of false alarms for that threshold combination. In calibrating and testing the different algorithms, an incident alarm generated by an algorithm is considered to be correct if the following set of rules apply:

- The date of the alarm matched the date of the incident record in the incident database.
- The location of the alarm matched the location of the incident record in the incident database.
- The time of the incident alarm is not earlier than 10 minutes prior to the reported incident start time and not greater than the reported incident end time in the incident database.

Incidents are recorded in the incident log at TransGuide as soon as they are detected. The 10-minute window was set to account for the typical difference between the time an accident actually happens and the time it was recorded in the incident log. The evaluation algorithm is set to detect multiple algorithm-generated alarms corresponding to the same entry in the incident database and removes duplicates in order to obtain accurate measures of performance. The sequence of events that constitute the evaluation function is presented in Figure 6.7. The same sequence of events repeats itself until all combinations of thresholds are tested and counts of incidents detected by type, as well as false alarm counts resulting from each threshold combination are generated. Those counts are used in determining the detection rate (DR) and FAR for each combination of thresholds.
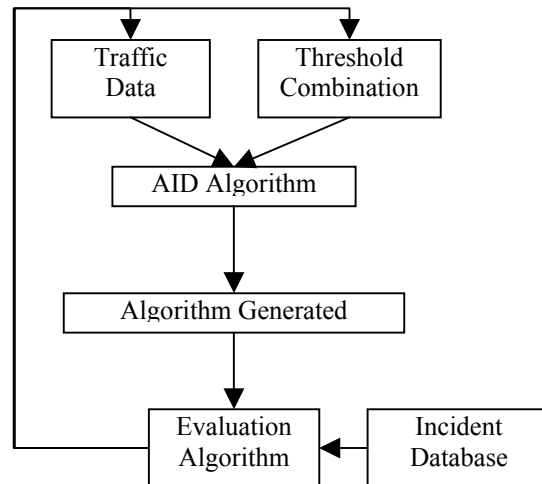
Figure 6.6 Detection Algorithm Execution Flowchart
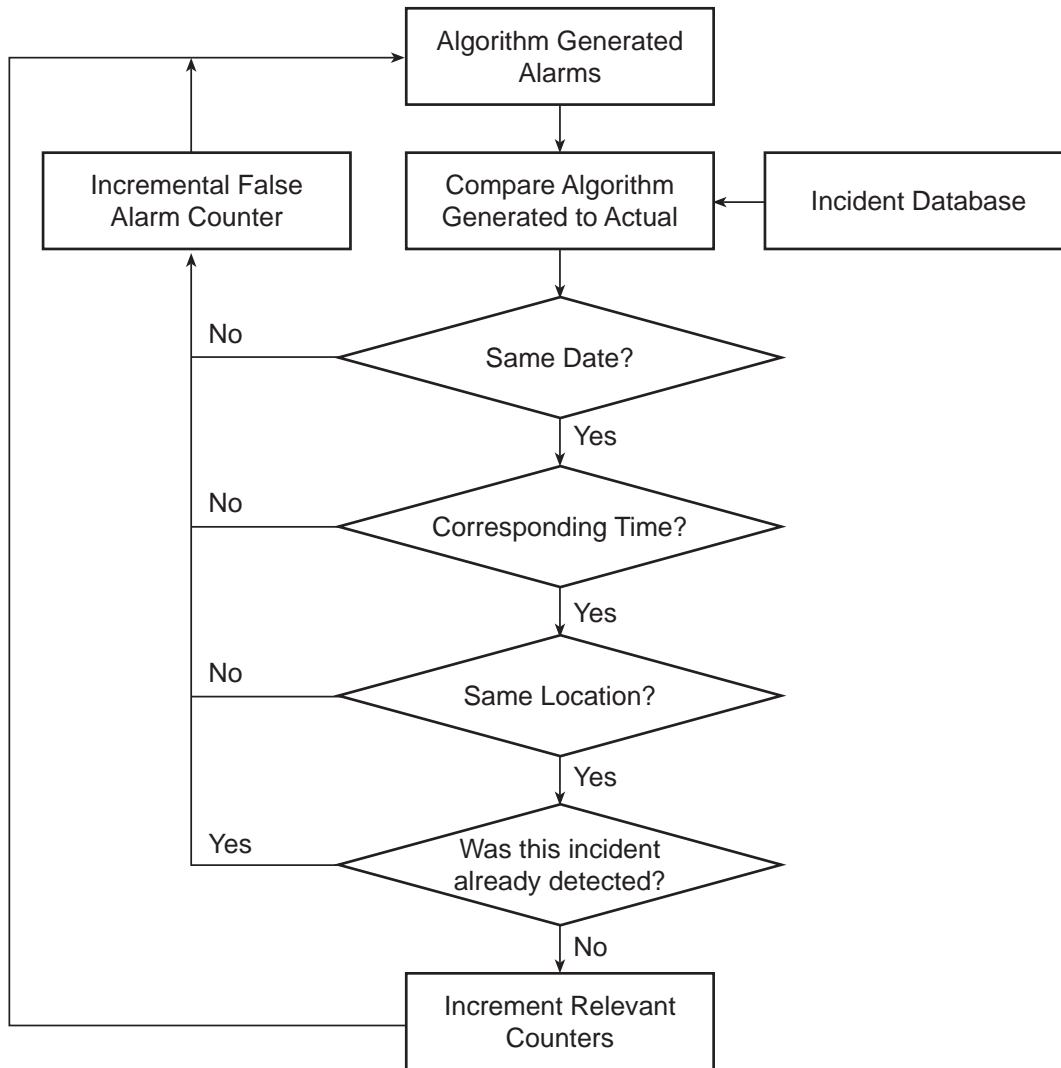
Figure 6.7 Evaluation Algorithm Flowchart

6.4 CALIBRATION METHODOLOGY

The performance of an algorithm in terms of DR, FAR, and TTD varies according to the threshold combination used. When calibrating an algorithm, the DR is plotted versus the FAR for various combinations of thresholds in order to determine the algorithm's "efficient frontier" or the "pareto-optimal" set of thresholds that produce maximum detection for given FARs. Refer to Figure 6.8 for an example of "pareto-optimal" threshold determination.
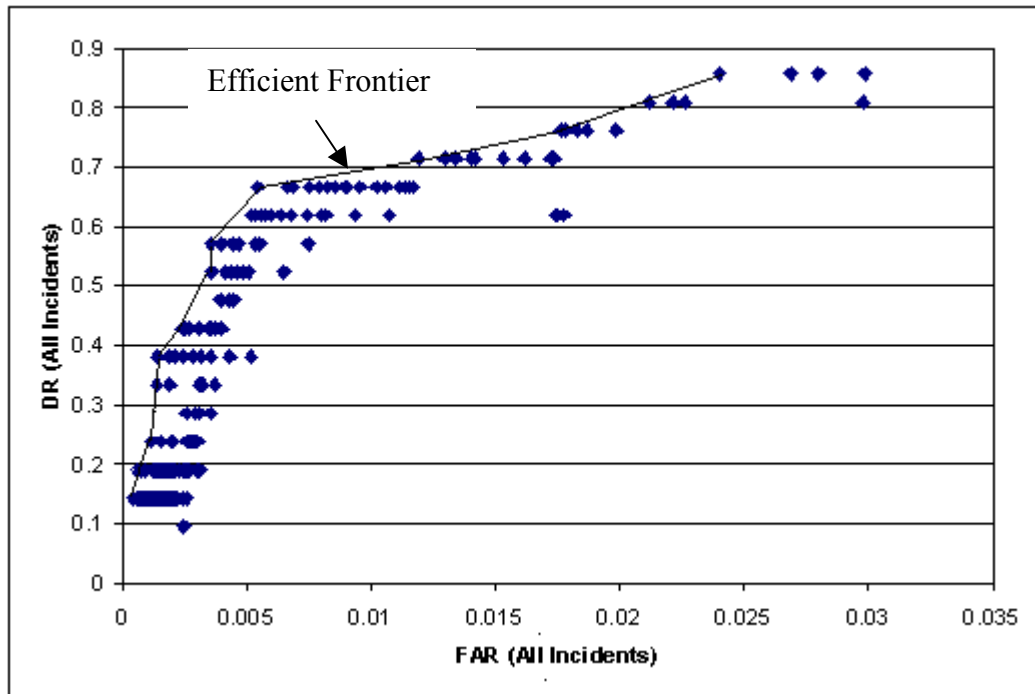
Figure 6.8 "Pareto-Optimal" Thresholds Determination for the California #8 Algorithm

The algorithm chosen for calibration and testing requires either a combination of thresholds (California #8 and Upper Confidence Limit) or a single threshold value (Texas algorithm). The DR and the FAR obtained from each threshold value or combination of thresholds are plotted against each other and points falling along the algorithm's apparent efficient frontier are identified. Those points represent the algorithm's best performance and are used to rate the performance of the algorithms against each other.

6.4.1. Loop Algorithms

A Monte Carlo simulation was developed to generate possible combinations of thresholds for the California #8 algorithm based on a uniform distribution over a range of possible threshold values determined from the literature (Peterman 1999). The California #8 algorithm uses five different thresholds described in Section 6.1.1.1. Three hundred different threshold combinations were generated using the Monte Carlo simulation. Limits for the ranges of values that each one of the five thresholds can take were identified from the literature and are summarized in Table 6.2.

Table 6.2 Threshold Limits for the California #8 Algorithm

Threshold	Minimum Value	Maximum Value
T1 (OCCDF)	5	30
T2 (DOCCTD)	-1	0
T3 (OCCRDF)	0.1	0.8
T4 (DOCC1)	10	30
T5 (DOCC2)	20	30

The Texas algorithm was relatively easy to calibrate due to the fact that it requires only one parameter, namely an occupancy value. Occupancy values ranging from 5 percent to 50 percent were used in the calibration process in increments of 1 percent.

6.4.2 AVI Algorithms

The Confidence Limit algorithm was tested with varying values of level of confidence (z) and of the number of events contained in the comparison window (n). Levels of confidence values ranging between 2 and 6 standard deviations were tested in increments of 0.6. Each value of (z) was tested using values of (n) ranging between 4 and 8 in increments of 1 resulting in a total of 45 threshold combinations.

The Texas algorithm is currently being used in TransGuide with a speed threshold of 30 mph. The algorithm was calibrated with all integer values of speed ranging from 5 to 50 mph.

Chapter 6 presented the algorithms chosen for calibration and testing along with the method used to prepare the traffic and incident data. Also, the chapter detailed the standard steps used in calibrating and testing the selected algorithms. Results of the calibration and testing processes for each algorithm are presented in Chapter 7.

CHAPTER 7 CALIBRATION AND TESTING RESULTS

The procedures detailed in the previous chapter were applied to test and calibrate the California #8 algorithm, the Upper Confidence Limit algorithm, and the Texas algorithm. The current chapter describes the results of the calibration and testing phases respectively. Section 7.1 presents the results of the calibration phase aimed at "training" the algorithms to produce "pareto-optimal" threshold values associated with superior algorithm performance. Section 7.2 presents the results of the testing phase aimed at examining the transferability of the best-performing threshold values determined from calibration to a different data set. "Pareto-optimal" thresholds were determined to maximize the performance of the algorithms in detecting both all incidents and accidents only (major and minor). While a total of twenty-one incidents were used in the calibration phase, totals of forty-four and fifty-one other incidents, respectively, were used to test the loop algorithms and the Automatic Vehicle Identification (AVI) algorithms. The three measures of performance described in Chapter 3, namely the detection rate (DR), the false alarm rate (FAR), and mean time-to-detect (TTD), are used to evaluate the performance of the automatic incident detection (AID) algorithms.

7.1 CALIBRATION RESULTS

Possible threshold values and combinations were generated for each algorithm based on ranges identified from the literature. The DR was plotted against the FAR for each threshold value or combination in order to determine the algorithm "efficient frontier" or the "pareto-optimal" set of thresholds. The steps followed in the calibration phase were detailed in Section 5.4. The results of the calibration phase are presented next starting with the loop algorithms.

7.1.1 Loop Algorithms Calibration Results

The loop algorithms were calibrated and tested using the loop data obtained from TransGuide. At its finest resolution, the data was available in 20-second intervals and was filtered prior to its use with the algorithms to eliminate the errors described in Chapter 4.

7.1.1.1 California #8 All 300 threshold value combinations obtained from the Monte Carlo simulation were tested. Two sets of "pareto-optimal" thresholds were determined, one for detecting all incidents and the other for detecting accidents only.

Figure 7.1 illustrates the performance of the California #8 algorithm in detecting all types of incidents (accident, congestion, and stall). Moreover, this figure illustrates the typical trade-off observed between DR and FAR for any automatic incident detection algorithm. In order to achieve high detection rates, the algorithm must be tuned to detect the lowest traffic fluctuations, thus resulting in high levels of false alarms. On the other hand, when the incident is tuned to detect only severe traffic fluctuations, the resulting false alarms are reduced at the expenses of the detection rate.
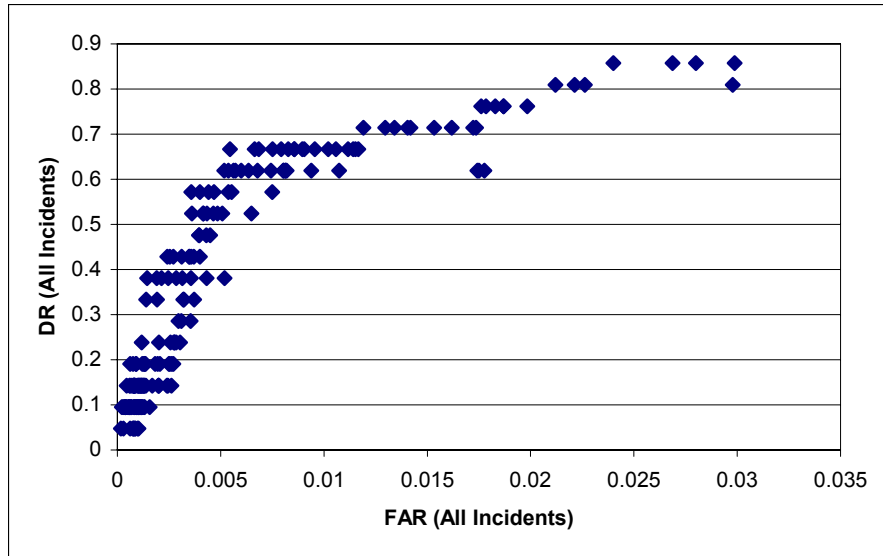
Figure 7.1 DR and FAR Trade-Off Curve for the California #8 Algorithm

Each data point on Figure 7.1 represents the performance of the algorithm for a particular combination of thresholds. The performance of the algorithms in terms of the DR and FAR depends on the threshold values used. Therefore, it is important to examine how the performance of the algorithm varies with respect to each one of the five thresholds, T1 through T5. Figures 7.2 through 7.6 depict the variation of the DR and FAR as a result of changing the thresholds T1, T2, T3, T4, and T5, respectively. If a trend in algorithm performance with respect to each one of the five thresholds can be observed, then the values of the thresholds can be chosen depending on the system objectives in terms of the DR and FAR.
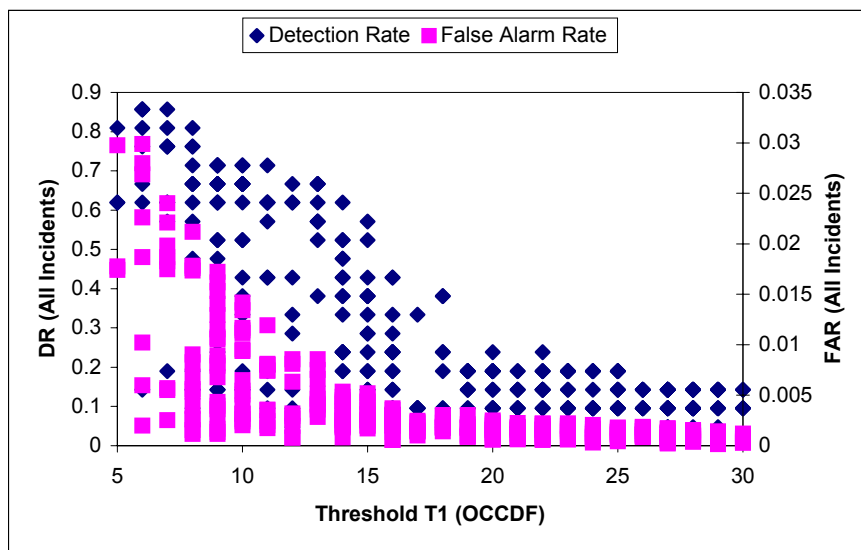
Figure 7.2 DR and FAR versus T1
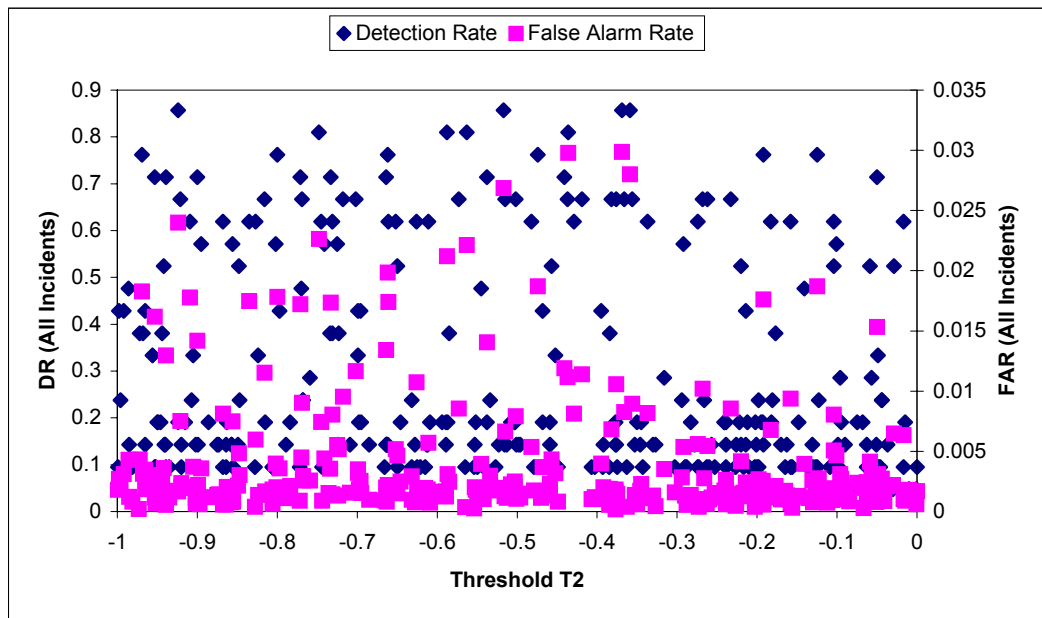
Figure 7.3 DR and FAR versus T2
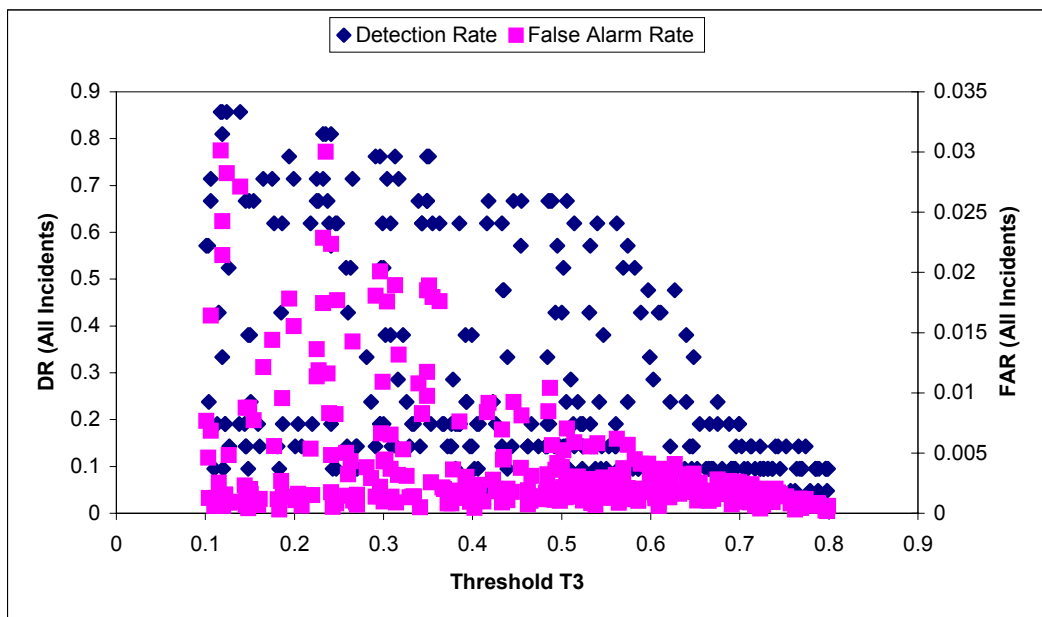
Figure 7.4 DR and FAR versus T3

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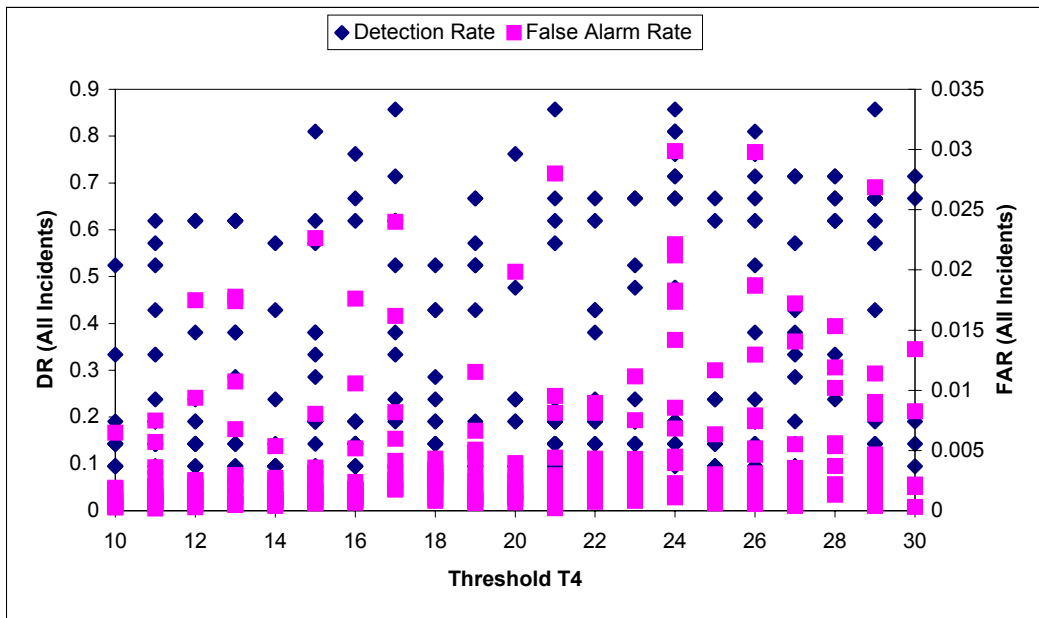
Figure 7.5. DR and FAR versus T4
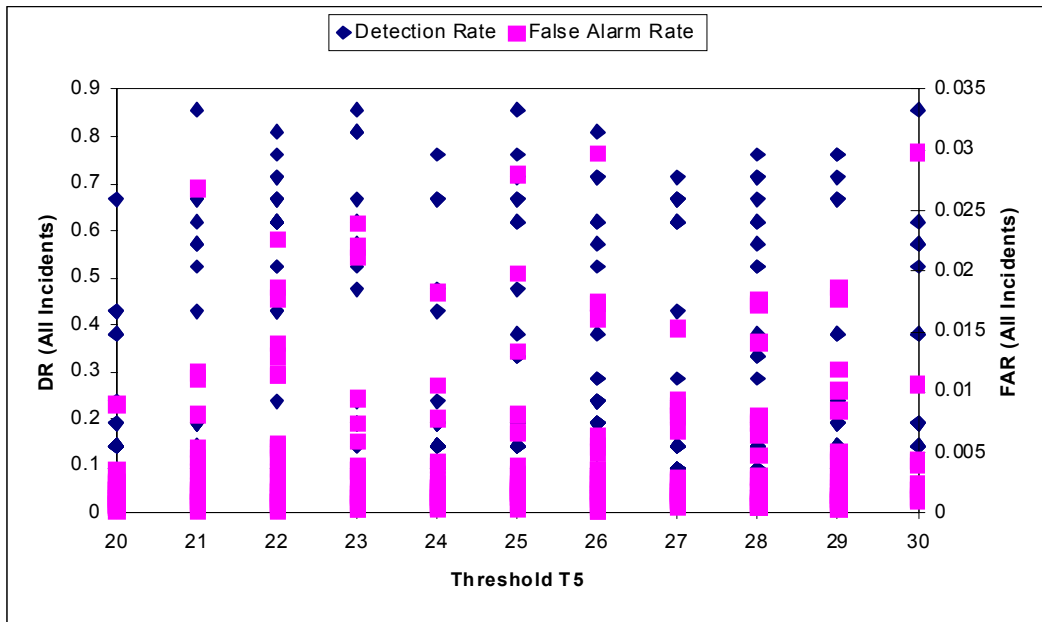
Figure 7.6 DR and FAR versus T5

By observing Figures 7.2 through 7.5, it is evident that the performance of the California #8 algorithm depends to the largest extent on the value of threshold T1. As the critical spatial occupancy difference (OCCDF) increases, the DR and FAR decreases. Moreover, the DR and FAR decreases rapidly for values of OCCDF greater than 20 and at a much slower rate for values ranging between 20 and 30. The calibration process did not

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reveal similar trends for the rest of the five thresholds. When considered individually, thresholds T2 through T4 did not seem to significantly affect the performance of the algorithm.

The average TTD incidents is defined as the difference between the time an incident was entered in the incident database and the time of the corresponding incident alarm generated by the algorithm. The inherent inaccuracies in reporting incident start and end times in the incident reports make TTD an imprecise measure of algorithm performance. Therefore, the DR and the FAR are relied on in comparing the performance of the algorithms. The performance of the California #8 algorithm in terms of TTD is illustrated in Figure 7.7.
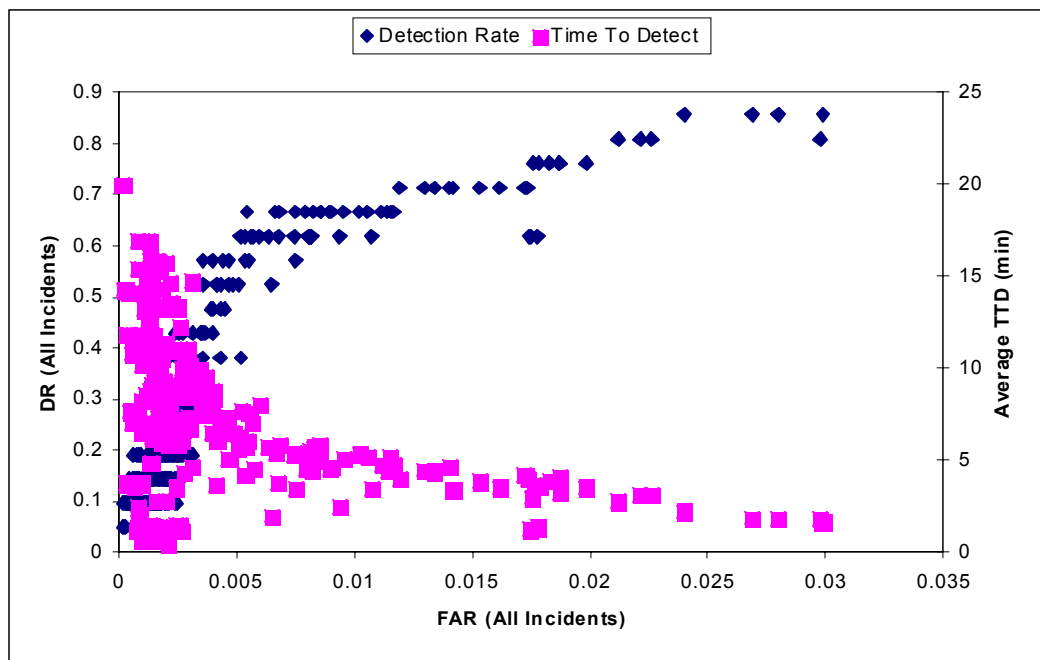
Figure 7.7 DR and TTD versus FAR, California #8 Algorithm

Figure 7.7 shows that in general, as the sensitivity of the algorithm to traffic variations increase, the DR and FAR increase, but the TTD decreases. That is, the algorithm will take more TTD incidents if tuned to detect only those incidents with severe repercussions on the flow of traffic. Negative TTD values indicate that incidents have been detected prior to their recorded start time in the incident report. This is possible since an algorithm-generated alarm is considered correct if it is within 10 minutes of the incident start time and the incident end time recorded in the incident report.

The calibration process resulted in the determination of "pareto-optimal" thresholds, or thresholds for which the performance in terms of the DR or FAR cannot be improved without negatively impacting the other. Two sets of "pareto-optimal" thresholds were determined, one for optimizing the detection of all incidents and the other for optimizing the

detection of accidents only. Some of the threshold combinations lie on the efficient frontier of the algorithm in detecting both all incidents and accidents only. Results indicate that the algorithm performed better in detecting all types of incidents rather than accidents only. The two sets of thresholds are presented with the associated performance measures in Tables 7.1 and 7.2 and are illustrated in Figure 7.8. Table 7.3 presents a breakdown of the incidents detected by type for the "pareto-optimal" sets of thresholds.

Table 7.1. All Incidents "Pareto-optimal" Thresholds, California #8 Algorithm

	T1	T2	T3	T4	T5	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	13	-0.652	0.218	16	22	267	13	0.619	0.0052	7.3
	10	-0.262	0.489	28	22	281	14	0.667	0.0054	7.0
	11	-0.441	0.165	28	29	615	15	0.714	0.0119	4.0
	8	-0.192	0.194	16	28	909	16	0.762	0.0176	3.7
	8	-0.588	0.119	24	23	1094	17	0.810	0.0212	2.7
	7	-0.924	0.119	17	23	1239	18	0.857	0.0240	2.2

Table 7.2. Accidents Only "Pareto-optimal" Thresholds, California #8 Algorithm

	T1	T2	T3	T4	T5	False Alarms	Accidents Detected	DR	FAR	Average TTD (min)
Accidents Only	19	-0.015	0.138	12	25	46	1	0.143	0.0009	-1.6
	17	-0.824	0.119	11	25	72	2	0.286	0.0015	4.0
	10	-0.968	0.64	15	26	162	3	0.429	0.0032	4.5
	8	-0.192	0.194	16	28	909	4	0.571	0.0178	3.2
	7	-0.924	0.119	17	23	1239	5	0.714	0.0243	-0.1
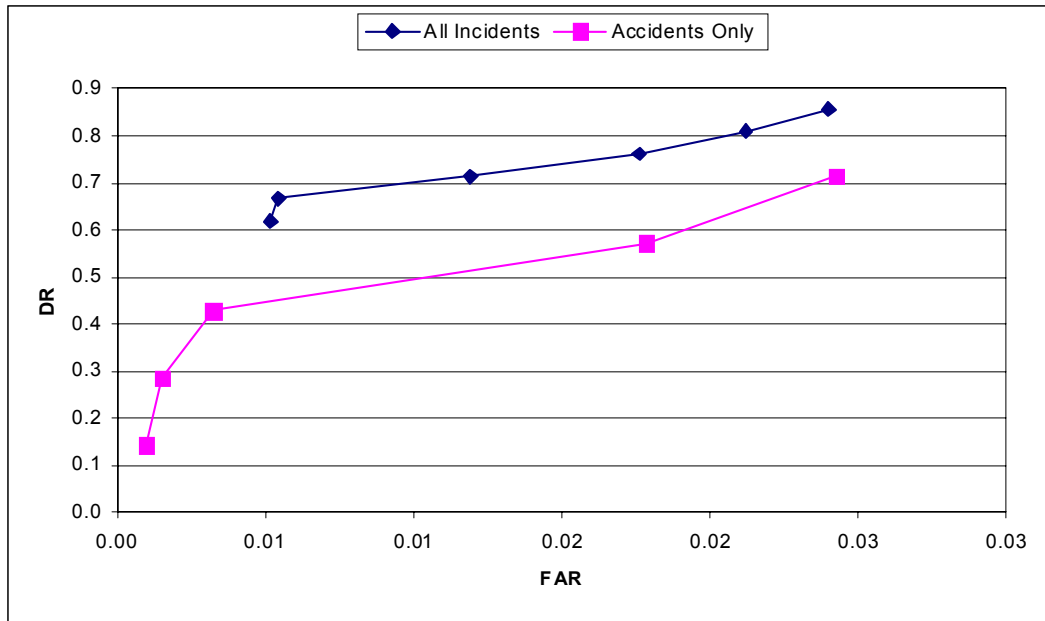
Figure 7.8. Efficient Frontiers for the California #8 Algorithm

Table 7.3. Breakdown of Incidents Detected by Type, California #8 Algorithm

	T1	T2	T3	T4	T5	Major Accidents	Minor Accidents	Congestion	Total
All Incidents	13	-0.652	0.218	16	22	2	1	10	13
	10	-0.262	0.489	28	22	2	1	11	14
	11	-0.441	0.165	28	29	2	1	12	15
	8	-0.192	0.194	16	28	3	1	12	16
	8	-0.588	0.119	24	23	3	1	13	17
	7	-0.924	0.119	17	23	3	2	13	18
Accidents Only	19	-0.015	0.138	12	25	0	1	3	4
	17	-0.824	0.119	11	25	1	1	5	7
	10	-0.968	0.64	15	26	2	1	5	8
	8	-0.192	0.194	16	28	3	1	12	16
	7	-0.924	0.119	17	23	3	2	13	18

Payne et al. (1976) studied the performance of the California #8 algorithm on data obtained from Los Angeles freeways. The incidents considered in this study included stall, accidents, gawking, and spills. The algorithm was able to achieve DRs of 61 percent or lower. In a similar study, Payne et al. (1976) evaluated the performance of the California #8 algorithm on data obtained from Minneapolis freeways. DRs of 80.6 percent or lower were achieved with corresponding FARs ranging from 0.002 to 0.4.

Peterman (1999) conducted a similar study on other sections of the San Antonio network. DRs of up to 99 percent were reported when considering all types of incidents with corresponding FARs ranging from 0.0309 to 0.0021. When considering accidents only, DRs of up to 100 percent were achieved with corresponding FARs ranging from 0.0298 to 0.002.

The results obtained in this study improve on the results obtained in both studies performed by Payne et al. (1976) in terms of the DR and FAR. However, although FARs obtained were lower than those reported by Peterman (1999), DRs were lower both when considering all incidents and when considering accidents only.

It is important to point out that DRs are readily comparable between studies because the number of incidents used in each study is well defined. However, FARs depend on the number of tests performed by the algorithm and, therefore, should only be used as a relative measure to compare the performance of algorithms tested within a study.

7.1.1.2 Texas Algorithm with Loop Data The calibration of the Texas algorithm was relatively simple due to the fact that only one threshold value is required. All occupancy values ranging between 5 percent and 50 percent were tested in increments of one. The tradeoff curve for the Texas algorithms is presented in Figure 7.9.
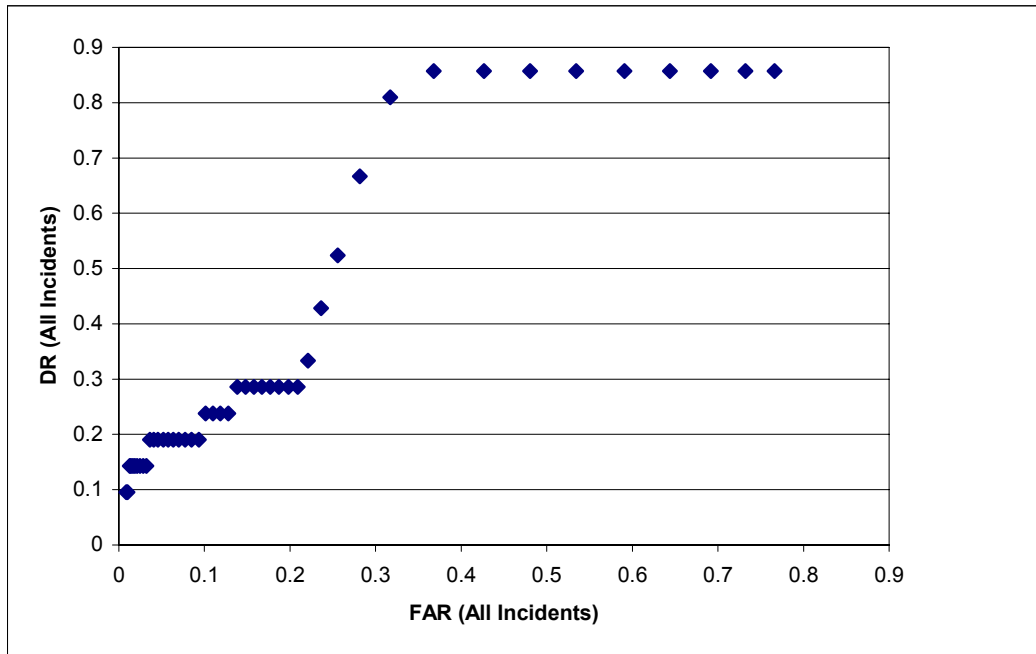
Figure 7.9 DR and FAR Trade-Off Curve for the Texas Algorithm Applied with Loop Data

The staggering exhibited by the data indicates that several values of the occupancy threshold gave the same results in terms of the DR but at different levels of FAR. The performance of the algorithm with respect to the occupancy threshold is illustrated in Figure 7.10. Figure 7.10 shows that both the DR and FAR decrease as the occupancy threshold increase. The TTD obtained from the Texas algorithm is depicted in Figure 7.11, which suggests that the algorithm exhibits similar tradeoffs in terms of TTD as the California #8 algorithm.

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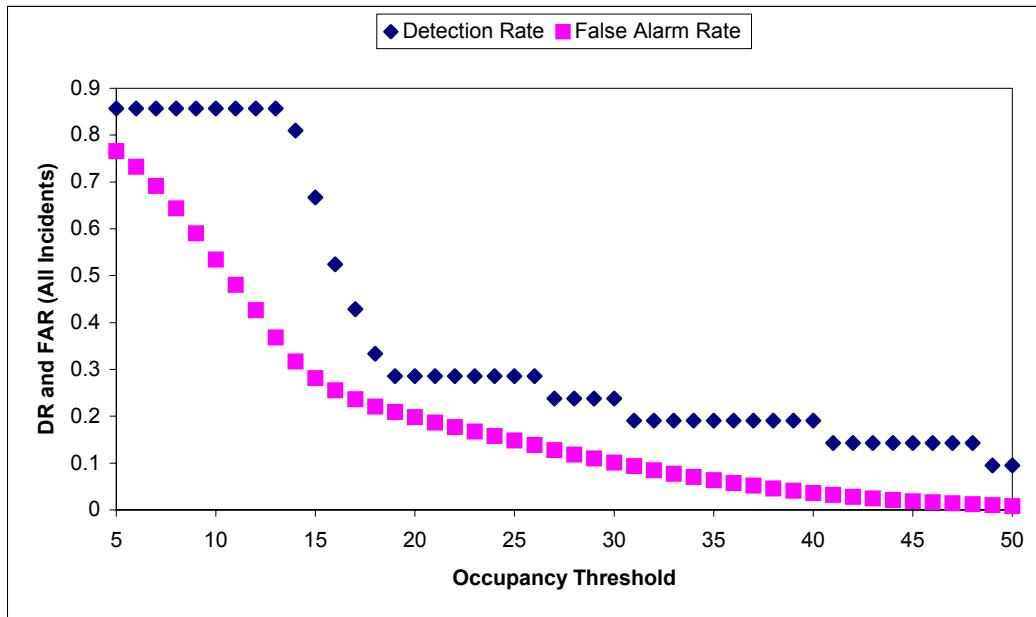
Figure 7.10 DR and FAR versus Occupancy Threshold, Texas Algorithm with Loop Data
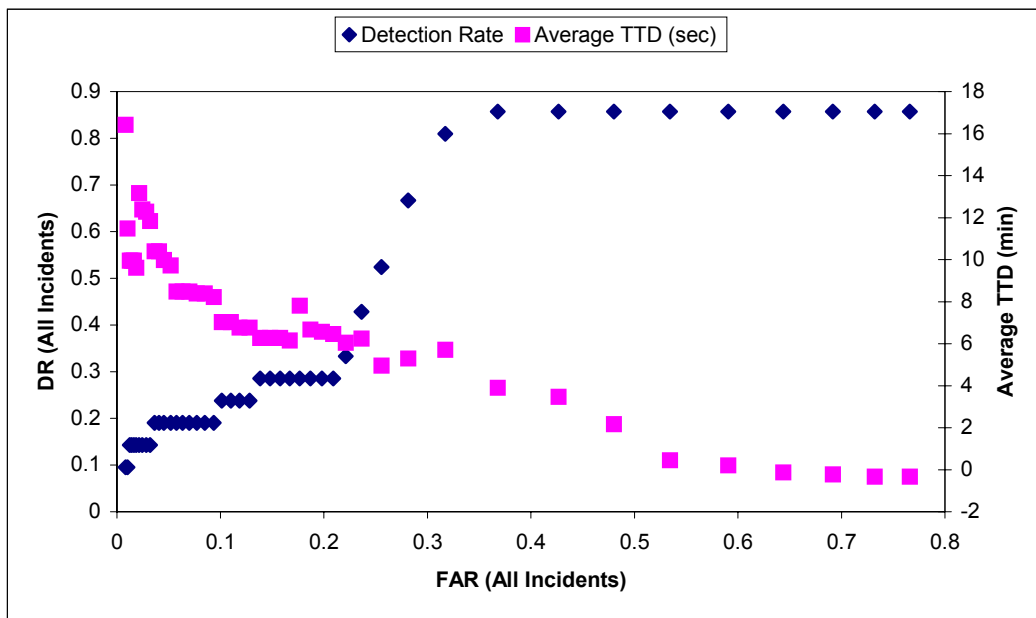
Figure 7.11 DR and TTD versus FAR, Texas Algorithm with Loop Data

The "pareto-optimal" sets of thresholds are presented along with the associated performance measures in Table 7.4 and 7.5 and are illustrated in Figure 7.12. The Texas algorithm performed better in detecting all types of incidents than in detecting accidents only. This is mainly due to the typically longer time span of congestion incidents, thus

allowing the algorithm more time to detect the incident. Here also, some threshold values were observed to lie on both of the efficient frontiers. Since the algorithm uses only one threshold value, it is expected not to be adequate in differentiating between different types of incidents. Table 7.6 presents a breakdown of the incidents detected by type for the "pareto-optimal" sets of thresholds presented in Tables 7.4 and 7.5.

Table 7.4 All Incidents "Pareto-optimal" Thresholds, Texas with Loop Data

	Occupancy Threshold	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	50	373	2	0.095	0.0085	17.4
	48	554	3	0.143	0.0126	10.0
	40	1596	4	0.190	0.0363	10.4
	30	4464	5	0.238	0.1014	7.0
	26	6097	6	0.286	0.1385	7.3
	18	9730	7	0.333	0.2210	7.1
	17	10402	9	0.429	0.2363	7.2
	16	11251	11	0.524	0.2556	5.0
	15	12395	14	0.667	0.2816	5.3
	14	13963	17	0.810	0.3172	5.7
	13	16203	18	0.857	0.3681	3.9

Table 7.5 Accidents Only "Pareto-optimal" Thresholds, Texas with Loop Data

	Occupancy Threshold	False Alarms	Accidents Detected	DR	FAR	Average TTD (Min)
Accidents Only	41	1413	1	0.143	0.0126	4.2
	17	10402	2	0.286	0.0363	-0.4
	16	11251	3	0.429	0.2558	-0.9
	15	12395	4	0.571	0.2818	-1.3
	5	33722	5	0.714	0.3175	-2.5
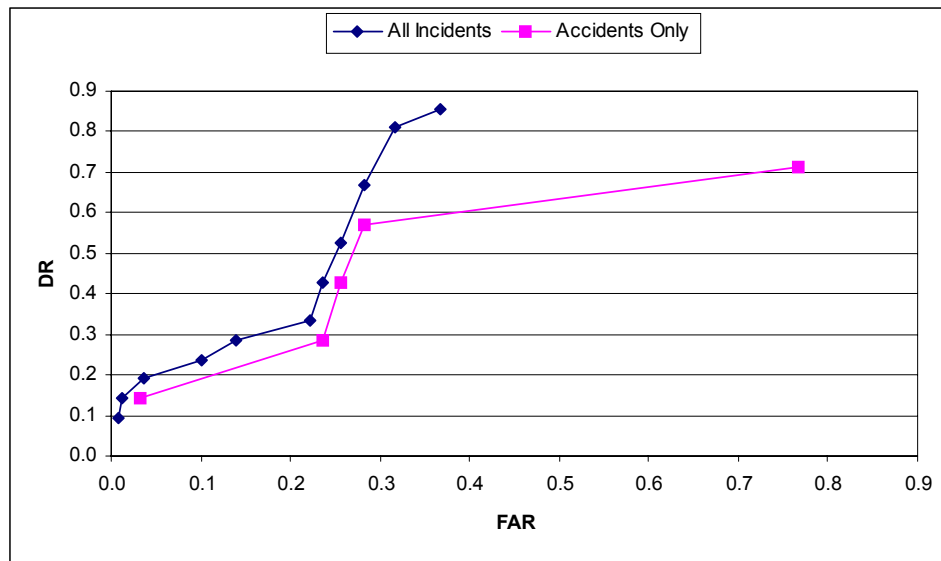
Figure 7.12 Efficient Frontiers for Texas Algorithm with Loop Data

Table 7.6 Breakdown of Incidents Detected by Type, Texas with Loop Data

	Occupancy Threshold	Major Accident	Minor Accident	Congestion	Total
All Incidents	50	0	0	2	2
	48	1	0	2	3
	40	1	1	2	4
	30	1	1	3	5
	26	1	1	4	6
	18	1	1	5	7
	17	1	1	7	9
	16	2	1	8	11
	15	2	2	10	14
	14	3	2	12	17
	13	3	2	13	18
Accidents Only	41	1	0	2	3
	17	1	1	7	9
	16	2	1	8	11
	15	2	2	10	14
	5	3	2	13	18

Peterman (1999) evaluated the performance of the Texas algorithm on other sections of the San Antonio network. Detection rates of up to 98.1 percent were reported when considering all types of incidents, with corresponding FARs ranging from 0.00147 to 0.3188. When considering accidents only, DRs of up to 100 percent were achieved, with corresponding FARs ranging from 0.00195 to 0.59388.

The Texas algorithm performance in terms of the DR was disappointing when compared to results obtained by Peterman (1999), especially in detecting accidents only. FAR obtained from both studies was comparable.

7.1.2 AVI Algorithms Calibration Results

The Upper Confidence Limit and the Texas algorithms were calibrated and tested using the AVI data obtained from TransGuide. The data had to be processed in order to produce link travel times by matching tagged vehicles at the upstream and downstream detectors of a given link before serving as input to the AID algorithms. Refer to Haynes (2000) for a detailed description of the travel time determination process.

7.1.2.1 Upper Confidence Limit Algorithm An event was defined for the Confidence Limit algorithm as a tagged vehicle that is detected at the upstream and downstream detectors of a particular link. The number of events considered in the comparison window set to calculate rolling averages of link's travel times (n) was varied between four and eight in increments of one. For each value of comparison window size, values of the level of confidence (z) ranging between two and six in increments of 0.5 were considered, thus resulting in a total of forty-five threshold combinations. Figure 7.13 illustrates the performance of the Upper Confidence Limit algorithm in detecting all types of incidents.
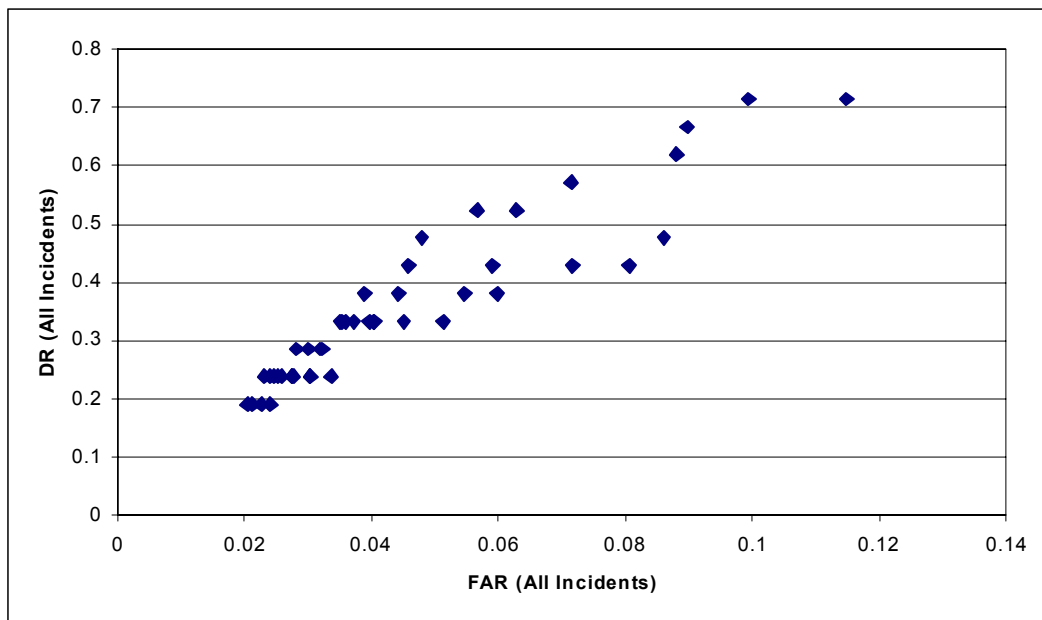
Figure 7.13 DR and FAR Trade-Off Curve for the Upper Confidence Limit Algorithm

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The algorithm performance exhibited a trend similar to that of the loop algorithms, i.e., the DR increases with FAR. When investigating the effects of the two threshold values on the performance of the algorithm, it was discovered that the Upper Limit algorithm is much more sensitive to variations in the value of (z) than it is to variations in the value of (n). The DR and FAR drop as the value of (z) increases from four to two and become almost constant for values of (z) between four and seven. Figures 7.14 and 7.15 illustrate the variations in the DR and FAR in function of the value of (n) and the value of (z), respectively.
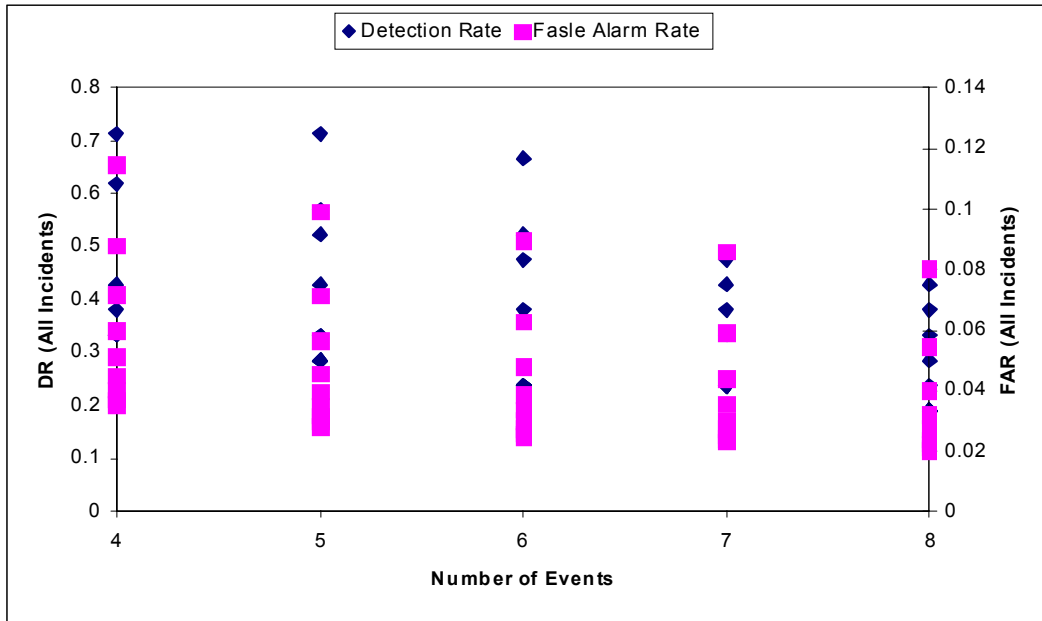
Figure 7.14 DR and FAR versus Number of Events (n)
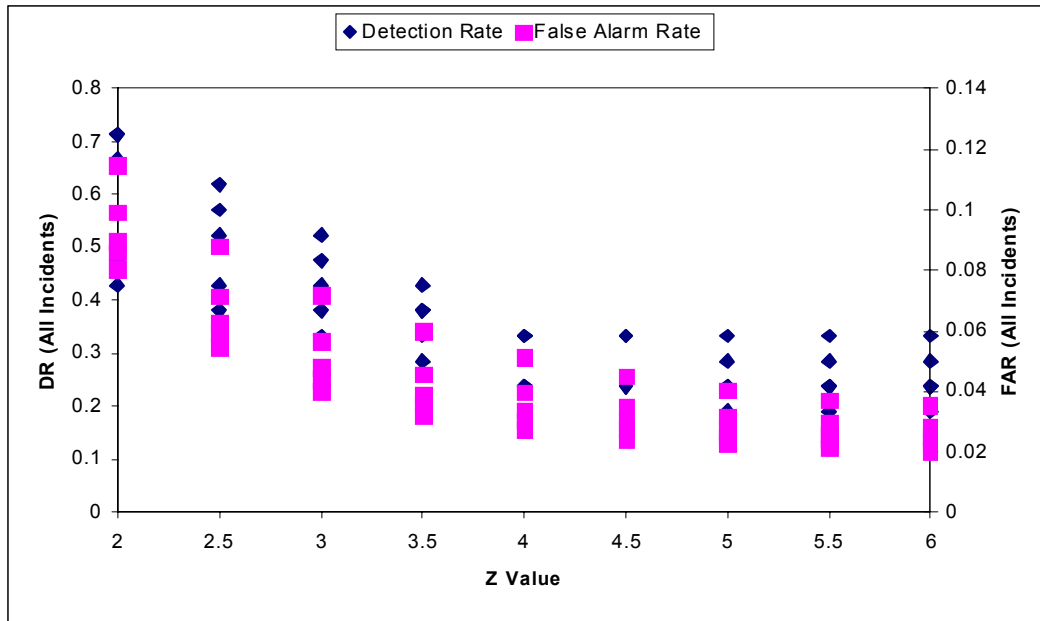
Figure 7.15 DR and FAR versus Level of Confidence (*z*)

The performance of the Upper Confidence Limit algorithm in terms of the TTD is illustrated in Figure 7.16. Figure 7.16 shows no correlation between the TTD and the DR or FAR. This is due mainly to the fact that with the current levels of tagged vehicle market penetration, detection time depends on the time headway between tagged vehicles rather than on the time it takes for the variation in travel times to be significant enough to trigger an incident alarm.
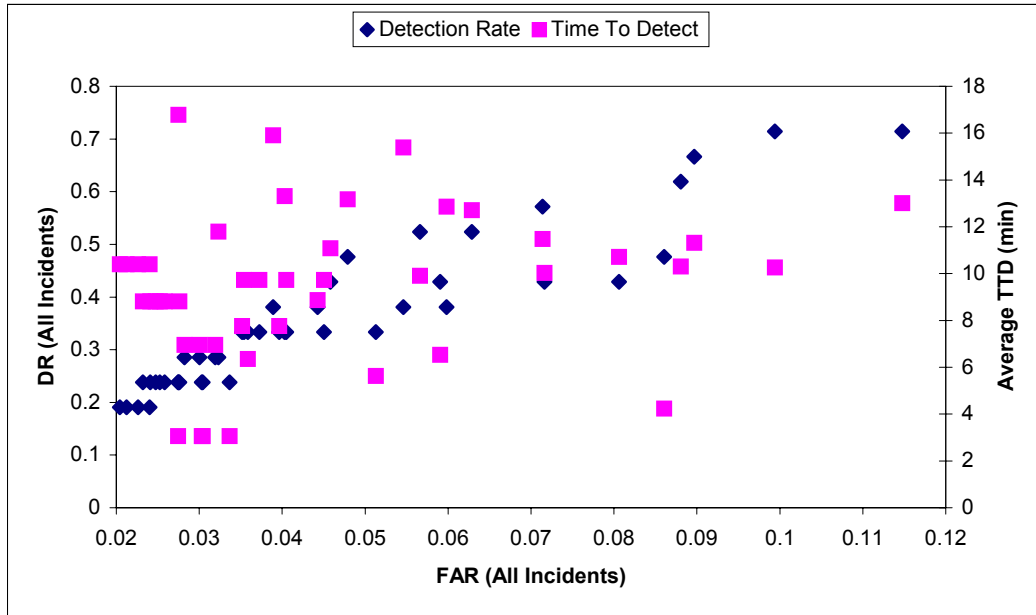
Figure 7.16 DR and TTD versus FAR, Upper Confidence Limit Algorithm

The "pareto-optimal" sets of thresholds are presented along with the associated performance measures in Tables 7.4 and 7.5 and are illustrated in Figure 7.17. The Upper Confidence Limit algorithm performed better in detecting accidents only as compared to detecting all types of incidents. The algorithm was able to detect 85.7 percent of the accidents in the calibration database at a low FAR of 0.0904. A maximum detection rate of 71.4 percent at FAR of 0.0994 was achieved when all incidents were considered. Table 7.6 presents a breakdown of the incidents detected by type for the "pareto-optimal" sets of thresholds presented in Tables 7.4 and 7.5. Table 7.6 suggests that unlike the California #8 and the Texas algorithms applied to loop data, the algorithm performance in detecting accidents is superior to its performance in detecting incidents classified as congestion.

Table 7.7 All Incidents "Pareto-optimal" Thresholds, Upper Confidence Limit

	Number of Events	Z-Value	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	8	6	236	4	0.190	0.0204	10.4
	7	6	270	5	0.238	0.0232	8.8
	5	6	335	6	0.286	0.0282	7.0
	5	4.5	417	7	0.333	0.0352	7.8
	6	3.5	455	8	0.381	0.0389	15.9
	5	3.5	543	9	0.429	0.0458	11.1
	6	3	561	10	0.476	0.0479	13.2
	5	3	670	11	0.524	0.0566	9.9
	5	2.5	843	12	0.571	0.0714	11.5
	4	2.5	1052	13	0.619	0.0880	10.3
	6	2	1047	14	0.667	0.0897	11.3
	5	2	1173	15	0.714	0.0994	10.3

Table 7.8 Accidents Only "Pareto-optimal" Thresholds, Upper Confidence Limit

	Number of Events	Z-Value	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
Accidents Only	8	6	238	2	0.286	0.0206	5.0
	8	3.5	376	3	0.429	0.0326	5.8
	6	3	567	4	0.571	0.0484	4.7
	6	2.5	739	5	0.714	0.0634	5.4
	6	2	1055	6	0.857	0.0904	5.4
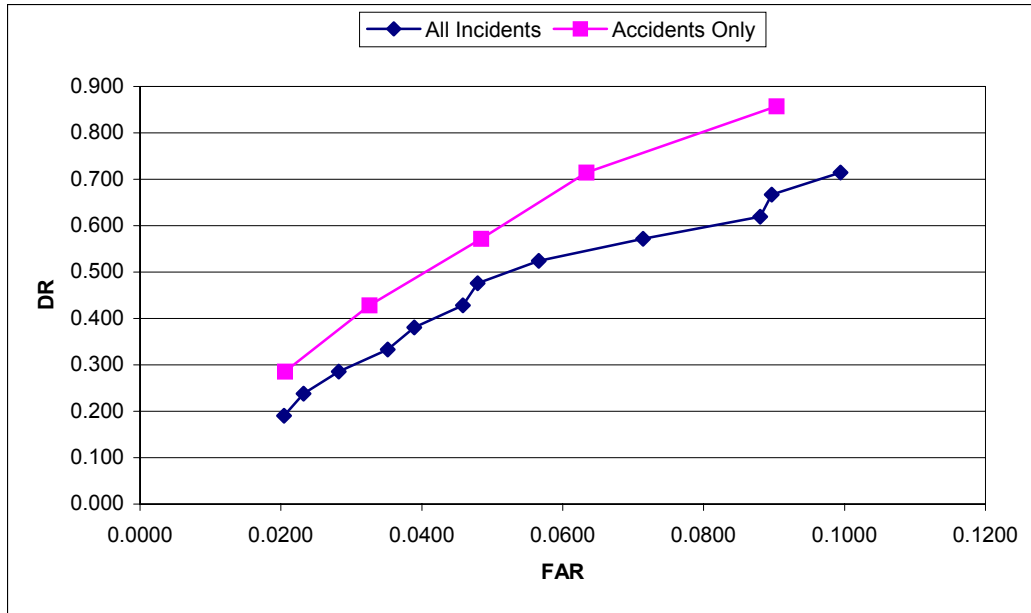
Figure 7.17 Efficient Frontiers for the Upper Confidence Limit Algorithm

Table 7.9 Breakdown of Incidents Detected by Type, Upper Confidence Limit

	Number of Events	Z-Value	Major Accidents	Minor Accidents	Congestion	Total
All Incidents	8	6	2	0	2	4
	7	6	2	0	3	5
	5	6	2	0	4	6
	5	4.5	2	0	5	7
	6	3.5	2	0	6	8
	5	3.5	2	1	6	9
	6	3	3	1	6	10
	5	3	3	1	7	11
	5	2.5	3	1	8	12
	4	2.5	4	1	8	13
	6	2	4	**2**	8	14
	5	2	4	2	9	15
Accidents	8	6	2	0	2	4
	8	3.5	3	0	3	6
	6	3	3	1	6	10
	6	2.5	3	2	6	11
	6	2	4	2	8	14

Hellinga et al. (1999) evaluated the performance of the Upper Confidence Limit algorithm using simulated data. The experimental setting was detailed in Chapter 3. The

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researchers reported a maximum detection rate of 30 percent at FAR of 0.13 for a tagged vehicle market penetration of 10 percent.

The modifications done to the logic of the algorithm before being applied to real AVI data obtained from the San Antonio network were presented in Chapter 5. The DRs and FARs achieved improve significantly on the numerical results obtained by Hellinga et al. (1999), both in terms of the DR and FAR.

7.1.2.2 Texas Algorithm with AVI Data Calibration of the Texas algorithm was performed using a single speed threshold. All speed values ranging between 5 percent and 50 percent were tested in increments of 1. The tradeoff curve for the Texas algorithm is presented in Figure 7.18.

Here also, the staggering in the data indicates that several values of the speed threshold performed equally in terms of the DR, but resulted in varying values of FAR. The trade-off curves would have been smoother had the incident report contained more entries.

The effect of the speed threshold on the performance of the Texas algorithm is depicted in Figure 7.19. The higher the speed threshold, the more sensitive the algorithm is and, therefore, the higher the number of incidents detected and the number of false alarms.
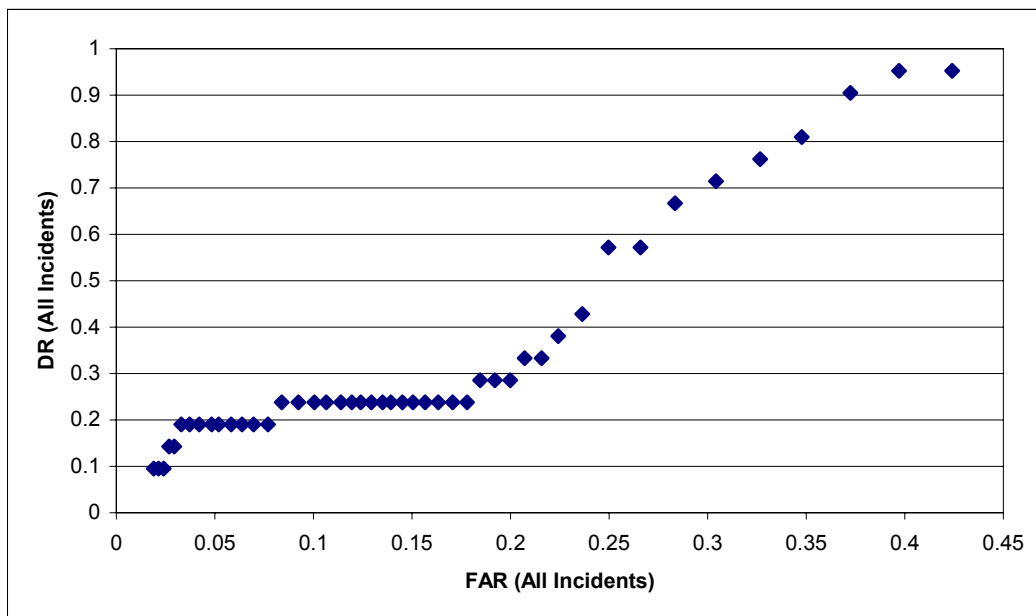
Figure 7.18 DR and FAR Trade-Off Curve for the Texas Algorithm with AVI Data
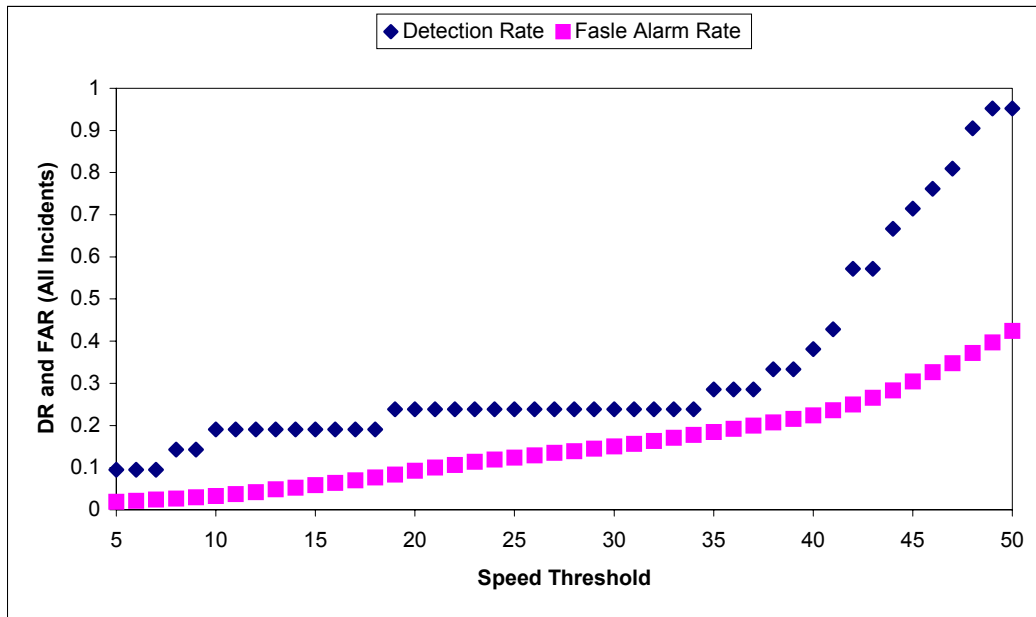
Figure 7.19 DR and FAR versus Speed Threshold, Texas Algorithm with AVI Data

Similar to the performance of the Upper Confidence Limit algorithm, the TTDs obtained from the Texas algorithm do not show any trend of variation with the DR or with FAR. Figure 7.20 illustrates the variation of the TTD and DR versus FAR.
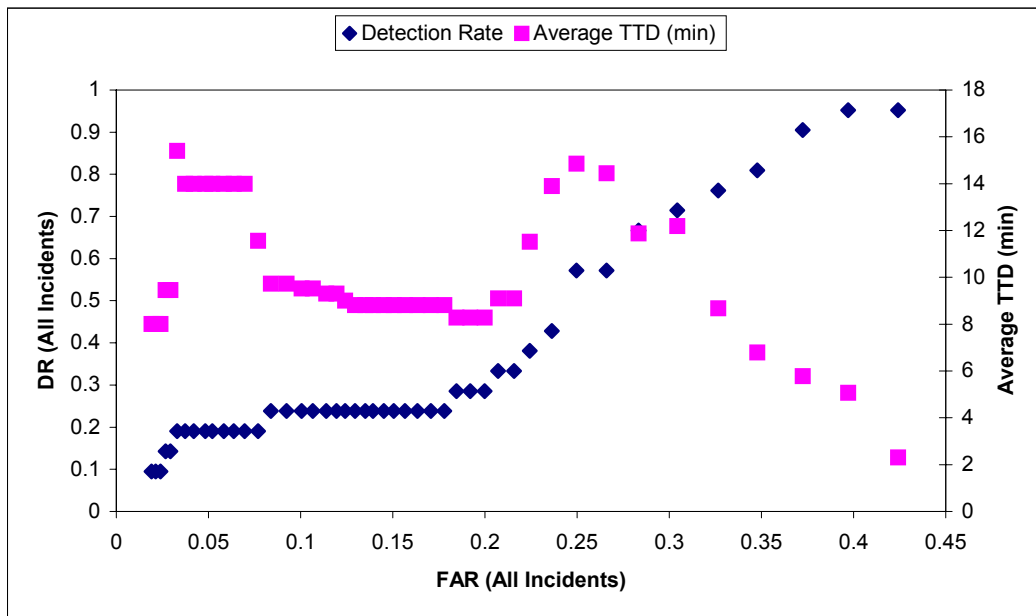
Figure 7.20 DR and TTD versus FAR, Texas Algorithm with AVI Data

The "pareto-optimal" sets of thresholds are presented along with the associated performance measures in Tables 7.7 and 7.8 and the efficient frontiers of the algorithm are illustrated in Figure 7.21. When applied with AVI data, the Texas algorithm achieved the DRs of 95.2 percent and 85.7 percent associated with FARs of approximately 0.4 when considering all incidents and accidents only, respectively. A breakdown of the incidents detected for the two sets of "pareto-optimal" thresholds is presented in Table 7.10.

Table 7.10 All Incidents "Pareto-optimal" Thresholds, Texas with AVI Data

	Speed Threshold	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	5	238	2	0.095	0.0192	8.0
	8	335	3	0.143	0.0269	9.5
	10	413	4	0.190	0.0331	15.4
	19	1056	5	0.238	0.0841	9.7
	35	2306	6	0.286	0.1848	8.3
	38	2591	7	0.333	0.2075	9.1
	40	2814	8	0.381	0.2247	11.5
	41	2974	9	0.429	0.2368	13.9
	42	3149	12	0.571	0.2503	14.9
	44	3591	14	0.667	0.2843	11.9
	45	3860	15	0.714	0.3052	12.2
	46	4150	16	0.762	0.3276	8.7
	47	4425	17	0.810	0.3488	7.8
	48	4737	19	0.905	0.3734	5.8
	49	5047	20	0.952	0.3981	5.1

Table 7.11 Accidents Only "Pareto-optimal" Thresholds, Texas with AVI Data

	Speed Threshold	False Alarms	Accidents Detected	DR	FAR	Average TTD (min)
Accidents Only	5	238	1	0.143	0.0192	-3.3
	10	413	2	0.286	0.0331	15.0
	35	2306	3	0.429	0.1848	5.2
	47	4425	4	0.571	0.3488	-1.0
	48	4737	5	0.714	0.3734	-1.7
	49	5047	6	0.857	0.3981	-0.2
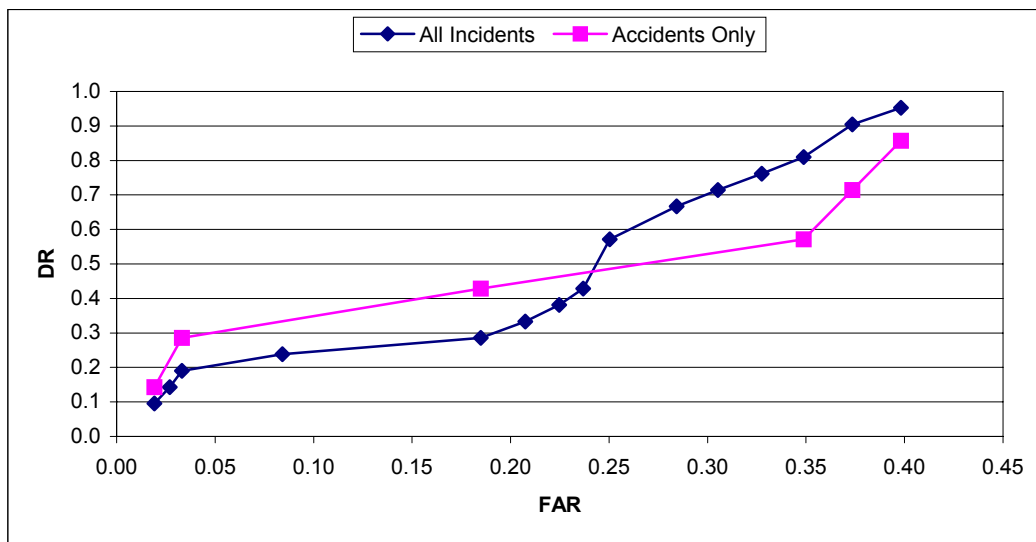
Figure 7.21 Efficient Frontiers for the Texas Algorithm with AVI Data

Table 7.12 Breakdown of Incidents Detected by Type, Upper Confidence Limit

	Speed Threshold	Major Accidents	Minor Accidents	Congestion	Total
All Incidents	5	1	0	1	2
	8	1	0	2	3
	10	2	0	2	4
	19	2	0	3	5
	35	3	0	3	6
	38	3	0	4	7
	40	3	0	5	8
	41	3	0	6	9
	42	3	0	9	12
	44	3	0	11	14
	45	3	0	12	15
	46	3	0	13	16
	47	3	1	13	17
	48	3	2	14	19
	49	4	2	14	20
Accidents Only	5	1	0	1	2
	10	2	0	2	4
	35	3	0	3	6
	47	3	1	13	17
	48	3	2	14	19
	49	4	2	14	20

7.1.3 Algorithm Calibration Comparison

In order to compare the performance of the calibrated algorithms, their efficient frontiers are compared for all types of incidents and for accidents only. Figure 7.22 illustrates the efficient frontiers for all the tested algorithms considering all incident types.
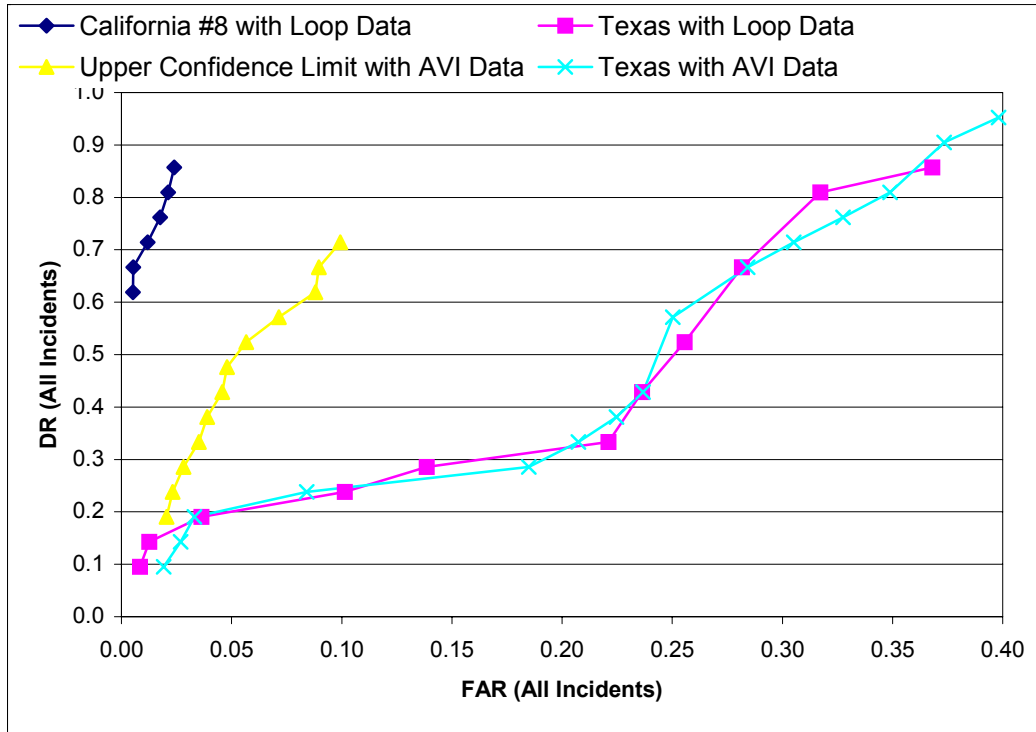
Figure 7.22 Efficient Frontiers for All Calibrated Algorithms Considering All Incidents

Figure 7.22 shows that the Texas algorithms applied with both loop and AVI data performed very closely in terms of the DR and FAR. The Texas algorithm applied with AVI data was able to detect more incidents reaching a maximum DR of 0.952, as compared to a maximum DR of 0.857 when applied with loop data.

The maximum detection achieved by the Texas Algorithm comes at the expense of FAR. Both applications of the Texas algorithm resulted in higher FARs than the California #8 and the Upper Confidence Limit algorithms. However, the maximum DRs achieved by the California #8 and the Upper Confidence Limit algorithms are lower than those presented by the Texas algorithm. Finally, when all types of incidents were considered, the California #8 algorithm outperformed the Upper Confidence Limit algorithm both in terms of the DR and FAR.

Figure 7.23 depicts the performance of the algorithms in terms of the TTD when calibrated to detect all types of incidents. The loop algorithms, particularly the California #8 algorithm, achieved lower detection times than the AVI algorithms. When comparing the AVI algorithms, the Upper Confidence Limit algorithm resulted in lower detection times than the Texas algorithm. The reported TTDs should be used only as a relative measure of algorithm performance. Precise TTD estimates cannot be achieved unless the incidents occur in a controlled environment, i.e., where the network is constantly being observed and exact incident start and end times are being recorded.

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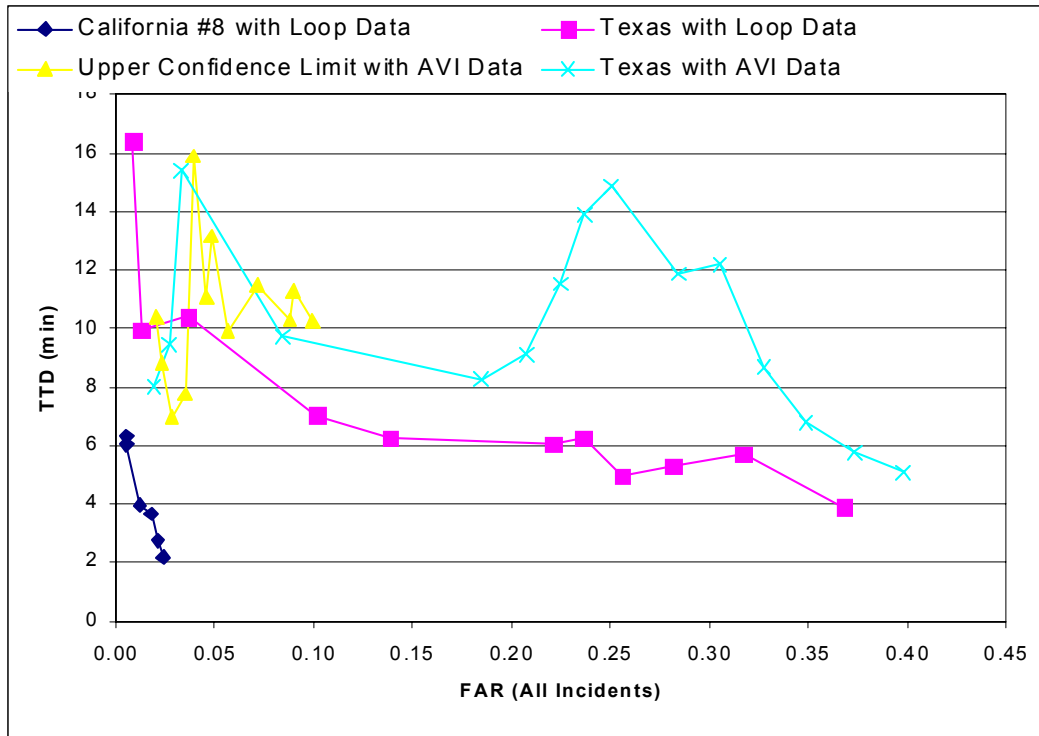
Figure 7.23 TTD versus FAR for all Calibrated Algorithms Considering All Incidents

The performance of the algorithms is compared next using the "pareto-optimal" thresholds obtained after calibrating for accidents only. Figure 7.24 illustrates the efficient frontiers for all the tested algorithms considering accidents only. The results obtained are similar to those obtained from calibrating for all types of incidents with the exception that the Upper Confidence Limit algorithm outperformed the California #8 algorithm in terms of the DR but not in terms of FAR. The Texas algorithm performed comparably with both types of data.

Figure 7.25 depicts the performance of the algorithms in terms of the TTD when calibrated to detect accidents only.
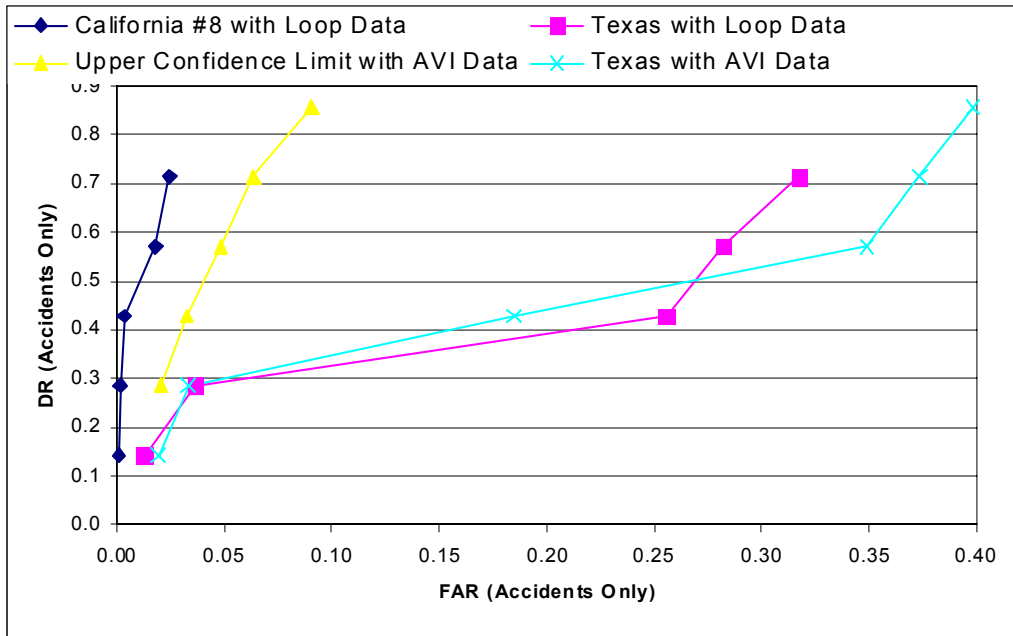
Figure 7.24 DR versus FAR for All Calibrated Algorithms Considering Accidents Only
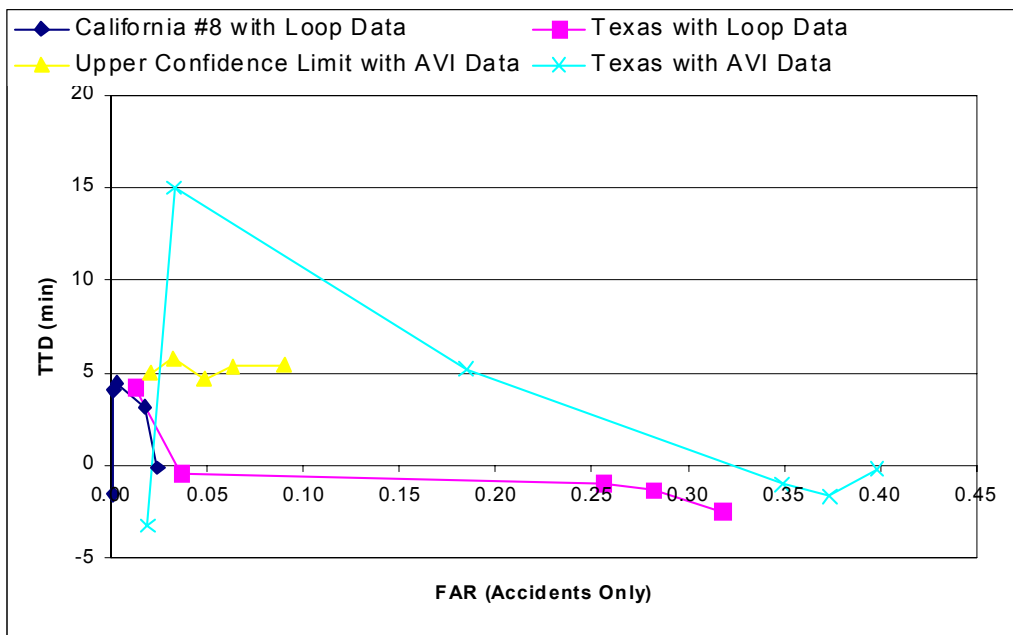
Figure 7.25 TTD versus FAR for All Calibrated Algorithms Considering Accidents Only

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The TTD exhibited by the algorithms when they are calibrated to maximize the detection of major and minor accidents exhibit the same trends as when they are calibrated to detect all types of incidents. It is important to note that while the TTD for loop algorithms depends on the severity of the incident on the flow of traffic, the TTD for AVI algorithms depends on both the severity of the incident on the flow of traffic and the time headway of matched tagged vehicles at the upstream and downstream detector of a link.

7.2 TEST RESULTS

The testing phase is aimed at assessing the transferability of the "pareto-optimal" thresholds determined from the calibration phase to a different data set. While twenty-one incidents from the incident database were used with the corresponding peak periods in calibrating the algorithms, forty-four and fifty-one incidents were used to test the loop and AVI algorithms, respectively. The seven incidents for which loop data was missing were included in the testing of the AVI incidents. For testing, data is included from both peak periods of every day considered for this research with the exception of those peak periods used for calibration.

7.2.1 Loop Algorithms Testing Results

The forty-four incidents used to test the loop algorithms consisted of seven major accidents, six minor accidents, twenty-nine congestion incidents, one incident labeled as debris, and one stall. The results of the testing phase are reported next for all types of incidents and accidents only.

7.2.1.1 California #8 The "pareto-optimal" sets of thresholds for the California #8 algorithm considering all incidents and accidents only were presented in Tables 7.1 and 7.2, respectively. Table 7.13 illustrates the testing results using the "pareto-optimal" set of thresholds developed for all incidents and Table 7.14 illustrates the results obtained after using the "pareto-optimal" set of thresholds developed for accidents only.

Table 7.13 All Incidents Testing Results, California #8

	T1	T2	T3	T4	T5	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	13	-0.652	0.218	16	22	11358	34	0.773	0.0069	19.0
	11	-0.441	0.165	28	29	14735	35	0.795	0.0090	15.3
	10	-0.262	0.489	28	22	23312	42	0.955	0.0142	11.9
	8	-0.192	0.194	16	28	43356	43	0.977	0.0264	11.5
	8	-0.588	0.119	24	23	48661	44	1.000	0.0296	10.0
	7	-0.924	0.119	17	23	59672	44	1.000	0.0363	5.5

Table 7.14 Accidents Only Testing Results, California #8

	T1	T2	T3	T4	T5	False Alarms	Accidents Detected	DR	FAR	Average TTD (min)
Accidents Only	19	-0.015	0.138	12	25	2000	9	0.692	0.0012	2.30
	17	-0.824	0.119	11	25	3230	11	0.846	0.0020	2.00
	10	-0.968	0.64	15	26	7820	11	0.846	0.0048	1.98
	8	-0.192	0.194	16	28	43356	13	1.000	0.0264	0.91
	7	-0.924	0.119	17	23	59672	13	1.000	0.0363	0.89

The same trend exhibited in the calibration phase repeats itself in the testing phase. As the DR increases, FAR increases and the TTD decreases. The testing results improve on the calibration results in terms of the DR but FAR were moderately higher for the testing phase. When all incidents were considered, the TTDs achieved in the calibration phase were significantly lower than those obtained in the testing phase. When only accidents were considered, the TTDs obtained from testing the algorithm compare closely to the values obtained during calibration.

7.2.1.2 Texas Algorithm with Loop Data The testing results of the Texas algorithm applied with loop data considering an occupancy threshold are presented in Tables 7.15 and 7.16.

Table 7.15 All Incidents Testing Results, Texas with Loop Data

	Occupancy Threshold	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	50	3221	9	0.205	0.0025	10.3
	48	4529	13	0.295	0.0035	11.8
	40	14847	20	0.455	0.0115	11.5
	30	41170	27	0.614	0.0319	10.1
	26	56442	28	0.636	0.0437	9.6
	18	110246	31	0.705	0.0854	4.7
	17	124977	35	0.795	0.0968	4.4
	16	145383	38	0.864	0.1126	3.9
	15	174883	41	0.932	0.1355	3.5
	14	218043	41	0.932	0.1689	3.3
	13	280558	44	1.000	0.2174	1.9

Table 7.16 Accidents Only Testing Results, Texas with Loop Data

	Occupancy Threshold	False Alarms	Accidents Detected	DR	FAR	Average TTD (min)
Accidents Only	41	13093	8	0.615	0.0102	7.8
	17	124977	9	0.692	0.0968	-5.2
	16	145383	10	0.769	0.1127	-5.4
	15	174883	11	0.846	0.1355	-4.8
	5	1109433	13	1.000	0.8596	-3.1

The testing results improve on the calibration results in terms of the DR and FAR for the "pareto-optimal" thresholds developed to maximize the detection of all types of incidents. For the accidents only threshold values, testing revealed a higher DR associated with a much higher FAR then the calibration phase. TTDs were comparable in both cases to the values obtained from calibration.

7.2.2 AVI Algorithms Testing Results

The fifty-one incidents used to test the AVI algorithms consisted of ten major accidents, six minor accidents, thirty-two congestion incidents, one incident labeled as debris, and two stalls. Results of the AVI algorithms testing phase are reported next for all types of incidents and accidents only.

7.2.2.1 The Upper Confidence Limit Algorithm Table 7.17 illustrates the Upper Confidence Limit testing results using the "pareto-optimal" set of thresholds developed for all incidents and Table 7.18 illustrates the results obtained after using the "pareto-optimal" set of thresholds developed for accidents only.

Table 7.17 All Incidents Testing Results, Upper Confidence Limit Algorithm

	Number of Events	Z Value	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	7	6	701	20	0.392	0.0234	22.3
	5	6	879	23	0.451	0.0287	14.5
	5	4.5	1108	26	0.510	0.0360	14.0
	6	3.5	1232	29	0.569	0.0407	12.4
	5	3.5	1460	30	0.588	0.0476	9.9
	6	3	1521	30	0.588	0.0500	10.4
	5	3	1781	32	0.627	0.0579	9.1
	5	2.5	2258	34	0.667	0.0732	7.9
	4	2.5	2744	39	0.765	0.0877	8.4
	6	2	2795	40	0.784	0.0916	11.7
	5	2	3120	42	0.824	0.1011	8.6

Table 7.18 Accidents Only Testing Results, Upper Confidence Limit Algorithm

	Number of Events	Z Value	False Alarms	Accidents Detected	DR	FAR	Average TTD (min)
Accidents Only	8	6	650	7	0.44	0.0219	4.49
	8	3.5	996	12	0.75	0.0336	2.39
	6	3	1538	12	0.75	0.0506	0.67
	6	2.5	2010	12	0.75	0.0660	-0.88
	6	2	2819	13	0.81	0.0924	-2.09

When all incidents were considered, the Upper Confidence Limit algorithm performed better in terms of the DR in the testing phase when compared to the calibration phase. When considering accidents only, the DRs achieved in the testing phase were lower than those observed in the calibration phase. The FARs and TTDs are comparable between the testing and calibration phases for all types of incidents as well as for accidents only.

7.2.2.2 *Texas Algorithm with AVI Data* The results of testing the Texas algorithm with AVI data considering a speed threshold are presented in Tables 7.19 and 7.20.

Results show lower detection rates and false alarm rates for the testing phase when compared with the calibration phase. Moreover, the TTD increased significantly between the calibration and testing phases.

Table 7.19 All Incidents Testing Results, Texas with AVI Data

	Speed Threshold	False Alarms	Incidents Detected	DR	FAR	Average TTD (min)
All Incidents	5	554	17	0.333	0.0171	35.5
	8	768	21	0.412	0.0235	32.8
	10	885	23	0.451	0.0269	31.3
	19	2113	25	0.490	0.0630	23.9
	35	4934	31	0.608	0.1478	13.8
	38	5535	31	0.608	0.1649	11.0
	40	6016	31	0.608	0.1783	10.8
	41	6352	33	0.647	0.1875	13.9
	42	6723	34	0.667	0.1978	13.8
	44	7690	39	0.765	0.2252	11.5
	45	8254	43	0.843	0.2412	9.8
	46	8900	43	0.843	0.2597	7.3
	47	9600	43	0.843	0.2801	7.1
	48	10384	43	0.843	0.3038	5.6
	49	11241	45	0.882	0.3300	5.0

Table 7.20 Accidents Only Testing Results, Upper Confidence Limit Algorithm

	Speed Threshold	False Alarms	Accidents Detected	DR	FAR	Average TTD (min)
Accidents Only	5	565	5	0.31	0.0175	25.9
	10	899	7	0.44	0.0273	24.7
	35	4951	12	0.75	0.1483	2.4
	47	9628	12	0.75	0.2809	-3.7
	48	10412	12	0.75	0.3046	-3.8
	49	11270	13	0.81	0.3309	-4.1

7.2.3 Algorithm Calibration Comparison

The performance of the tested algorithms in detecting all types of incidents is illustrated by the efficient frontiers presented in Figures 7.26.
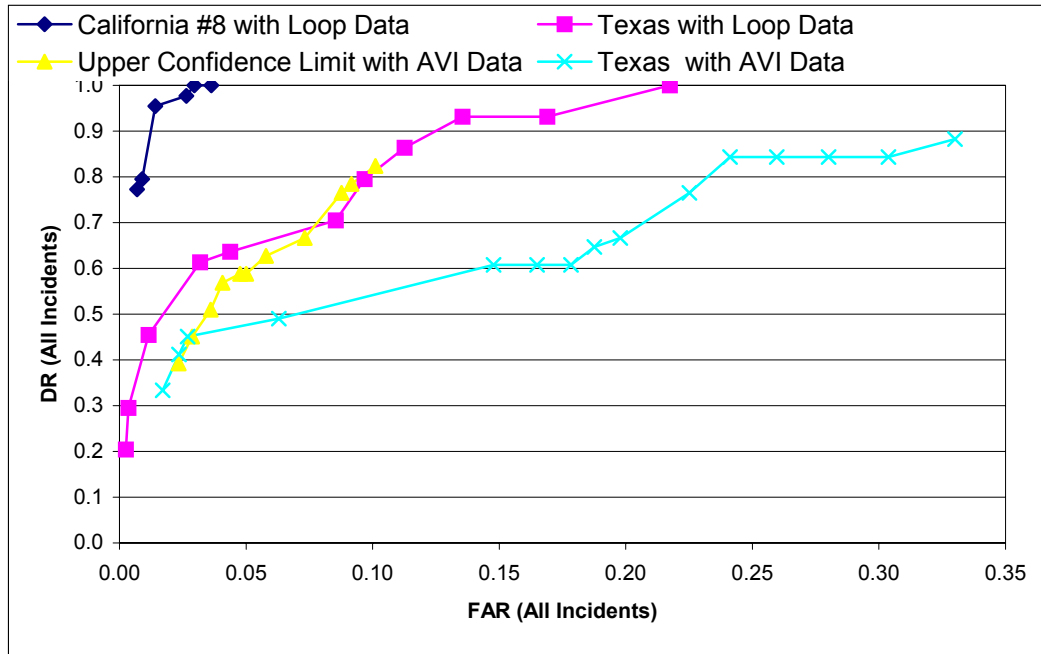
Figure 7.26 Efficient Frontiers for All Tested Algorithms Considering All Incidents

Results show that when all types of incidents were considered, the California #8 algorithm resulted in the best performance both in terms of DR and FAR reaching 100 percent detection at relatively low levels of FAR. The Texas algorithm applied with the loop data performed comparably to the Upper Confidence Limit Algorithm in terms of FARs but resulted in higher DRs. The Texas algorithm applied with AVI data resulted in the worst performance both in terms of the DR and FAR relative to the other tested algorithms.

Figure 7.27 depicts the performance of the algorithms in terms of TTD when tested for the "pareto-optimal" set of thresholds determined for all types of incidents.
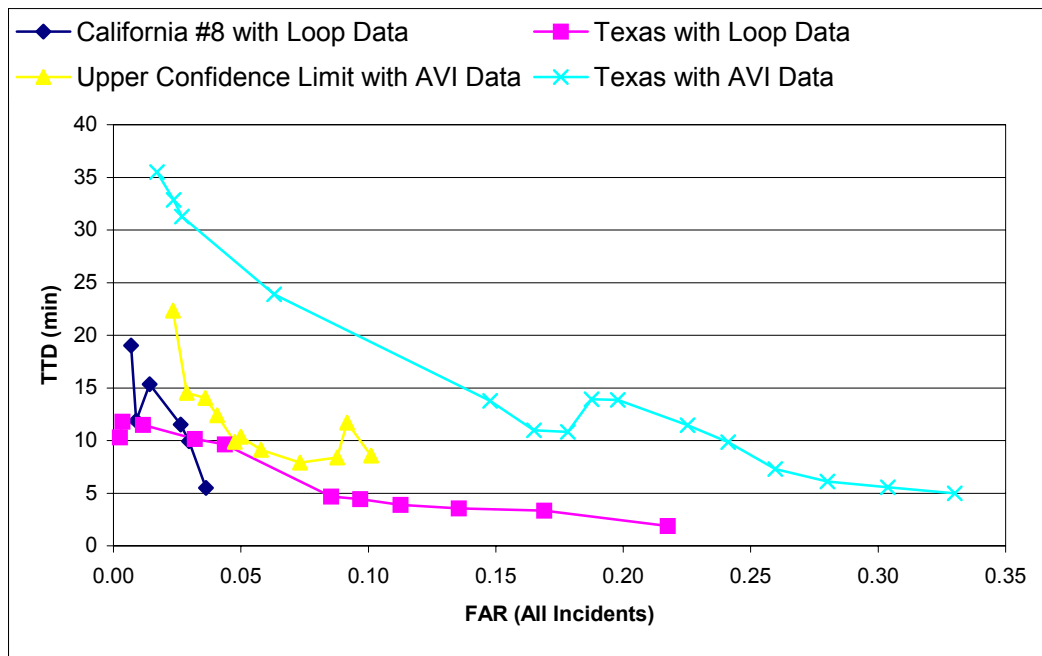
Figure 7.27 TTD versus FAR for All Tested Algorithms Considering All Incidents

The loop algorithms consistently achieved lower detection times than did the AVI algorithms. When comparing the AVI algorithms, the Upper Confidence Limit algorithm resulted in lower detection times than the Texas algorithm. These results are consistent with those observed in the calibration phase with the exception that the Texas algorithm applied with loop data exhibited higher detection times when compared with the California #8 algorithm.

Figure 7.28 illustrates the efficient frontiers of the algorithms in detecting accidents only.
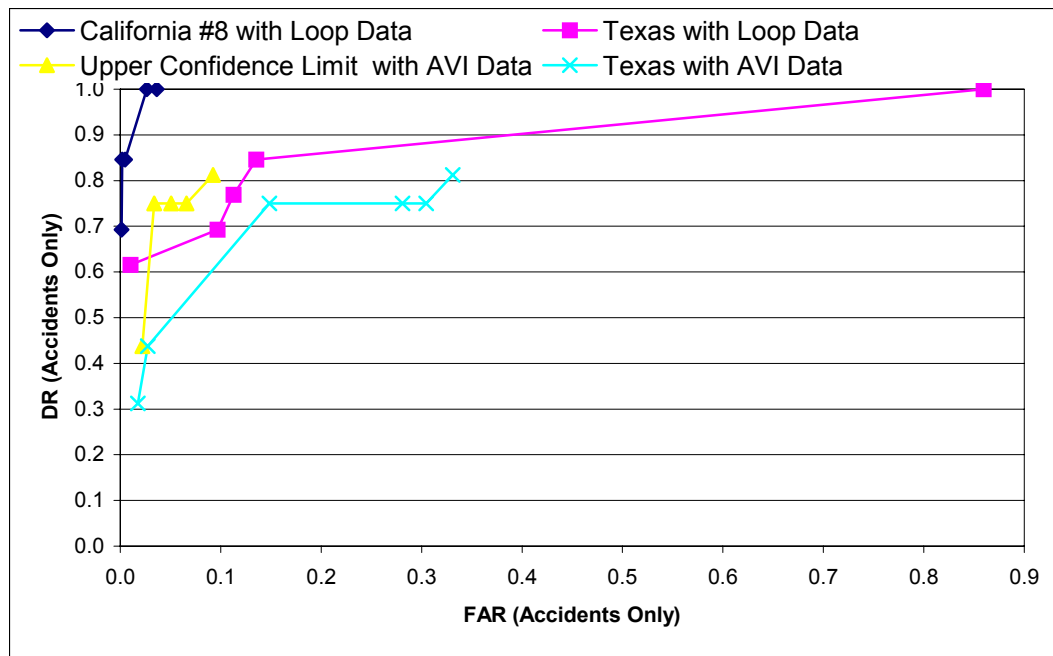
Figure 7.28 Efficient Frontiers for All Tested Algorithms Considering Accidents Only

When the performance of the tested algorithms was investigated considering major and minor accidents only, similar results were obtained as when all types of incidents were considered. The California #8 achieved higher detection levels at lower FARs when compared to the rest of the algorithms. The Upper Confidence Limit algorithm achieved lower FARs when compared to both applications of the Texas algorithm but could not reach the levels of detection achieved by the Texas algorithm applied with loop data. When comparing the performance of the Texas algorithm between its application with loop data and its application with AVI data, it was found that it performed better when applied with data obtained from Inductive Loop Detectors (ILDs).

The results differ from those obtained during the calibration phase in that the Upper Confidence Limit algorithm resulted in the highest detection rates with respect to detecting accidents only. The results of the testing phase should be, however, the ones considered in evaluating the overall performance of the algorithms since they result from the application of the algorithms to a larger and, therefore, more representative data set than the one considered for calibration. Furthermore, the results obtained from testing the California #8 and the Texas algorithms with loop data are comparable to the results obtained by Peterman (1999) in his previously described experiments as shown in Figure 7.29.
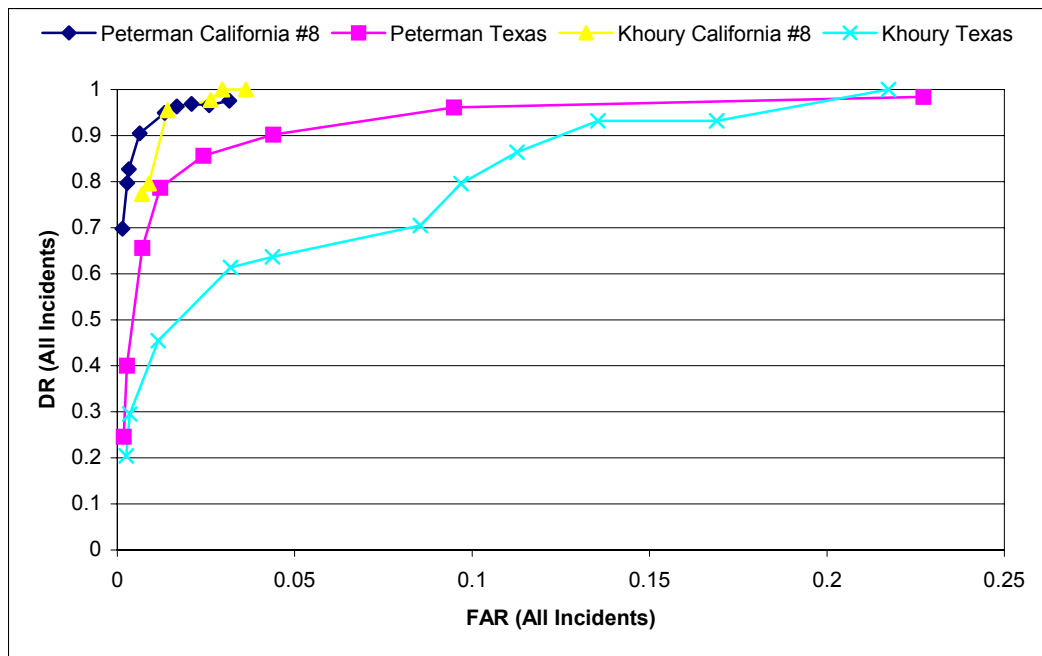
Figure 7.29 Comparison of Peterman (1999) and Khoury Testing Results

Figure 7.30 displays the performance of the algorithms in terms of the TTD when considering major and minor accidents only.
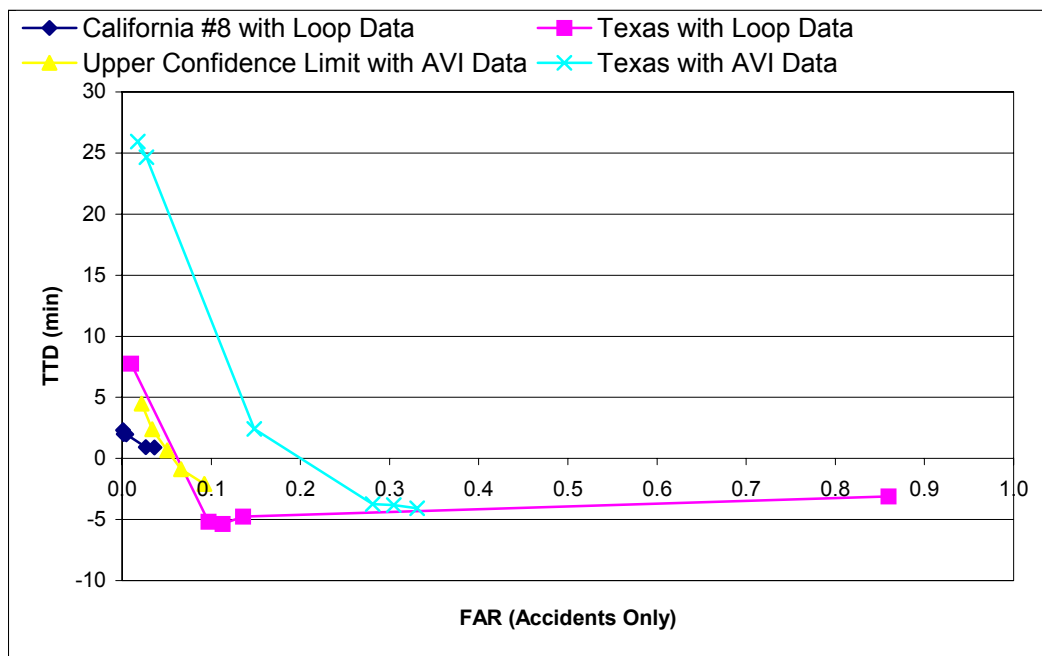
Figure 7.30 TTD versus FAR for All Tested Algorithms Considering Accidents Only

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The results are in accordance with those obtained when testing the algorithms with all types of incidents. The TTDs achieved were lower than those achieved with the AVI algorithms. However, the Upper Confidence Limit exhibited detection times close to those achieved with the loop algorithms. When comparing the AVI algorithms, here again the Upper Confidence Limit algorithm resulted in lower detection times than the Texas algorithm.

The findings of the calibration and testing phase were presented in this chapter. The calibration phase resulted in the determination of two sets of "pareto-optimal" thresholds for each algorithm, one for all incident detection and the other for detecting accidents only. The testing phase revealed that the loop algorithms, i.e., the California #8 algorithm and the Texas algorithm applied with an occupancy threshold were the most effective for detecting all six types of incidents or for detecting accidents only. The loop algorithms achieved higher DRs and lower FARs and TTDs than the AVI algorithms. However, the AVI algorithms, and particularly the Upper Confidence Limit algorithm, achieved promising detection levels and FARs. The TTDs reported in this study should be considered only in comparing the relative performance of the algorithms investigated in this study due to discrepancies in the incident reports obtained.

CHAPTER 8 TAGGED VEHICLE PENETRATION

An important metric in evaluating and using an automatic vehicle identification system is the fraction of vehicles that are tagged. If the tagged vehicle penetration is known accurately at all times, Automatic Vehicle Identification (AVI) becomes an extremely valuable system, for many facets of advanced traffic management and information systems. The tagged vehicle population is typically only a very small fraction of the total vehicular population on a facility, especially in San Antonio. It will be many years before all vehicles are equipped with some type of AVI transponder. Even with a low tag penetration, significant benefit can be obtained from an AVI system. If accurate estimates of the penetration are available greater benefits are achieved from AVI for Intelligent Transportation System (ITS) purposes.

This chapter explores various techniques for estimating the tagged vehicle penetration and relates these estimates to computation of the previously defined state descriptors. The first method compares total AVI daily counts to past Average Annual Daily Traffic (AADT) counts provided by the Texas Department of Transportation (TxDOT). Next, using inductive loop detectors (ILDs) to obtain volume estimates at discrete points along a link, an average link volume is compared to the matched AVI data for a link-based penetration estimate. Another method compares point-based volume measurements from each technology at two locations. Finally, tag penetration by the tag identification type (or city of origin) is presented, followed by concluding comments in the final section.

8.1 PENETRATION ESTIMATION FROM ANNUAL AVERAGE DAILY TRAFFIC

A first method for gaining a general understanding of the level of tagged vehicle penetration is to compare the number of tagged vehicles passing a location to an existing vehicle count. A common yearly measure is the AADT, which is the total number of vehicles that pass a given point for an entire year divided by the 365 days in the year. The AADT considers travel in both directions and is not used directly for design or planning purposes (May 1990). AADT estimates are available for most facilities in the state from the state department of transportation.

8.1.1 San Antonio

AADT volumes were obtained from TxDOT for 1996 and are shown in Figure 8.1. The 1996 data is the most recent available on CD-ROM and accessible to the author. The purpose here is to obtain a rough estimate of the tagged vehicle penetration. The errors associated with the TxDOT 1996 AADT data are not known. The total count of AVI-equipped vehicles was obtained for weekdays during the month of June 2000. The sites do not record direction, therefore the count at one station is directly applicable to the AADT estimation, which is also directionless. The sum of the total weekday daily AVI counts was computed and divided by the number of days in the sample to obtain an estimate of the AADT, from the limited AVI data available. Figure 8.1 portrays the results; the individual AVI sites are identified in Figure 8.2.

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Date	42	43	44	45	47
1-Jun	1657	1320	2232	2911	1473
2-Jun	1630	1285	2123	2979	1452
5-Jun	1397	1062	1766	2574	1021
6-Jun	1562	1194	2007	2707	1320
7-Jun	No Data	1193	2106	2845	1344
8-Jun	1561	1273	2069	2882	1403
9-Jun	1567	1282	2060	2909	1350
12-Jun	1376	1089	1902	2691	1232
13-Jun	1489	1160	2058	2791	1367
14-Jun	1662	1314	2177	2838	1413
15-Jun	1604	1296	2224	2953	1492
16-Jun	1711	1366	2236	3073	1583
19-Jun	1450	1125	1878	2628	1282
20-Jun	1529	1171	2027	2768	1241
21-Jun	1671	1280	2262	2979	1427
22-Jun	1730	1350	2204	2948	1478
23-Jun	1738	1355	2259	3073	1509
26-Jun	1437	1110	1785	2609	1174
27-Jun	1574	1157	1974	2756	1256
28-Jun	1702	1342	2239	3026	1386
29-Jun	1586	1254	1494	2958	1504
30-Jun	1750	1421	2300	3059	1505
Weekday Monthly Total	33,383	27,399	45,382	62,957	30,212
AADT from AVI	1,590	1,245	2,063	2,862	1,373
1996 AADT	146,000	127,000	158,000	146,000	151,000
2000 AADT Estimate	165,581	143,886	177,124	174,067	171,771
Market Penetration	0.96%	0.87%	1.16%	1.64%	0.80%
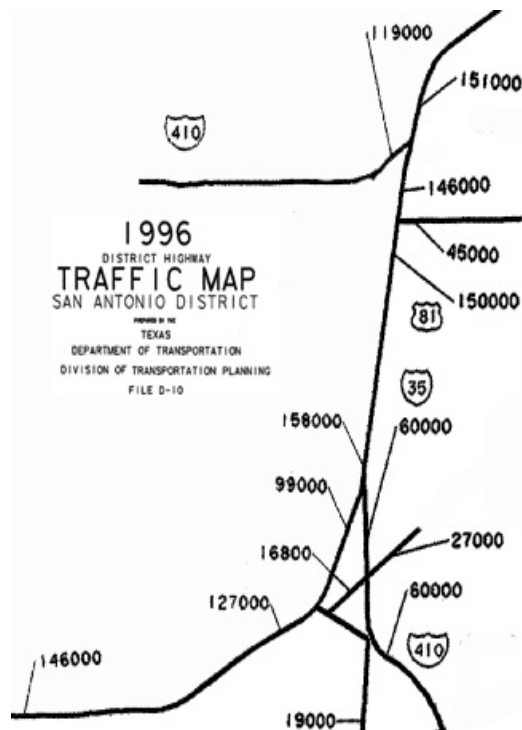
Figure 8.1 San Antonio AADT Data

Considering the numerous sources of variability in both sources of data, these results can be used only as an initial estimate of tag penetration. The average tagged vehicle penetration appears to be on the order of 1 percent of the total flow. It will be shown later that this estimate compares favorably with tagged vehicle estimates from the loop detector data for San Antonio.

8.1.2 Houston

Using the same TxDOT district transportation maps, estimates for the Houston 1996 AADT were obtained. A projection to current values is not performed because past data were not obtained to define the trend. Figure 8.2 shows the Houston study area and AADT values; refer to Figure 1.3 for the locations of the AVI reader sites.

Date	28,29	31,26	33,24
6-Mar	14364	14266	2640
7-Mar	16120	16295	3284
8-Mar	15567	15729	3431
9-Mar	15676	15540	5674
10-Mar	16022	15309	3093
13-Mar	15325	15005	2648
14-Mar	14419	14335	3675
15-Mar	15064	9546	8633
16-Mar	15284	10919	2874
17-Mar	15497	15137	2884
20-Mar	14351	14395	2429
21-Mar	14787	14405	2374
22-Mar	14675	14349	2346
23-Mar	15011	14610	9053
24-Mar	14638	13864	5020
Weekday Monthly Total	226,800	213,704	60,058
AADT from AVI	15,120	14,247	4,004
1996 AADT	227,000	188,000	175,000
Market Penetration	6.66%	7.58%	2.29%
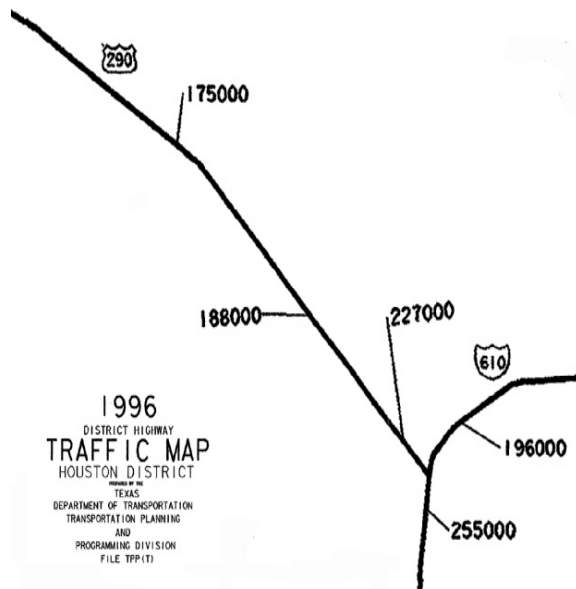
Figure 8.2 Houston AADT Data

The Houston AADT data is sparse along the US 290 corridor; however, is it clear that the penetration of tagged vehicles is more than twice the penetration observed in San Antonio. As mentioned previously, Houston has distributed many more tags, most for the purpose of toll collection.

8.2 PENETRATION ESTIMATES FROM LOOP DATA

The most logical method for estimating tag penetration is to compare the AVI count with a count from another traffic-monitoring device. The recently installed loop detectors along the IH-35 study corridor permit a comparison of loop counts with AVI counts with the San Antonio data. Unfortunately, the Houston loop detectors are not operational and are not useful for tag penetration estimation.

The main difficulty with penetration estimations from loop data is that direction can only be discerned with valid matched data, as mentioned earlier. Two penetration estimates are made from the loop data, using a single AVI link with three loop detectors. The first is a node-based estimation where the AVI node "directionless" count is compared to the total flow, in both directions, from the closest loop detector. The second is a link-based estimation in which the total link flow observed from the AVI system is compared to a loop detector installed in the middle of the link. The penetration estimation is made independently for both directions of the link.

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Another difficulty in comparing the volumes measured with AVI to the loop volumes is that the AVI system does not monitor all lanes of travel. The AVI installation in the San Antonio test sections monitors only the inner two higher speed lanes, while the loop counts are for all lanes of the facility. The analysis compares the AVI on the inner four lanes to the loop count of all vehicles that pass the facility. When all lanes are monitored, the system is able to detect more first-order matches (Links 1 to 8, as shown in Figure 4.8), that is, a match from an immediate upstream detector.

8.2.1 Selection of Penetration Study Link

For a proper estimate of the link-based comparison, a measure of the link volume that traverses the entire length of the link must be made from the loop data. One method is to use an upstream detector and detectors on the exit ramps. The total flow on the link is obtained from the count at the upstream detector (located close to an AIV site) excluding the vehicles that exit the facility prior to the downstream AVI detector. In contrast, a downstream detector count minus the vehicles that enter the link between the two AVI sites, can be used. TransGuide provides ramp data; however, it was not obtained for the analysis period. Identification of a configuration where a single loop detector would capture only the vehicles that would traverse the entire distance between two AVI sites was required.

The middle loop detector on Links 5 and 6 provides a unique opportunity to directly measure the volume between AVI sites 44 and 43. The penetration estimation segment is shown in Figure 8.3.
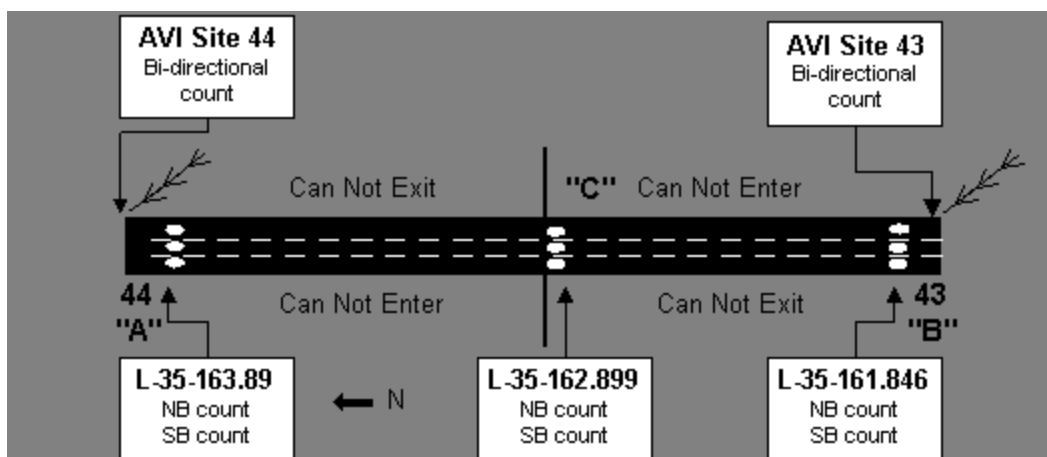
Figure 8.3 Penetration Test Segment (Links 5 and 6)

The segment was selected because of the unique properties of the link detector configuration and location of entrance and exit ramps. Eight counts are required for each day of the study period, both AVI counts and loop counts from the three loops for each direction. Figure 8.4 displays the eight numbers required for the penetration analysis from a typical day. The numbers are shown in bold highlight.

Southbound   Northbound

Link ID	Count			
5	77	AVI Total Count:	**136**	
13	27	Comparison Loop:		
11	16	0035S-163.893	0035S-162.899	0035S-161.846
15	2	**10243**	**5262**	**8316**
17	14			
19	0			

Link ID	Count			
6	42	AVI Total Count:	**55**	
14	10	Comparison Loop:		
12	1	0035N-161.846	0035N-162.899	0035N-163.896
16	0	**8945**	**7121**	**9759**
18	2			
20	0			

Figure 8.4 Sample AVI and Loop Counts for Penetration Analysis

The following discussion outlines the methods and results of the node and link penetration estimations. Labels A, B, and C in Figure 8.3 refer to loops at mileposts 163.89, 162.899, and 161.846, respectively.

8.2.2 Node Penetration

The node penetration for the study link, shown in Figure 8.3 requires closely spaced loop and AVI detectors. The two loop detectors at the end of the segment (A and B) are both within a few hundred feet of the AVI detector. The northbound (V^{NB}) and southbound (V^{SB}) peak period counts are summed and a fraction α of tagged vehicles to total vehicles is obtained, as shown in the equations below:

$$\alpha_A = \frac{V_A^{AVI}}{V_A^{NB} + V_A^{SB}} \qquad \alpha_B = \frac{V_B^{AVI}}{V_B^{NB} + V_B^{SB}}$$

The weighted average of the two fractions is taken to obtain a single estimate of the nodal penetration. The equations below outline the procedure:

$$\omega_A = \frac{V_A^{NB}}{V_A^{NB} + V_A^{SB} + V_B^{NB} + V_B^{SB}} \quad \omega_B = \frac{V_B^{NB}}{V_A^{NB} + V_A^{SB} + V_B^{NB} + V_B^{SB}}$$

where ω_A is the weight associated with the fraction at A, the weight at B is similarly defined.

$$\alpha = \omega_A \alpha_A + \omega_B \alpha_B$$

where α is the weighted nodal average of tagged vehicles on the study link for the peak period defined in Section 4.2.2.

The procedure was performed separately for both morning and afternoon peak periods for all days of the study period discussed in Section 4.1.1.1. Figure 8.5 is a chart of the results of the morning and afternoon peak period tag penetrations based on node measurements.

Tag Penetration by Node (Nodes 44 and 43)

	19	20	21	22	23	26	27	28	29	30	11	12	13	14	15	18	19	20	21	22	25	26	27	28	29
AM	1.25	1.43	1.67	1.48	1.37	1.36	1.36	1.45	1.53	1.43	1.32	1.56		1.58	1.60	1.42	1.41	1.48			1.41	1.64	1.39	1.48	1.49
PM	1.30	1.30	1.31	1.43	1.51	1.15	1.34	1.46	1.23	1.50	1.27	1.28		1.58	1.40	1.38	1.48	1.41		1.29	1.22	1.37	1.35	1.40	1.29
	June										September														

Date
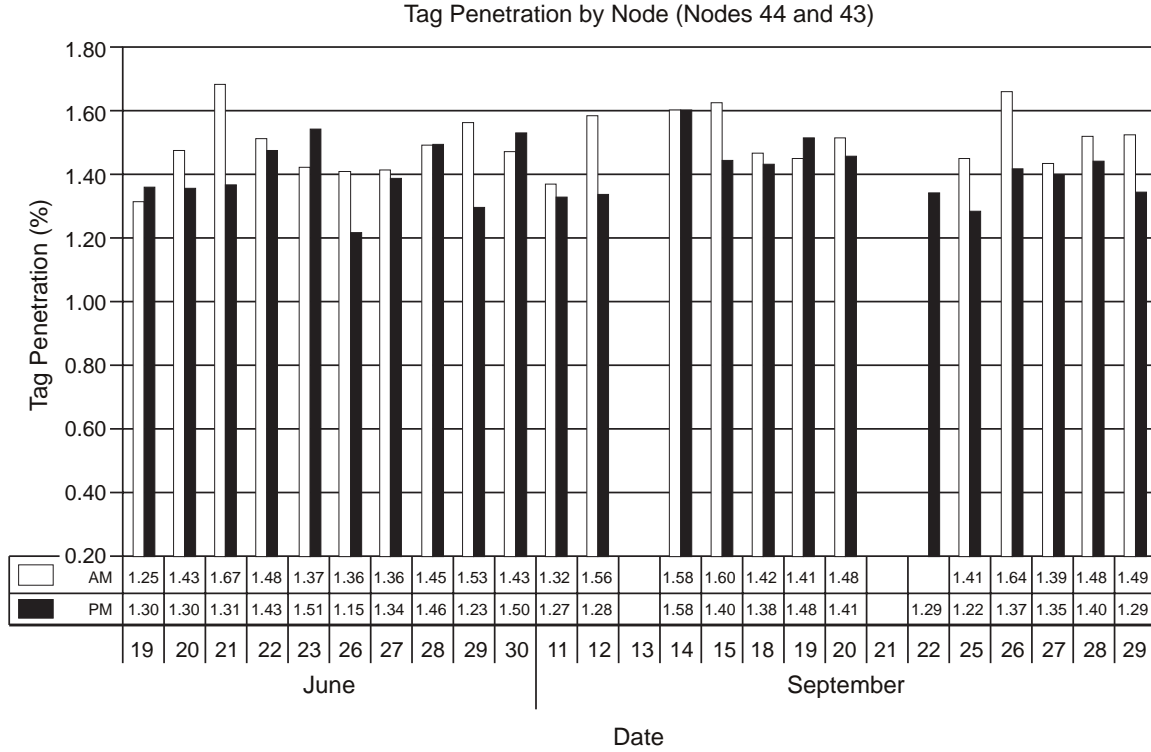
Figure 8.5 Tag Penetration by Node (Nodes 44 and 43)

The weighted average for an individual peak period *(λ_peak)* across all study days is obtained as follows:

$$\omega_i = \frac{V_A^i + V_B^i}{\sum_{i=1}^{days}\left(V_A^i + V_B^i\right)}$$

Where ω_i is the weight, V_A^i is the total loop volume at location A on day *i*.

$$\lambda_{peak} = \sum_{i=1}^{days}\omega_i\alpha_i$$

The morning peak tagged vehicle penetration by node *(λ_AM)* is 1.46 percent and 1.35 percent for the afternoon peak *(λ_PM)*. The times where either one of the loop detectors or AVI detectors were down were omitted from the analysis.

8.2.3 Link Penetration

The tagged vehicle penetration by link is also weighted by the total loop volume counts. The sum of the AVI counts from the first and second order links (refer to Figure 4.8) is computed for both Links 5 and 6, as shown in Figure 8.3. The northbound AVI volume (V_{AVI}^{NB}) consists of Links 5, 13, 11, 15, 17, and 19; likewise, the southbound AVI volume

(V_{AVI}^{NB}) consists of Links 6, 14, 12, 16, 18, and 20. The link-based fraction of AVI-equipped vehicles $(\alpha^{direction})$ is computed as follows:

$$\alpha^{NB} = \frac{V_{AVI}^{NB}}{V^{NB}} \text{ and } \alpha^{SB} = \frac{V_{AVI}^{SB}}{V^{SB}}$$

where $V^{direction}$ is the volume in the specified direction from loop C in Figure 8.3. The weights $(\omega^{direction})$ are computed as:

$$\omega^{NB} = \frac{V^{NB}}{\sum\limits_{i=1}^{days} V_i^{NB}} \quad \text{and } \omega^{SB} = \frac{V^{SB}}{\sum\limits_{i=1}^{days} V_i^{SB}}$$

where $V_i^{direction}$ is the volume for the specified direction from loop C during the peak period on day i. Finally, the tagged vehicle penetration $(\lambda_{peak}^{direction})$ for a given direction and peak period is computed as the sum product of the weights and individual daily fractions.

$$\lambda_{peak}^{direction} = \sum\limits_{i=1}^{days} \omega_i \alpha_i$$

The directional peak period tagged vehicle fractions for Links 5 and 6 are shown in Figure 8.6.

Tag Penetration by Link (Links 5 and 6)

	19	20	21	22	23	26	27	28	29	30	11	12	13	14	15	18	19	20	21	22	25	26	27	28	29
AM NB	0.50	0.84	0.97	0.93	0.73	0.61	0.77	0.84	0.87	0.78	0.45	0.79	0.75	0.79	0.68	0.47	0.80	0.70		1.30	0.73	0.86	0.61	0.58	0.61
AM SB	2.53	2.63	3.08	2.58	2.40	2.88	2.58	2.82	2.87	2.60	3.01	2.90	2.80	3.62	3.18	3.46	2.72	3.12		3.15	3.45	3.21	3.05	3.49	
PM NB	1.45	1.45	1.53	1.63	1.63	1.40	1.51	1.57	1.28	1.50	1.44	1.42	1.59	1.59	1.81	1.74	1.79	1.79		1.54	1.51	1.64	1.82	1.52	1.79
PM SB	1.01	0.94	1.01	1.08	1.17	0.78	1.07	1.16	1.01	1.17	0.81	1.04	0.93	0.95	0.77	1.06	1.02	1.09		1.06	0.84	0.90	0.79	1.09	0.89

June: 19–30   September: 11–29

Date

Figure 8.6 Tag Penetration by Link (Links 5 and 6)

The morning tagged vehicle penetration by link is 2.95 percent in the southbound direction (λ_{AM}^{SB}) and 0.74 percent in the northbound direction (λ_{AM}^{NB}). Likewise for the afternoon peak period, the penetration by link is 0.95 percent and 1.51 percent in the south (λ_{PM}^{SB}) and northbound (λ_{PM}^{NB}) directions respectively.

8.2.4 AVI-Loop Penetration Conclusions

Table 8.1 shows the summary of results from the AVI Loop penetration estimation.

Table 8.1 AVI-Loop Penetration Summary

	Node	Link	
		Northbound	Southbound
AM	1.46%	0.74%	2.95%
PM	1.35%	1.51%	0.95%

There are obvious conclusions from the penetration estimation presented in Table 8.1. The tagged vehicle penetration is higher in the peak direction and much greater in the

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morning. There are also some limitations from the assumptions in the presented method. One important assumption is that the loop at location C in Figure 8.3 is representative and adequately captures the total volume of vehicles that traverse the study segment. The location of entrance and exit ramps was verified to ensure that any vehicle detected by the loop at C would also have to pass locations A and B (Purcell 2000).

The accuracy of the loop detectors is critical to the interpretation of the penetration estimation. If the loop detectors consistently fail for any length of time, the tagged vehicle penetration will be overestimated. Analysis of the reliability of the loop detectors is beyond the scope of this work. The computation of the weighted average properly computes the average across the days; however, consistent lapses in loop data could result in overestimation.

8.3 TAG PENETRATION BY TAG TYPE

More vehicles across the country are obtaining tags for a variety of reasons. The rise in popularity of parking, ground access, and electronic toll facilities increases the tag population among all road users in a given region. Provided that standards and interoperability between vendors is maintained, a significant percentage of the tag reads can be obtained from simply installing readers. In implementing an AVI system for ATIS data collection purposes, sources of probe vehicles already in the network should be identified.

As an example, TxDOT acquired 15,000 tags for an initial feasibility study for AVI in Houston. The Hardy Toll Road and Sam Houston Tollway then purchased 517,000 tags for the purpose of Electronic Toll and Traffic Management on the toll facilities in Harris County. The tags are also providing travel time information for the other highways in the Houston network. As stated in Section 1.4.1, 644,031 tags have been distributed in Houston in addition to the TxDOT pilot 15,000 tags.

An assessment of the San Antonio AVI system would not be complete without investigating how many of the tags distributed by TransGuide are actually read. San Antonio purchased 78,000 tags and 58,500 have been distributed freely to the public as of November 2000 according to Rodrigues (2000). As computed in Section 2.2.1, there are about 8,000 unique tag reads per day. As many as 60 percent of the tag reads per day are not San Antonio-distributed tags, for the last week of March 2000. That is to say, of the 8,000 tags read by the system, only 3,200 tags were San Antonio tags distributed for the Model Deployment Initiative project. Figure 8.7 outlines the sources of the other tag reads for the last week of March 2000. TransGuide staff processed the raw tag read data for one week in March to obtain the fractions of tags read by the first four fields in the tag identifier.
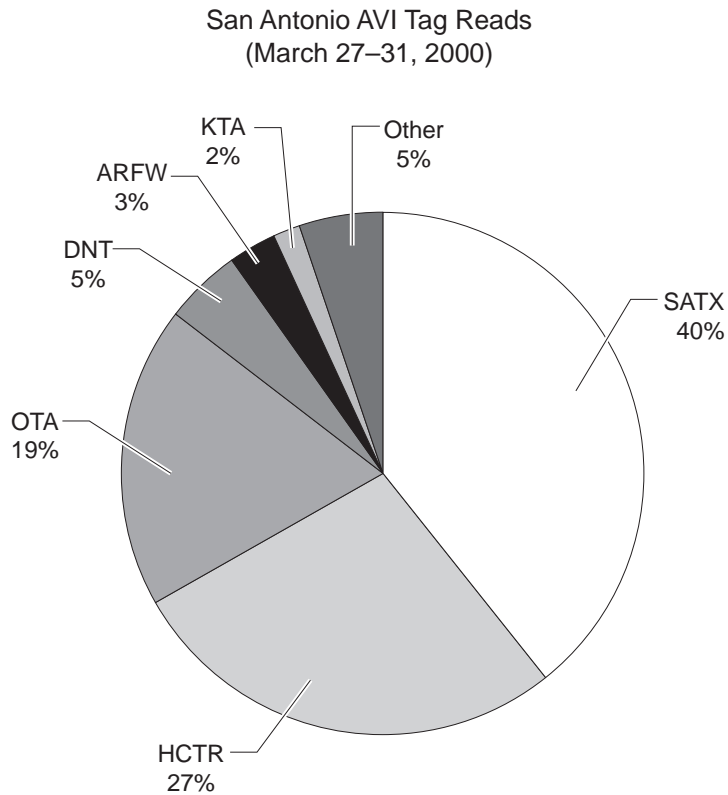
San Antonio AVI Tag Reads
(March 27–31, 2000)

Figure 8.7 San Antonio Tag Reads by Tag Type

SATX are San Antonio tags, HCTR are tags from Houston, and OTA tags come from the Oklahoma Turnpike Authority. DNT tags are most likely from Dallas and KTA tags from Kansas. It is important to note that TransCore (formerly Amtech) tags are most popular in the Southwest.

Tag penetration by type is important for system evaluation and to estimate the amount of tags necessary to realize a given level of total tag penetration. From the analysis in previous sections, the average penetration is on the order of 1 or 2 percent. Less than half of the tag reads are from the city under investigation. Tags from vehicles that reside within the city are more likely to provide a recurring snapshot of traffic conditions, than through travelers who are often traveling for other purposes at off-peak times.

AVI transponder tags can also be distributed for parking or to grant access to a multitude of private complexes. Security is an important concern as the tag identification should be encrypted to prevent tracking of individuals through the network.

8.4 TAG PENETRATION CONCLUSION

From the analysis presented, we can conclude that the tagged vehicle penetration is less than 3 percent of the total vehicles in San Antonio. Note that not all of these are San Antonio vehicles. As the popularity of AVI grows, there is a greater benefit to installing the system for AIT data collection. Incentives such as electronic toll collection, ground access management, or electronic parking can substantially increase the tagged vehicular volumes.

CHAPTER 9 SAN ANTONIO ADVANCED TRAVELER INFORMATION SYSTEM ASSESSMENT

The goal of the work presented here is the assessment of an on-line automatic vehicle identification (AVI) system for the purpose of data collection for advanced traveler information systems (ATIS's). Chapter 3 presented guidelines for evaluating an ATIS data collection system and Chapter 4 outlined the properties of the test data and the proper methods for defining state estimators. Chapter 5 explored the current level of tagged vehicle penetration in an operational system. With the background and analysis presented, attention is now directed toward assessing the current system installation in San Antonio.

Metrics of assessment were identified and related specifically to the properties of an AVI system. Match effectiveness, or the ability of the system to efficiently match equipped vehicles, is an important metric for AVI evaluation. The nature of the three primary traffic state estimators (flow, density, and speed) is assessed based on a comparison with loop data keeping the proper definitions in focus. Accuracy is also determined by comparing aggregate AVI data with aggregate loop data. The confidence, delay, and availability of the AVI data for ATIS applications is evaluated based on results from the study period analysis. The breadth and depth of coverage by AVI in San Antonio is discussed. Finally, a cost-benefit analysis of the AVI system is provided as a conclusion to the chapter. Recommendations and future research are presented in a separate chapter.

9.1 MATCH EFFECTIVENESS

Match effectiveness is the ability of the system to adequately track vehicles and compute derived data for ATIS purposes.   The San Antonio system has room for improvement to effectively capture an accurate picture of the movements of tagged vehicles. The major drawback to match effectiveness is that not every lane is monitored at most sites. Some sites monitor all four lanes of travel, while most only monitor the two inner lanes of travel of a three-lane facility. An assessment of the ability of the system to match tag reads is made by comparing the number of tag reads to the number of matches. The difficulty in the analysis arises because vehicles enter and exit the facility at multiple locations and may only be on the highway for one or two links. The definition of the fraction of total tags read to total matches is made, followed by an analysis with San Antonio data.

Using the fraction of vehicles that are read by total matches as a metric for match and ultimately system effectiveness, involves some assumptions. If all vehicles traversed the entire study network and were read by all sensors (assume that all lanes are monitored and all equipment is functioning), then for the San Antonio study network of five sites and eight first- order links, 1,700 tag reads should produce 1,360 matches. Consider a simple case where one vehicle passes five sensors and creates four matches. Eighty percent of the reads produce valid matches because there are five sensors. Therefore, 80 percent would be the theoretical upper limit on the number of total tag reads that can turn into matches. If we had 80 percent of the tag reads becoming matches, they all would be on Links 1-8 (as shown in Figure 5.14) and there would be no need for incorporating the additional second-order links,

based on the assumption of a perfect system and that every vehicle traverses the entire study corridor.

The 80 percent theoretical maximum of the fraction of tag reads becoming matches varies by the number of reader sites under investigation. The percent of tag reads is related to the total number of possible matches by

$$\frac{n-1}{n}$$ (Eq. 9.1)

where *n* is the number of sites in the study network. This relationship is shown in Figure 9.1.
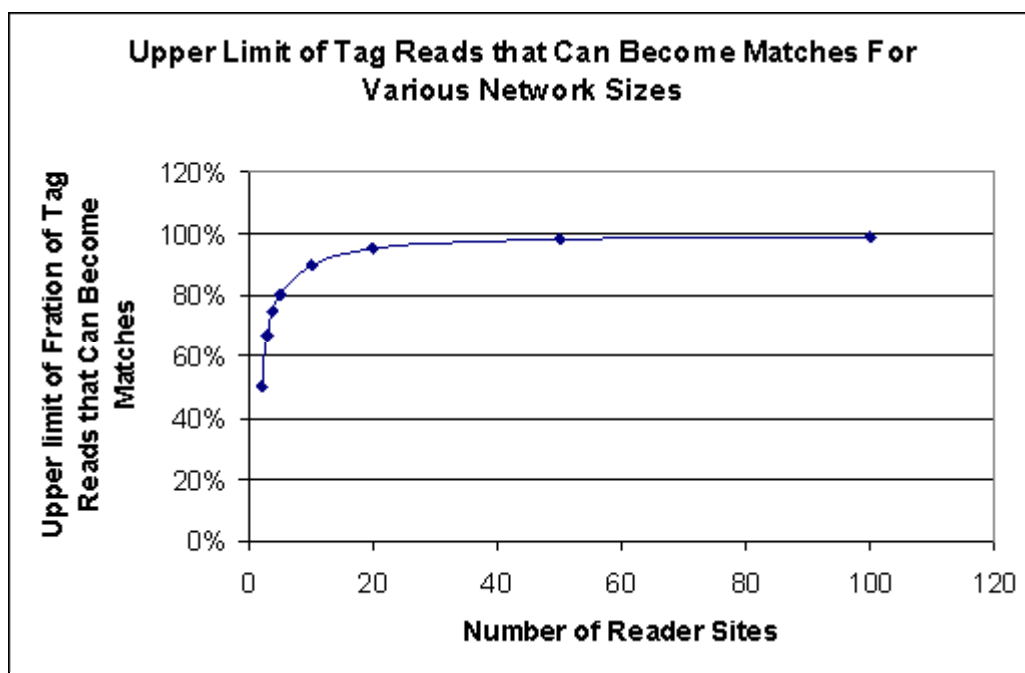
Figure 9.1 Limit of Fraction of Tag Reads That Can Become Matches

A larger number of available reader sites allows for more tag reads that can become matches.

To evaluate the match effectiveness for the San Antonio study corridor, the number of total tag reads is plotted with the total number of valid matches. The average, 51.1 percent total tag reads, become valid matches with a standard deviation of 2.3 percent. Considering the limitations of the current installation in San Antonio, the system is effective at matching tagged vehicles. Half of all tag reads become a tag match, with a narrow spread of less than 3 percent. Vehicles are typically traveling past at least two sites.

Total Number of Reads & Total Number of Valid Matches

Figure 9.2 Total Number of Tag Reads and Total Number of Valid Tag Matches

For example, on September 12 we have 1,700 tag reads with 862 valid matches (51 percent). Of those matches, seventy-seven are from second-order links, indicating vehicles that skipped detectors (i.e., those that somehow missed being detec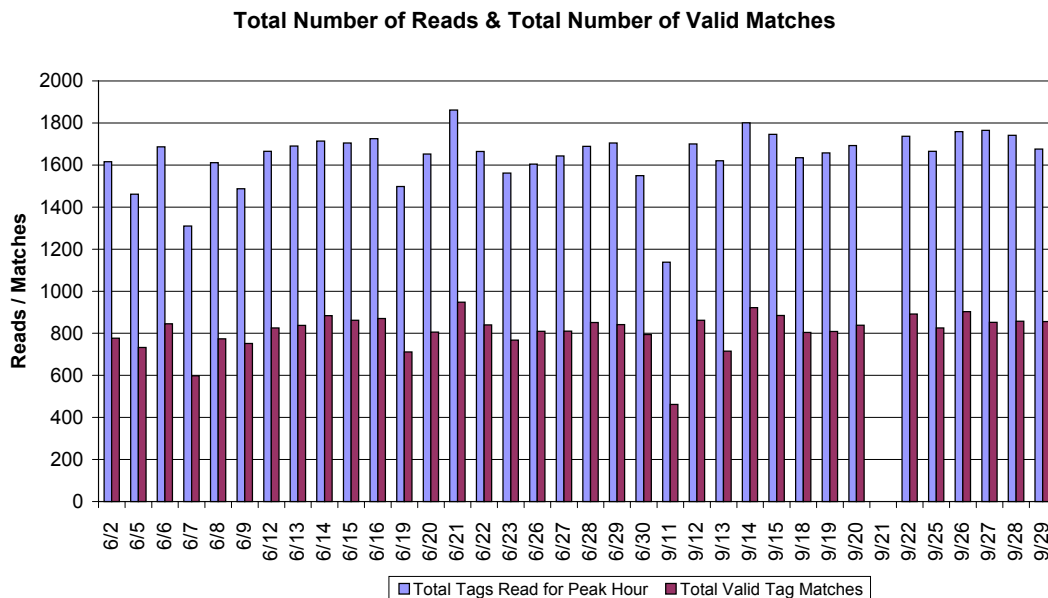ted). Also, it should be safe to assume that some vehicles enter the network mid-study section and others may leave prior to the end of the study section; however, these counts cannot be determined with the current installation.

The effectiveness of the San Antonio tag matches is adequate, as over 50 percent of the tag reads become matched tags. Even with a completely reliable system, the match effectiveness may be considerably lower if the reader spacing precludes reasonable tag matches. Considering the theoretical maximum number of tag reads is 80 percent, if just over half the tag reads become useful matches, this justifies the San Antonio system as capable of obtaining useful data for traffic management and information purposes.

9.2 NATURE AND ACCURACY

The assessment of the nature and accuracy of data collection methods for ATIS applications are interrelated and, therefore, are discussed together. The nature of the data and limitations of collection methods directly impact the accuracy evaluation. The program developed output loop and AVI data to standard spreadsheet files for quick analysis of individual links. Charts are obtained from selected days in the study period to serve as examples of the accuracy obtained for the given peak period (defined previously). The goal is to illustrate aspects where the AVI system performs well and to identify weaknesses in the effectiveness of the system in order to provide valuable information to an ATIS.

9.2.1 Travel Time and Speed

The speed is derived from the travel time and length of the link, therefore speed and travel time are investigated together. For most ATIS applications, the speed estimated to within 1 mile per hour is adequate. There are two primary factors that affect speed computation. The first is the accuracy of the time stamp a tag receives when passing a reader site; the second is the accuracy of the distance measurement between reader sites. The sensitivities of both time stamps and distances to travel time and speed are discussed.

The time stamp applied to tag data at the reader sites is of critical importance to accurate travel time and speed measurements. An early problem with the system in San Antonio was unsynchronized clocks at the reader sites, resulting in unreasonable speed estimates from invalid travel times. The clocks were repaired in early June 2000 after invalid time stamps had been applied since November 1999.

The sensitivity of AVI speed computation to clock inaccuracy was investigated. Table 9.1 uses a valid tag match on Link 3 to simulate an inaccurate clock, by decreasing and increasing the downstream time stamp. Speeds are recomputed and compared to the actual speed of 63.48 miles per hour for the 2.43 mile link.

Table 9.1 Impact of Clock Synchronization on Speed Measurement

		Upstream		Downstream		Travel Time	Speed
Link length (miles)			2.431				
		(mm:ss.s)	(seconds)	(mm:ss.s)	(seconds)	(seconds)	(mph)
Downstream DECREASE Clock Deviation	5-minutes	29:31.0	30572	26:51.0	30412	-159.83	-55.67
	2-minutes	29:31.0	30572	29:51.0	30592	20.17	441.12
	1-minute	29:31.0	30572	30:51.0	30652	80.17	110.98
	30-seconds	29:31.0	30572	31:21.0	30682	110.17	80.76
	10-seconds	29:31.0	30572	31:41.0	30702	130.17	68.35
	1-second	29:31.0	30572	31:50.0	30711	139.17	63.93
Actual		29:31.0	30572	31:51.0	30712	140.17	63.48
Downstream INCREASE Clock Deviation	1-second	29:31.0	30572	31:52.0	30713	141.17	63.03
	10-seconds	29:31.0	30572	32:01.0	30722	150.17	59.25
	30-seconds	29:31.0	30572	32:21.0	30742	170.17	52.29
	1-minute	29:31.0	30572	32:51.0	30772	200.17	44.45
	2-minutes	29:31.0	30572	33:51.0	30832	260.17	34.20
	5-minutes	29:31.0	30572	36:51.0	31012	440.17	20.21

For a 2.4 mile link, the clocks at both reader sites cannot differ more than two seconds from each other without seriously affecting data integrity.

The length of the link plays an important role in defining the accuracy of time synchronization. Figure 9.3 shows the effect of a 10-second deviation in the downstream clock for a vehicle traversing various link lengths at a constant speed of 60 miles per hour.
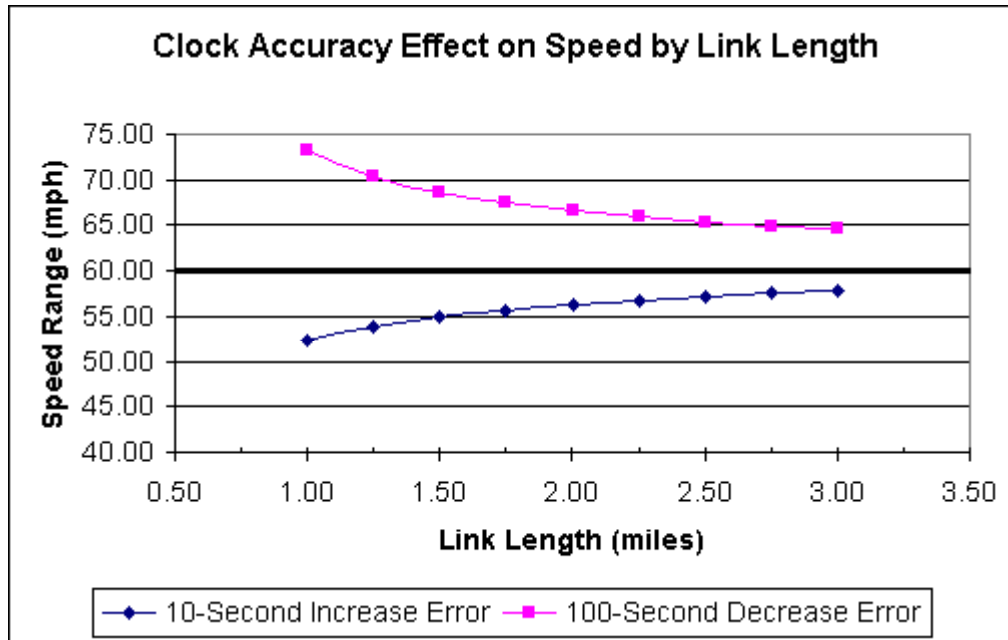
Figure 9.3 Clock Accuracy Effect on Speed by Link Length

Note that as the length of the link increases, the sensitivity to clock synchronization decreases. For longer range CVO applications, clock synchronization is not a critical factor.

The distance between the reader sites only needs to be accurate to within ±100 feet of the actual distance to achieve speeds accurate to within 1 mile per hour. Table 9.2 outlines the sensitivity of computed speeds to reader spacing accuracy.

Table 9.2 Impact of Reader Spacing on Speed Measurements

	Reader Spacing	Travel Time	Speed	Speed Difference
-500 feet	2.363	2.437	58.185	2.331
-200 feet	2.420	2.437	59.584	0.933
-100 feet	2.439	2.437	60.050	0.466
-10 feet	2.456	2.437	60.470	0.047
Actual	2.458	2.437	60.517	
+10 feet	2.460	2.437	60.563	0.047
+100 feet	2.477	2.437	60.983	0.466
+200 feet	2.496	2.437	61.449	0.933
+500 feet	2.553	2.437	62.848	2.331

The distances in San Antonio are measured to a thousandth of a mile, implying an accuracy of 5 feet.

In comparing the AVI speeds to the loop speeds for accuracy assessment, it is important to consider the differences in the definition of the space mean speed obtained from the AVI and the point speed obtained from the loop detectors. The reader is referred to Section 4.3.9. According to the guidelines outlined in Chapter 3, discrete section data is preferred to discrete point data or aggregated section data. An AVI system by definition generates discrete section data, which is considered the best method for limited access highways. For accuracy comparison, aggregated section data is compared to aggregated point data from the loop detectors.

A typical plot comparing AVI 15-minute average speeds with the average speed obtained from loop detectors is shown as Figure 9.4.
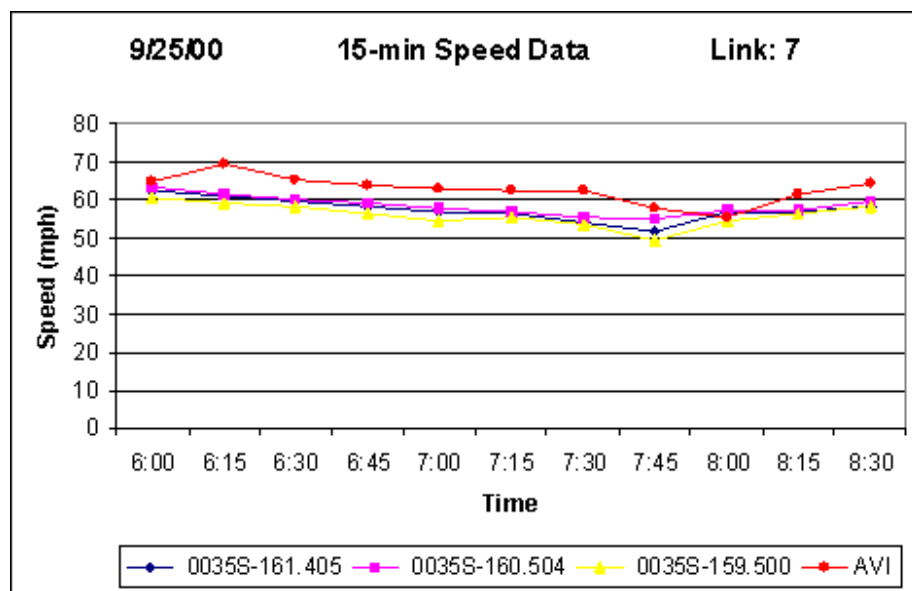

Figure 9.4 Loop and AVI Speed Data (9/25/00, Link 7)

The three lines clustered together represent the three loops on southbound Link 7 during the morning peak. The AVI average speed is higher than the loop speeds in this case; often the difference in loop speeds is much greater. The above instance is indicative of little or no congestion experienced on the link across the peak period. The AVI system closely matches the loop data and the measurements are within 5 and 10 percent. From the discussion presented in Section 4.4.2 because the loop speed and AVI speeds do not vary considerably from each other, the link can be classified as stable or uncongested.

From the guidelines presented in Chapter 3, the AVI system could be classified as "better" than other traffic detection technologies when the AVI space mean speeds are compared to the time mean speeds of loop detectors. The accuracy of AVI may actually be higher as the speed measurements should be compared to another direct space mean speed measurement.

It is, of course, prudent to look at other sections, particularly those that experience congestion. Figure 9.4 is from June 28, where a significant reduction in speed is observed from 07:00 to 08:30.
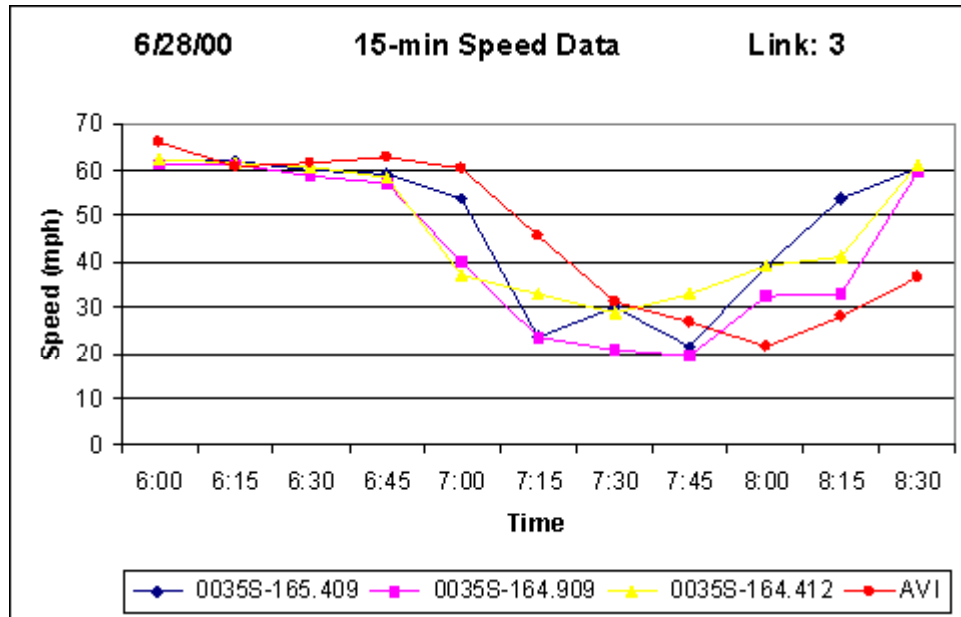

Figure 9.5 Loop and AVI Speed Data (6/28/00, Link 3)

Note that the AVI speed data responds to the congestion, and the variability of all four measurements increases significantly. The trends and onset of congestion are captured by the AVI system. The accuracy of both systems declines during periods of congestion, as the variability in travel times and speeds increases.

A final test of the accuracy of the San Antonio AVI system was performed by driving a probe vehicle through the network and comparing actual speedometer readings to the travel times computed from the match tag process. On two occasions, the network was driven with a tagged vehicle and the time passing under the AVI antennae was noted. The difference in times in the archive data file and those observed with a watch set to the atomic clock was on the order of a few seconds, well within the margin of reaction time error. The speeds computed between the locations from the AVI or manual data would therefore be within 1 or 2 miles per hour.

Speed data from AVI is directly related to the observed link travel times. The value in AVI data for ATIS applications lies in the link travel time and speed data. Even with a low penetration rate, less than 2 percent in most cases, vehicular probes adequately and accurately represent current space mean speed conditions.

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9.2.2 Volume

The challenge in comparing AVI volume counts with loop counts lies in the fact that the AVI does not monitor all lanes in all cases. Figure 9.5 shows the volume comparisons between AVI and loop data for Link 5 on June 15 during the peak morning period. The second y-axis, shown on the right, represents the AVI volumes; both volume measurements are in vehicles per hour.
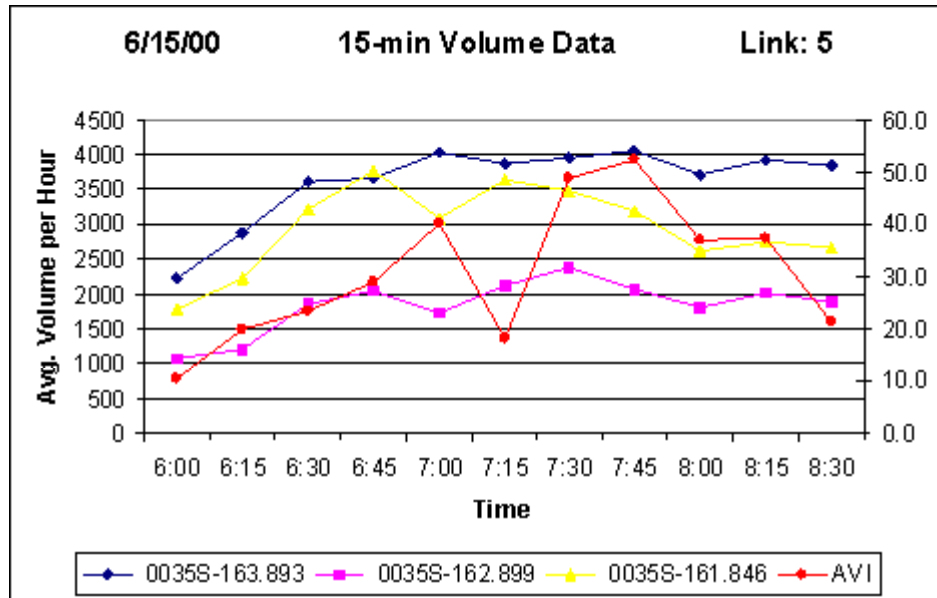
Figure 9.6 Loop and AVI Volume Data (6/15/00, Link 5)

As with the speed data, the general trends are maintained; however, the counts vary substantially from one loop detector to another. The link shown is three lanes and the upstream and downstream AVI both monitor the two inner lanes. The first loop detector is upstream of the interchange with southbound Interstate 410, which explains the higher volumes.

Another example of the volume data from a more congested period is shown in Figure 9.9. The plot is of the same study period and link as the congested example in Figure 9.4.

Figure 9.7 Loop and AVI Volume Data (6/28/00, Link 3)

Both volume measurements are in terms of vehicles per hour. The AVI data is representative of the general volume trends obtained from the loops. The market penetration discussed in Chapter 4, relates the volume obtained from AVI to that obtained from the loop detectors. Analysis of how the penetration may vary across the peak hour would be necessary. The general trend in the data is maintained from the three loops.
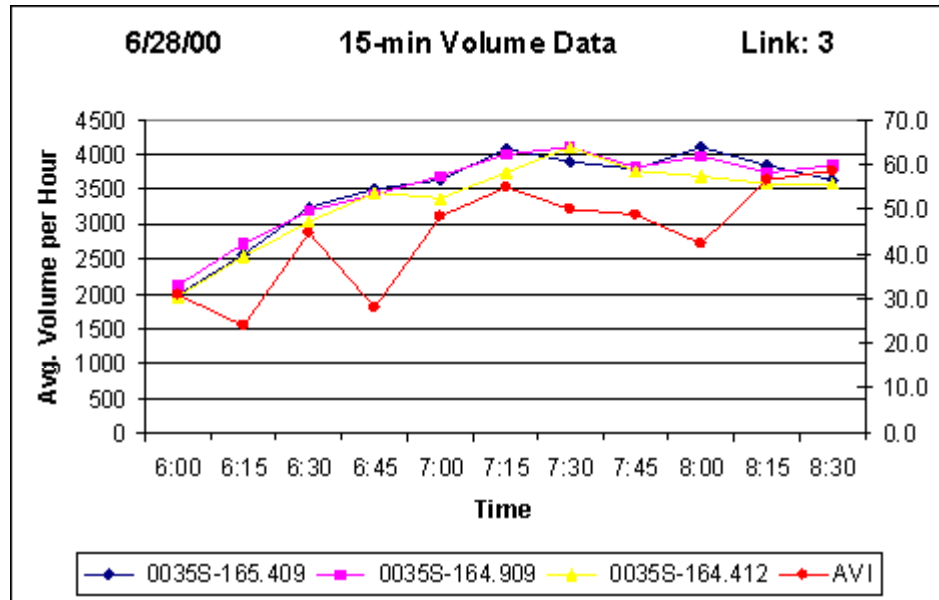
9.2.3 Density

The accuracy of the density measurements is more difficult to ascertain. The AVI density is accurate and consistent with the Edie definitions as shown in Section 4.3.1. Therefore, the accuracy is limited by the accuracy of the volume and travel time measurements. The loop density is derived from the percent occupancy and an assumed average vehicle length and length of the detection zone, as outlined in Section 4.3.4. Comparing the two measurements is for illustrative purposes. If the loop data were calibrated perfectly, the AVI data should be less than the loop density by the tagged penetration factor.

AVI density data is compared in the following Figure 9.8 and Figure 9.9. Figure 9.8 is from a typical day and Figure 9.9 is the third in the series of plots from June 28, which experienced some congestion. The general trends in the data are maintained, but not as well as with the speed and volume count data. Accurate density measurements would likely require a greater tagged vehicle penetration rate. However, density information is not as meaningful to ATIS users, relative to the measurements of speed and travel time.
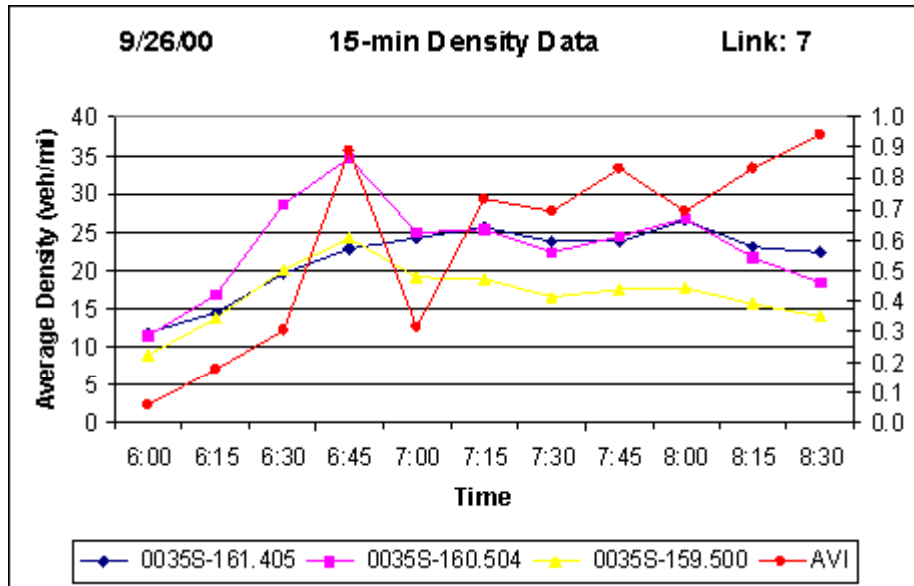
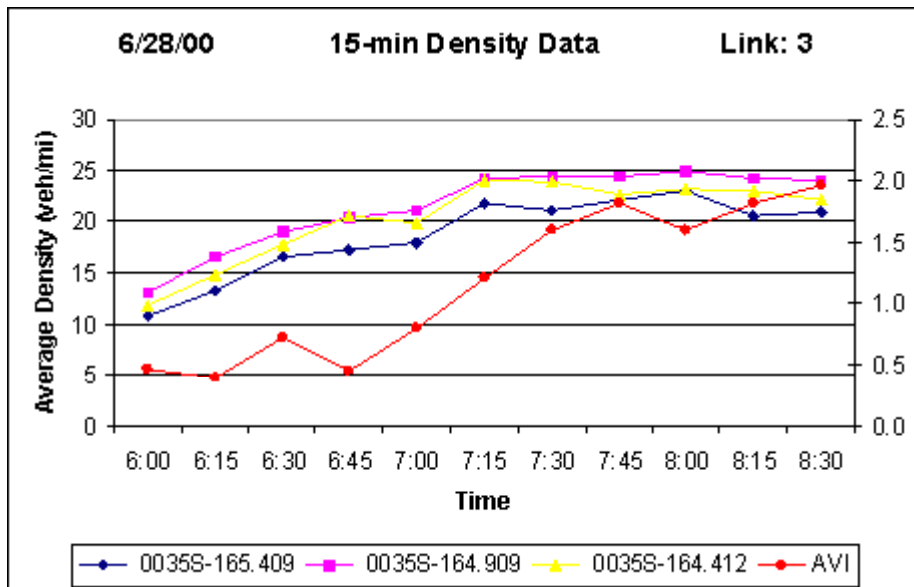Figure 9.8 Loop and AVI Density Data (9/26/00, Link 7)

Figure 9.9 Loop and AVI Density Data (6/28/00, Link 3)

9.3 CONFIDENCE, DELAY, AND AVAILABILITY

Driving a tagged test vehicle through the system and noting the time passing the sensors is one method to assess the confidence of AVI data. The confidence, as introduced in

Section 3.2.3, relates to the ability of the system read tagged vehicles that pass and report information (time and tag ID) correctly. Delay in reporting data is the time it takes for the raw field data to be transferred and available to the Traffic Management Center (TMC). Data availability refers to when and how often the data is made available to interested parties.

9.3.1 Confidence

The confidence of the network is difficult to assess, as it is impossible to determine the number of tagged vehicles that pass undetected. One option is driving the network and comparing noted times with detector results. The tags are scrambled and it is difficult to ascertain the correct tag results in the raw data files. Also, having multiple tags in the vehicle seems to adversely affect the performance of the system. A given site installation is tested as part of the installation process to read 95 percent of the tags that pass in a controlled test by the installation team.

A better measure of the confidence of the AVI system is the number of tag reads that are able to produce tag matches. A tag read is most valuable when matched with another tag read to obtain travel time and speed. The reader is referred to the earlier Section 9.1, where it was determined that at least 50 percent of the tag reads became valid tag matches. Considering the assumptions of a perfect closed system with only five reader sites, a maximum of 80 percent of tag reads could become tag matches. Under the present circumstances (incomplete lane coverage and the absence of entry/exit control), obtaining 50 percent tag reads becoming useful matches, is very good.

9.3.2 Delay and Availability

The field reader sites operate on a buffer and send approach. There are no set polling times and the data is sent on an as-needed basis. It is impossible to determine if data is available and not being sent, because no data can also be interpreted as an absence of tagged vehicles passing the detector station. The system employs ample phone lines for the fifty-two field sites to call in simultaneously and update the data. A direct dedicated link from the reader sites to the TMC would be preferable, however the cost and desire to have AVI sites on the periphery of the metropolitan region leaves this questionable.

The match tag algorithms and speed computation take place at TransGuide. Average vehicle speeds and travel times are then updated as the raw tags are matched. The delay with AVI data, after two successive readers have identified a vehicle, increases as the distance between the readers increases and speeds decrease. In highly congested regions, AVI sensors should be located closer together to achieve minimum delay in processing matches. The downstream data need to be sent from the field to the TMC and a match processed.

The raw scrambled tag data is made available to the TransGuide anonymous FTP site at midnight. The data is maintained for a single week when it is then removed for the new data. Therefore, there is always a single week of AVI data available on the public servers. No AVI data is currently available to the public in real time.

To apply the ATIS data-quality guidelines, an estimate of the percentage of time the AVI is operational is required. For the 25 study days, data from September 21, 2000, were

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not available for the entire day and are therefore removed from analysis. From the remaining days across the five AVI sites in the study corridor, only two were down for the entire day throughout that time. The availability of AVI data is "better" than other similar systems, according to the ATIS data-quality guidelines outlined in Chapter 3, as the data are available between 95 and 99 percent of the time.

9.4 BREADTH AND DEPTH OF COVERAGE

The San Antonio AVI system covers 89 miles of freeways and some arterial streets. All major limited-access highways in San Antonio are AVI equipped. However, the breadth of coverage is limited to the periphery of the city. There are sensors between major interchanges, but the system lacks infrastructure in the downtown area. In the study corridor provided for analysis, there are sensors between every major interchange. According to the guidelines, the AVI system is "better" than other methods of data collection in terms of breadth of coverage.

The distance between reader sites is typically greater than 2 miles. The exception is the link between sites 45 and 47 where the spacing is only 1 mile. Table 9.3 outlines the lengths between the reader sites; the average spacing is 2 miles. Simulation analysis, where the level of tagged vehicles and reader spacing could be adjusted, would be required to test benefits of increased reader spacing, as moving AVI reader sites is extremely cost prohibitive. AVI spacing could be increased to distances much greater than 2 miles for rural ATIS applications where there are fewer interchanges.

Table 9.3 San Antonio Link Lengths

Link	Upstream	Downstream	Length
1	47	45	1.340
2	45	47	1.101
3	45	44	2.431
4	44	45	2.458
5	44	43	1.905
6	43	44	1.910
7	43	42	2.675
8	42	43	2.675
		Min	1.101
		Max	2.675
		Average	2.062

Because not every interchange is monitored, the AVI system only ranks in the middle, "better" data-quality category for depth of coverage for ATIS applications. Facilities such as turnpikes where all vehicles must pass a toll facility when entering or leaving the facility would be ideal to meet this goal.

9.5 COSTS AND FINANCIAL BENEFITS OF AVI

An important consideration when evaluating any system is the cost of implementation relative to an estimated economic benefit of an AVI system. A formal cost/benefit analysis is beyond the scope of the work presented here; however, it is of interest to provide available figures concerning the known costs of the system tested for this work. The costs of the AVI and loop systems will be outlined in the next two sections. One additional cost that is often overlooked is the cost of the TMC, which serves as the central data collection and dissemination site for the system. TransGuide is estimated to be a $23 million operation (TransGuide 2000). Both detection systems share the resources of the TMC. The relative additional cost of detection infrastructure is investigated in Sections 9.5.1 and 9.5.2.

9.5.1 AVI Costs

The cost of the entire San Antonio AVI development and installation was $2.4 million in 1997, according to TransGuide. That figure includes all fifty-three sites, hardware, and installation. A monthly maintenance contract with TransCore is $12,000 per month for the entire fifty-three-site network of AVI detectors (Rodrigues 2000). The breakdown of individual field installations along our study corridor is outlined in Table 9.4.

Table 9.4 San Antonio AVI Costs by Site (Rodrigues 2000)

Location	Hardware & Amtech Labor	Civil & Electrical	Total	Total Cost per Lane
142 IH-35 @ New Braunfels Street Overpass	$20,905	$23,065	$43,970	$10,992
143 IH-35, OSB.2 mile North of Splashtown	$20,905	$18,906	$39,811	$9,953
144 IH-36, OSB.2 mile South of Riftiman	$20,905	$27,836	$48,742	$12,185
145 IH-35,.3 mile South of IH-410 North	$25,791	$30,678	$56,469	$7,059
147 IH-35,.3 mile North of IH-410	$24,332	$33,751	$58,083	$7,260
Average	$22,568	$26,847	$49,415	$9,490
Total	$156,034	$184,671	$584,066	

The average site installation is over $48,000 with a total cost of $583,069. The total cost per lane was estimated as sites 42, 43, and 44 monitor four lanes and sites 45 and 47 monitor eight lanes. The average cost per lane is over $9,000. The incremental cost of an additional lane is clearly less than $9,000, probably closer to $7,000. Such an estimate is important when determining whether to install partial or full coverage of all lanes in a given direction.

9.5.2 Loop Costs

The loop costs are lower than those of an AVI setup, however the infrastructure is more versatile in the latter case. The estimated cost of the loop detector equipment was

provided by Rodrigues (2000). The communication cabinet, which can also control communications to other ATIS/ITS systems, is $16,000. Each loop requires a controller card that cost $800. The actual Austin Local Control Units cost $3,300 each and contained a card rack that cost $3,600 each. The loops cost $500 each for the saw cut and wire for each loop. An additional $550 per location is required per location for lane closures, however this cost would also be required for AVI installation. The Civil Hardware (i.e., metal conduit, boring, etc.) is $4,800 for a loop installation.

The cost of the loop detectors installed in the study corridor presented in Section 1.4.1 is $319,500. The cost presented is for nine local control communication units with racks and installation at $27,700 each ($16,000 + $3,300 + $3,600 + $4,800). Plus, $70,200 for nine sites with six loops, each costing $1,300 ($500 + $800). The maintenance cost for the loop detectors is unknown as they are less than a year old. However, the loop detector maintenance is combined with other ITS maintenance performed by TxDOT staff at TransGuide. The loop detection system is less expensive than the AVI system; however, the AVI system infrastructure costs may decline as more systems are brought on-line.

9.6 ASSESSMENT CONCLUSIONS

This chapter outlined the major points and evaluation for the San Antonio AVI system related to an ATIS implementation. While there are some areas where the system can be improved, overall an operational AVI system is in place and should be used to further ATIS applications. The quality of AVI data meets or exceeds many of the guidelines for ATIS data. The next chapter provides final conclusions and recommendations.

CHAPTER 10 CONCLUSIONS

The primary objective of this study was to test the performance of Automatic Vehicle Identification (AVI) systems for incident detection. An extensive literature review was performed on existing traffic detectors and automatic incident detection (AID) algorithms. Results of the literature review were presented in Chapters 2 and 3. Three incident detection algorithms were chosen among the logics described in Chapter 3: the California #8 algorithm, the Texas algorithm, and the Upper Confidence Limit algorithm. The algorithms were calibrated and tested using data acquired from TransGuide, San Antonio's Traffic Management Center (TMC). A standard procedure was developed to calibrate and test the selected algorithms. The use of AVI for ITS applications and Advanced Traveler Information System (ATIS) data requirements were presented in Chapter 4. The steps followed in the calibration and testing effort were detailed in Chapter 6. Calibration and testing results were presented in Chapter 7. Chapter 9 contains an assessment of the San Antonio AVI system, and this last chapter presents the achievements of the research, which is divided into data summary, algorithm test/calibration summary, San Antonio AVI system assessment, recommendations, and future work.

10.1 DATA SUMMARY

The data obtained from AVI systems are shown to be useful to the traffic management operations of a metropolitan region. Once the raw data is processed to obtain vehicle matches, care should be taken to properly define traffic state estimators. The link-based nature of AVI should be correctly exploited. Even at low market penetration rates, as observed in San Antonio, the system is very effective at obtaining travel time and speed information. The promise of an ATIS lies in the ability to gather accurate, timely, and relevant traffic stream information for distribution to users. AVI data directly provide travel times and derived speeds.

10.2 ALGORITHM TEST/CALIBRATION SUMMARY

Results obtained from the calibration and the testing phases showed some variations mainly due to the small number of incidents recorded during the time span considered for this study. In the absence of visual observation of the network, accurate start and end times for the recorded incidents could not be obtained. Therefore, the time to detect (TTD) presented in this study can serve only as a relative measure of performance among the tested algorithms. Furthermore, some incidents might have actually occurred, but were not recorded in the incident logs at TransGuide, thus contributing to the false alarm rate (FAR) exhibited by the algorithms.

The selected algorithms are ranked in Table 10.1 based on the results exhibited from the testing phase. The ranking is done according to the three measures of effectiveness defined in Chapter 3, namely detection rate (DR), FAR, and TTD.

Table 10.1 Summary of Results (Incident Detection Algorithm Reading)

Algorithm	DR	FAR	TTD
California #8 with Loop Data	1	1	1
Texas with Loop Data	2	2	3
Upper Confidence Limit with AVI Data	3	3	2
Texas with AVI Data	4	4	4

The results indicate that, with the exception of the Upper Confidence Limit algorithm which exhibited lower TTD values than the Texas algorithm when applied with loop data, the loop-based incident detection performed better than the AVI-based incident detection. The loop algorithms were able to achieve detection rates of 100 percent at relatively low FAR in the case of the California #8 algorithm. The Texas algorithm was expected to have poor results in terms of FAR since it relies only on one threshold value, thus making it vulnerable to slight variations in the traffic flow. Effectively, although the Texas algorithm achieved high DRs, the corresponding FARs were consistently higher than those observed from other detection logics, and would result in significant TMC operations' disruptions.

When comparing the performance of the Texas algorithm between its application with loop data and its application with AVI data, better results were obtained when the logic was implemented with loop data. This is due to the fact that the loop occupancy is being averaged over 3-minute intervals before being compared with the corresponding threshold. In order to offset the problem associated with the low level of tagged vehicles' market penetration and thus achieve fast detection, the speed obtained from individual tagged vehicles traveling on a certain link was compared to the speed threshold. Not averaging the speeds experienced by individual vehicles on a certain link is at the root of the high false alarms exhibited by the Texas algorithm when it was applied with AVI data.

When an incident is detected by one of the loop algorithms, its location can be determined more precisely than when the same incident is detected by one of the AVI algorithms. While loop detectors are placed on average every 0.5 miles, the average AVI link length in the study corridor approached 2 miles. The operator would have to determine the location of the incident before being able to take any action.

Although the loop algorithms performed better than the AVI algorithms considered in this study, the performance of the AVI algorithms, especially the Upper Confidence Limit algorithm, hold the promise of comparable, if not superior, performance if the AVI readers are properly spaced and the level of tagged vehicles' market penetration is adequate. Also, due to the fact that AVI provides section speed data rather than point speed data, faster incident detection is anticipated if AVI tags are widely used. If a system has AVI installed but no loop detectors, the AVI sensors may still be useful as a source of incident detection information.

AVI allows for the computation of travel time and delay information needed for additional operational and planning functions such as automatic toll collection, route travel

time generation, etc. If the AVI data is used as input for several applications, the data users can share the original cost of the AVI system.

10.3 SAN ANTONIO AVI SYSTEM ASSESSMENT

Chapter 4 presents an assessment of the San Antonio AVI installation for ATIS applications. While the system meets basic quality standards, there is opportunity for significant system expansion and improvement.

The results of the on-line evaluation of the San Antonio AVI system primarily include the identification of technical difficulties that should be avoided in future AVI implementations. These include proper synchronization, monitoring all lanes of travel, and capturing the direction of tagged vehicles. The system is useful as installed, however, improved ATIS and incident detection systems are limited by the current installation. The quality and usefulness of AVI data was assessed and the ability to obtain a proper representation of traffic state conditions was achieved. Based on the investigation presented in Chapter 8, the current tagged vehicle penetration of San Antonio is less than 3 percent. Volume estimates must be made with an additional detector installation that is capable of reliably counting all vehicles. Simple estimates of the tagged vehicle penetration can be made from historical average annual daily traffic (AADT) data, but should only be used for planning purposes. The advantage of an AVI system is the ability to obtain travel times from a sample of vehicle probes.

10.4 RECOMMENDATIONS

There are many new and emerging applications for the AVI and areas for further development of the technology to better serve travelers. The popularity of probe vehicle detection technology is poised to expand rapidly with the E-911 cellular location requirement. If an AVI system is installed, the collected data should be used for AID since the marginal cost to implement an AID algorithm based on AVI data is low. The following section provides recommendations for further expansion of the San Antonio AVI system as well as suggestions for new AVI implementations.

10.4.1 Installation Configuration

The installation of an AVI system for ATIS applications is the most critical phase in AVI implementation. The reader spacing should be no more than 2 miles for metropolitan systems. Each AVI site should monitor all lanes of travel. Where the decision on whether to implement an inductive loop detector (ILD) or an AVI system is to be made, the decision would be based not just on incident detection considerations, but on considerations regarding all the anticipated users of the data. The AVI system implemented in San Antonio should be modified to reflect the direction of travel of a tagged vehicle, thus increasing the usable data obtained from the system for incident detection. The tagged vehicle penetrations are typically very low; the system should attempt to capture every tagged vehicle that passes a fixed detector location. Additional sensors at all entrance and exit ramps would provide a

significant benefit to transportation planners and allow for effective toll collection. Origin-destination information could then be obtained for calibration of demand models. Other recommendations for TransGuide would be to investigate the causes of errors in traffic and incident data and proceed in order to minimize their occurrence before the data is used as input for an AID algorithm. Regular monitoring and inspection of detectors, whether the ILDs or AVI, is recommended to ensure continuous operation and swift remedial action in case problems are detected.

10.4.2 Tag Types and Uses

Tag reliability and accuracy is the most important factor in selecting a tag type for implementation. The battery powered tags used in Houston are much more reliable for detection at high-speed applications. The San Antonio tags are not powered and rely on reflecting the radio signal from the reader antenna. Powered tags are preferred as greater confidence can be obtained from the system. Tags should be distributed to the widest number of travelers and traveler types. Transit vehicles, trucks, state vehicles, and passenger cars should all be represented for an effective system. The San Antonio AVI project initially desired to tag every vehicle registered in the county, however, cost and privacy concerns preclude such distribution. The ideal method to get travelers to obtain tags is to provide an incentive. The most obvious is for toll collection, however, there are many other potential incentives for equipped vehicles with AVI tags. Different systems and organizations should be encouraged to use tags compatible with the traffic management center implementation to facilitate resource sharing.

10.4.3 Regional Applications

AVI systems installed between the major cities could provide intercity travelers with corridor congestion information both pre-trip and enroute. The AVI system typically communicates to the traffic management center over plain old telephone lines (POTS) and no special dedicated communication link is required, The large numbers of businesses along major corridors provide ample telephone connectivity. Examples in Texas include the San Antonio to Austin IH-35 corridor, San Antonio to Houston IH-10 corridor, Houston to Dallas IH-45 corridor, and Austin to Dallas/Ft. Worth IH-35 corridor. Variable message signs could be installed along the corridor to provide travel time estimates to the major cities. Information could also be updated on a Web page to allow travelers to modify their departure time if conditions are congested. The implementation challenge lies in the need for centralized coordinated control and cooperation between multiple agencies. The initiative must come from a state level and system coordination should occur at one of the metropolitan traffic management centers or at a statewide center. Sufficient tagged vehicles would be required as fewer vehicles are likely to traverse the entire study corridor. Commercial vehicle operations can provide the fleet an increased intercity penetration. Trucks would bias the travel times as they typically travel slower than the average vehicular travel stream.

10.4.4 Dynamic Traffic Input

The raw data obtained from a properly installed AVI system can provide real-time data to dynamic traffic assignment models. The output from such models can yield predictive information about travel time, speed, and suggest alternative routes. The delayed nature of AVI data limits the ability of AVI data for real-time dynamic traffic applications. However, the origin-destination demand data can be of significant benefit for calibrating dynamic traffic algorithms in near real-time. An AVI system can be used for dynamic traffic assignment verification. Fully integrated systems of the future will provide directions to users based on user characteristics (reduce delay, through traveler, optimize the system). It will be of value to actually determine the final path for a subset of users that are provided with route information.

10.4.5 Travel Demand Modeling

Similar to using AVI data for travel demand modeling, the system can be used to calibrate the origin-destination patterns of travel demand models. The San Antonio AVI system could be enhanced to allow for improved parameter estimation for off-line origin-destination planning models. Cooperation between the metropolitan planning organizations (MPOs) and the Texas Department of Transportation would be required.

One challenge to the use of AVI for travel demand modeling lies in security concerns. Demand models need to determine the consistency of demand across days. Determination of the number of users who make the same trip or set of trips with regularity across days and weeks is of interest.

Current security precautions preclude this, as the tag identification is scrambled differently each day in the San Antonio installation.

10.4.6 CVO Applications

Traffic management centers can obtain valuable truck and commodity flow information if existing AVI installations are compatible with technologies employed in CVO applications. With readers located at entry and exit points of the network able to detect commercial vehicles, information about origin-destination and through truck travel is obtainable. The difficulty in obtaining commodity flow data is often institutional and not technical.

10.4.7 ATIS Implementation

The ATIS strategy for a metropolitan region must be carefully established before an AVI system, or any other traffic detection system, can be effectively installed. The goals of the system should be developed and data collected accordingly. Applying an existing system to a new strategy is more difficult as the system will require modifications from a system integration perspective. The ATIS vision and requirements are required for proper

implementation. Consistency with a regionwide or statewide architecture is essential in this regard.

10.5 FURTHER WORK

There is still research to be conducted in developing more sophisticated AVI algorithm logic. It is possible that testing other detection logics with actual AVI data could produce better results than those reported in this study. The same standard steps used in calibrating and testing the algorithms in this research could be employed to investigate other logics.

Zhou (2000) investigated loop algorithm fusion and found that combining the outcome of several loop detector algorithms can produce better incident detection than any algorithm taken separately. The same can be done with AVI detection logics. Fusing the outcome of AVI algorithms might lead to better results at little additional cost. Integrating AVI and ILD data would prove beneficial as well for improved incident detection.

Future effort should also concentrate on conducting similar experiments on real AVI data collected from other networks with varying conditions such as tagged vehicle market penetration, link length, etc. in an attempt to determine guidelines to be used in the design of new AVI systems, and their application for traffic management purposes. The rise in wireless technology will increase the demand for real-time traveler information. The increase in wireless location technology will further increase the potential for probe vehicle tracking through the network. The exploration of the differences in link-based and point-based vehicle detection technologies should be expanded.

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