Technical Report Documentation Page

1. Report No. FHWA/TX-04-0-4156-1	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle INTEGRATION OF POINT-BASED AND LINK-BASED INCIDENT DETECTION AND TRAFFIC ESTIMATION		5. Report Date October 2002 Revised March 2004 6. Performing Organization Code
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9. Performing Organization Name and Address Center for Transportation Research The University of Texas at Austin 3208 Red River, Suite 200 Austin, TX 78705-2650		10. Work Unit No. (TRAIS) 11. Contract or Grant No. 0-4156
12. Sponsoring Agency Name and Address Texas Department of Transportation Research and Technology Implementation Office P.O. Box 5080 Austin, TX 78763-5080		13. Type of Report and Period Covered Research Report September 2000-August 31, 2002 14. Sponsoring Agency Code

15. Supplementary Notes
Project conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration, and the Texas Department of Transportation.

16. Abstract

The implementation of Intelligent Transportation Systems (ITS) carries the promise of more efficient use of already existing transportation networks. Reliable speed estimation and timely incident detection reduces congestion on highways. The Inductive Loops Detectors (ILD) and Automated Vehicle Identification (AVI) are the main sensing systems deployed by many traffic management agencies to collect speed and travel time data. They represent point and link type data, respectively. This study utilized the Bayesian Updating and Weighted Average methods to estimate highway speed and travel time by integrating the AVI and ILD data extracted from San Antonio's Traffic Management Center (TransGuide). The analysis considered the sensors' accuracy, reliability, and level of penetration. The results of the analysis support the reliability of the AVI system for speed and travel time estimation and the ILD system for occupancy, point-based speed measurement and for Automatic Incident Detection (AID) algorithm processing. Additionally, Monte Carlo simulation model was designed to model sensors fusion to detect traffic incidents. The Monte Carlo model showed promising results when validated using traffic and incident data from the San Antonio network. It could be used as a performance predictor that supports traffic sensing systems investment decisions.

17. Key Words Automatic Vehicle Identification, Inductive Loops, Speed Estimation, Incident Detection, Monte Carlo Modeling, TMC Architecture	18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service, Springfield, Virginia 22161.

19. Security Classif. (of report)	20. Security Classif. (of this page)	21. No. of pages	22. Price
Unclassified	Unclassified	100	

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Integration of Point-Based and Link-Based Incident Detection and Traffic Estimation

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CTR Research Report:	0-4156-1
Report Date:	October 2002
	Revised: March 2004
Research Project:	0-4156
Research Project Title:	*Integration of Point-Based and Link-Based Vehicle Detection Data*

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Acknowledgments

The authors express appreciation to TxDOT Project Director, Brian Fariello and the Project Coordinator, David Rodrigues for their contributions and insight. We would also like to express our appreciation to the key personnel at the main Traffic Management Centers in Texas respectively, San Antonio TransGuide, Houston's TranStar, Fort Worth's TransVision, and Dallas's DalTrans for providing data essential for the completion of this research.

Research performed in cooperation with the Texas Department of Transportation and the U.S. Department of Transportation, Federal Highway Administration.

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1. Introduction

The implementation of Intelligent Transportation Systems (ITS) carries a high promise of more efficient use of already existing transportation networks. The main elements of ITS are Advanced Transportation Management Systems (ATMS) and Advance Traveler Information Systes (ATIS). Advance Traffic Management Systems (ATMS) are intended to assist operators of the Traffic Management Center (TMC) to manage the traffic network, and to provide assistance to travelers in order to reach a particular destination via a private vehicle, public transportation, or a combination of the two. ATMS systems rely mainly on real time traffic data collection for incident detection and traffic estimation.

Traffic Management Centers (TMCs) are metropolitan agencies charged with managing traffic on highways to enable better and safer driving conditions for motorists. Most major U.S. cities house traffic management centers in one location to facilitate communications and collaboration between agencies to detect, eliminate, and inform motorists about hazardous road conditions. To carry out their tasks, TMC agencies utilize several automated and non-automated methods to estimate the conditions on highways. Examples of automated methods are Inductive Loop Detectors (ILD), Automated Vehicle Identification (AVI), and machine vision (e.g. Autoscope). Examples of non-automated methods are Police Patrols (PP), reports from motorists with cellular phones, and Closed-Circuit TVs (CCTV).

In the past, the majority of surveillance systems were location based, and measured occupancy, flow rate, and average vehicle speeds, describing traffic flow characteristics at a fixed point on the highway. The most widely used detector for point-based estimation is the inductive loop, which provides speed, volume, and occupancy data. Inductive loops are extremely useful in determining traffic conditions at a particular point, but provide no direct information on the traffic conditions between successive detectors. More sophisticated sensors such as Automated Vehicle Identification (AVI) have the capability of measuring densities (usually indirectly) over a section of a road.

Currently the San Antonio traffic management center, TransGuide, deploys side-by-side ILD and AVI systems in a study corridor along the I-410. The two systems have different levels of performance, based on the percentage of breakdowns, sensor penetration, accuracy, and consistency. These two sensor systems are also different in the nature of the data they collect. ILDs are capable of estimation of speed, occupancy, and flow for a specific point but are not very reliable to estimate travel time. Conversely, the AVI system is reliable in measuring travel time of highway links but doesn't reliably measure point-based speeds. Currently, the AVI system has a very low level of penetration in San Antonio (2 – 5 %) compared to the ILD system (Haynes 2000).

1.1 Research Motivation

This study served three main objectives. First, it analyzes the information flow and architecture of traffic management centers in Texas; secondly, it proposes ways to integrate the data of the AVI and ILD systems for speed and travel time measurement; and thirdly, it develops a simulation model to integrate incident detection sensors. Additional goals of this study were to compare the performance of AVI and ILD detector systems in terms of accuracy, reliability, range of use, and net benefits, and to develop guidelines to integrate the respective advantages of both systems, while compensating for their weaknesses.

This study achieved its objectives primarily through analysis of field data, made possible through the study corridor installation in San Antonio. Some data from a previous study conducted by the same research team was used. Part of the information for this study was collected from visits and interviews with TransGuide operators, as well as operators of the other major TMCs in the state.

1.2 Research Structure

This report is divided into seven chapters. Chapter 1 is an introduction to the repor,t while Chapter 2 is a review of the literature and of the background of the research. Chapter 3 investigates the ITS national and local architecture along with the information flow in different Texas Traffic Management Centers as they relate to the objectives of the study. Chapter 4 investigates the performance of the point-based and link-based traffic sensors, as well as their weaknesses and strengths. Chapter 5 contains analysis of speed and travel estimation using ILD and AVI systems and guidelines to integrate their performance. Chapter 6 presents a proposed Monte Carlo model that simulates sensors integration for incident detection. Chapter 7 summarizes the research results, findings, conclusions, and recommendations for future work.

2. Background

2.1 Incident Detection Methodologies

Typical incident detection systems might include police patrol, motorist reports by cellular phone or call boxes, and surveillance cameras. Each of these systems are discussed in further detail below.

2.1.1 Police Patrols (PP) and Motorist Assistance Programs (MAP)

Until recently, Police Patrol (PP) and Motorist Assistance Programs (MAPs) were the most widely used incident detection methods. They provide several advantages over "blind" Automated Incident Detection systems. When an incident is detected immediately by Police Patrol passing though the incident site, no incident verification is required since police officers are trained to provide concise incident information. The mean time to detection by PP depends upon the staffing level, since there is a direct correlation between the number of officers available to be dispatched or assigned to cover a specific area and the length of time before an incident is detected. Prior research (Tavana 1999) supports the fact that at normal staffing levels, Police Patrols do not detect all incidents in a reasonably short time.

2.1.2 Closed Circuit TV (CCTV)

Surveillance cameras are the main technology relied upon to visually verify incidents and determine response action by TMCs. CCTVs like most conventional incident detection methods are very reliable and provide incident verification capabilities when incidents are detected using AID systems. However, visual detection using surveillance camera systems is labor intensive and inefficient. The detection resources are often wasted because of the lack of the advanced data processing technologies and integration with other approaches. Practically, the number of false alarms generated from CCTV systems is minimal and occur only during extreme weather conditions (i.e., snow, fog, and rain).

2.1.3 Automated Incident Detection

Conventional Police Patrol and motorists' reports via cellular phones are still the primary traffic management approaches utilizez; however, many large North America cities are seeking alternative approaches using Automated Incident Detection (AID) systems to relief congestion on highways.

The AID systems collect traffic data from highways by utilizing electronic sensors, such as ILD and AVI, and process the data sets using online algorithms. Traffic incidents cause differences in highway occupancy and speed in the areas upstream and downstream of the incident. A number of ILD algorithms have been developed to implement incident detection. These include the comparative algorithms (California logic), time-series algorithms, and the catastrophe theory algorithms (McMaster). These algorithms operate on typical detector outputs of occupancy, volume, and average speed data (Zhou 2000).

2.2 Comparison of Traffic Detection Technologies

Klein et al. (1996) conducted a comprehensive field test on the accuracy of the emerging traffic detection technologies in different locations between 1993 and 1994. Table 2.1 summarizes the quantitative advantages and disadvantages of these technologies and other options (Klein 2001).

Although some of the technologies included in Table 2.1 perform satisfactorily, only AVI and ILD systems were considered in this study.

Table 2.1 Strength and Weakness of Commercially Available Sensor Technologies

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

Table 2.1 Strength and Weakness of Commercially Available Sensor Technologies (Continued)

Technology	Strengths	Weaknesses
Passive Infrared	* Multizone passive sensors measure speed	* Passive sensor may have reduced sensitivity to vehicles in heavy rain and snow and dense fog * Some models not recommended for presence detection
Ultrasonic	* Multiple lane operation available * Capable of overheight vehicle detection * Large Japanese experience base	* Environmental conditions such as temperature change and extreme air turbulence can affect performance; temperature compensation is built into some models * Large pulse repetition periods may degrade occupancy measurement on freeways with vehicles traveling at moderate to high speeds
Acoustic	* Passive detection * Insensitive to precipitation * Multiple lane operation available	* Cold temperatures may affect vehicle count * Specific models are not recommended with slow-moving vehicles in stop-and-go traffic
Video Image Processing	* Monitors multiple lanes and multiple detection zones/lane * Rich array of data available * Provides wide-area detection when information gathered at one camera location can be linked to another	* Inclement weather such as fog, rain, and snow; vehicle shadows; vehicle projection into adjacent lanes; occlusion; day-to-night transition; vehicle/road contrast; and water, salt grime, icicles, and cobwebs on camera lens can affect performance * Requires 50 to 60 ft (15 to 18 m) camera mounting height (in a side-mounting configuration) for optimum presence detection and speed measurement * Some models susceptible to camera motion caused by strong winds * Generally cost-effective only if many detection zones within the field view of the camera or specialized data are required

3. National and Local ITS Information Flow Architecture

The National ITS architecture provides a common framework for planning, defining, and integrating intelligent transportation systems. It is a product that reflects the contribution of a broad cross-section of the ITS community (transportation practitioners, systems engineers, system developers, technology specialists, consultants, etc). The architecture defines: 1) functions that are required for ITS, 2) physical entities or subsystems where these functions reside, and 3) information flow and data flows that connect these functions and physical subsystems together into an integrated system (USDOT & Odetics 1996).

The architecture consists of four major physical subsystems: 1) traffic management, 2) roadside equipment, 3) vehicles (passenger cars and commercial vehicles), and 4) traveling population. Figure 3.1 shows the different physical components of the National ITS Architecture. This research focuses only on parts of the first and second subsystems.

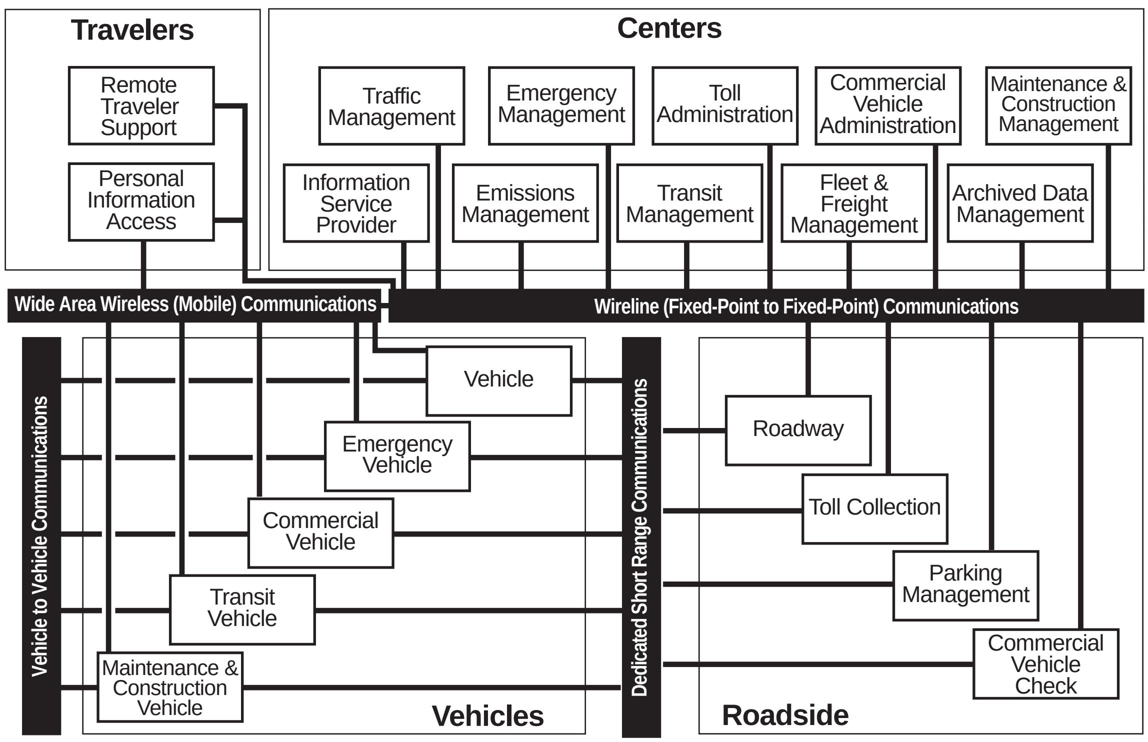


Figure 3.1 The National ITS Architecture Physical Subsystems (USDOT & Odetics 1996)

3.1 Roadway Subsystems

Roadway subsystems consist of all equipment distributed on and along the roadway which monitors and controls traffic. Equipment includes highway advisory radios, dynamic message signs, cellular call boxes, CCTV cameras and video image processing systems for incident detection and verification, vehicle detectors, traffic signals, grade crossing warning systems, and freeway ramp metering systems. This subsystem also provides the capability for emissions and environmental condition monitoring including weather sensors, pavement icing sensors, and fog detectors. In advanced implementations, this subsystem supports automated vehicle safety systems by safely controlling access to and exit from an Automated Highway System (AHS) through monitoring of and communications with AHS vehicles. The four primary traffic parameters used in ATIS applications are travel time, speed, volume, and percent of occupancy. These parameters are affected by:

1. Nature (types of data collected)
2. Accuracy
3. Confidence
4. Delay (time elapses before data collect is made available)
5. Availability
6. Breadth of Coverage
7. Depth of Coverage (sensor spacing).

3.2 Traffic Management Subsystems

The Traffic Management Subsystem operates within a traffic management center or other fixed location. This subsystem communicates with the Roadway Subsystem to monitor and manage traffic flow. Incidents are detected and verified and incident information is provided to the Emergency Management Subsystem, travelers (through Roadway Subsystem Highway Advisory Radio and Dynamic Message Signs), and to third party providers. The subsystem supports High Occupancy Vehicles (HOV) lane management and coordination, road pricing, and other demand management policies that can alleviate congestion and influence mode selection. The subsystem monitors and manages maintenance work and disseminates maintenance work schedules and road closures. It also manages reversible lane facilities, and processes probe vehicle information and communicate with other Traffic Management Subsystems to coordinate traffic information and control strategies in neighboring jurisdictions. In addition, it coordinates with rail operations to support safer and more efficient highway traffic management at highway-rail intersections. The Traffic Management Subsystem also provides the capabilities to exercise control over those devices utilized for AHS traffic and vehicle control.

Most major U.S. cities have a Traffic Management Center (TMC) that houses personnel, equipment, and computer systems that communicate to highway devices and sources to estimate and control traffic conditions. Collecting data and information from the highway follows a systematic procedure that differs from one TMC to another. The information flow setup varies between TMCs based on 1) size of highway system covered, 2) number and diversity of traffic sensors and sources, 3) level of staffing, 4) level of automation in the TMC, and 5) quality of services to travelers. The project team visited San Antonio's TransGuide, Houston's TranStar, and Fort Worth's TransVision to analyze the different information flows of Texas TMCs for the purpose of ultimately determining the potential application and the most appropriate methods for combining point and link data.

Information flow provided by a TMC is documented to provide up to four services. These include incident detection, travel time and average speed, lane closure and construction, and special events.

3.2.1 TransGuide TMC

TransGuide is San Antonio's Traffic Management Center designed by the Texas Department of Transportation (TxDOT). This "smart highway" project provides information to motorists about traffic conditions, such as accidents, congestion, and construction. The TMC collects information about traffic situations on highways from several sources (Inductive Loop Detectors, Automatic Vehicle Identification, Closed-Circuit TV, Police Patrols, etc). The TMC operators utilize the collected information to make informed decisions and take systematic steps to expedite incident management and minimize undesirable situations on highways.

Inductive loop detection is a mature sensing technology that most Traffic Management Centers use to collect traffic speed. TransGuide maintains two thousand ILDs distributed an average of a half a mile interval throughout the San Antonio highway network. According to its operators, an estimated fifteen percent break down rate is experienced for the whole network annually, while there are some ILD sites that have not required any maintenance over the last six years. TransGuide recently conducted several experiments to evaluate the merits of acoustic sensors for traffic speed estimation. The majority of the acoustic sensors evaluated, which are mounted over I-410 and I-10 highways, were not functional due to thunder.

The second important source of traffic data in TransGuide is the Automated Vehicle Identification (AVI) technology. The cost of installing one AVI station ranges from $48,000 to $49,000 based on the number of monitored lanes and type of equipment. Only forty out of the total fifty-three AVI stations originally installed are functional. In the last two years, overloaded vehicles hitting AVI stations have rendered a high number of AVI stations non-functional (60–65 %). TransGuide operators see the maintenance cost of AVI stations as high (approximately $12,000 per month for all stations). This high maintenance cost has motivated some TMC managers to search for better alternatives. Consultations between the TMC and the City of San Antonio have called for expansion of the ILD network rather than future AVI system expansion.

Traffic data collected by different sensors are transferred to the TMC building through fiber optics phone lines. Data collected from ILD systems are processed using the Texas Algorithm, which fires an alarm when traffic speed reaches a value lower than 25 miles per hour (mph). The TransGuide operators estimated that the Texas Algorithm produces from 200 to 215 false alarms a day (30–35% FAR). Currently, San Antonio witnesses 140 to 150 incidents a day in normal conditions and 400-500 incidents on rainy days. TransGuide deploys several Variable Message Signs (VMS) to communicate an incident occurrence to travelers.

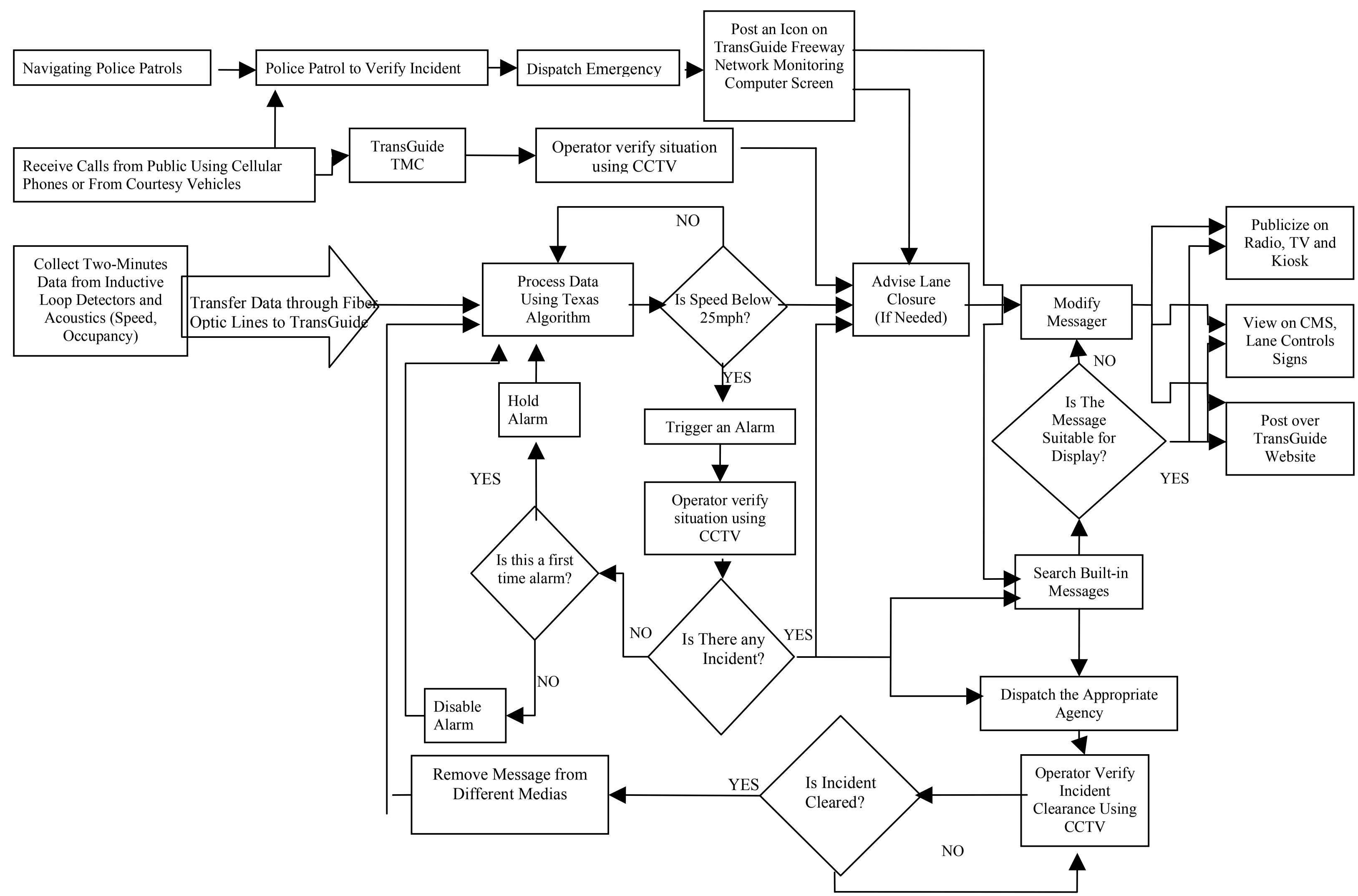


Figure 3.2 Information Flow Architecture for Incident Detection, TransGuide, San Antonio, Texas

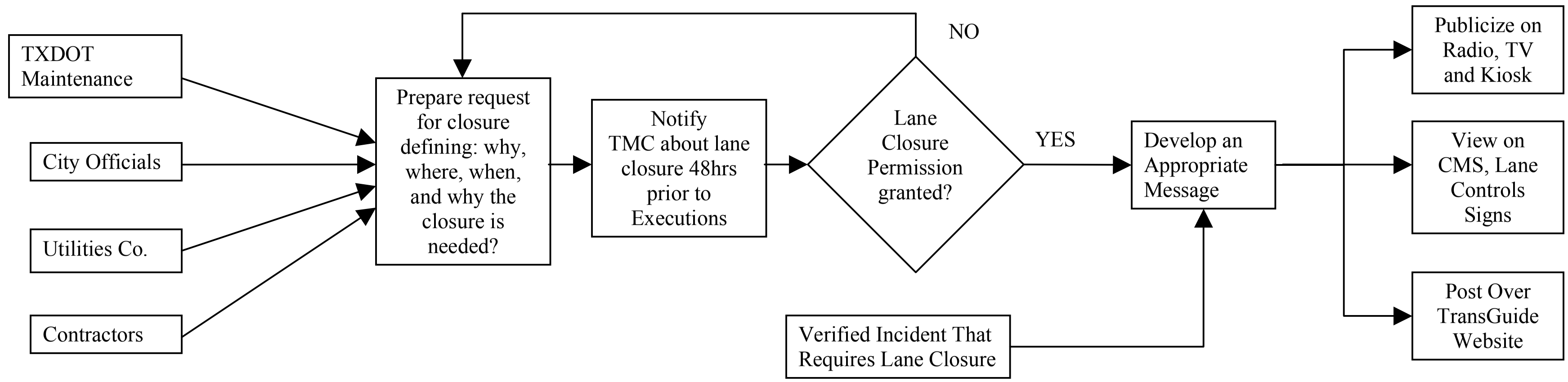


Figure 3.3 Information Flow Architecture for Lane Closure, TransGuide TMC, San Antonio, Texas

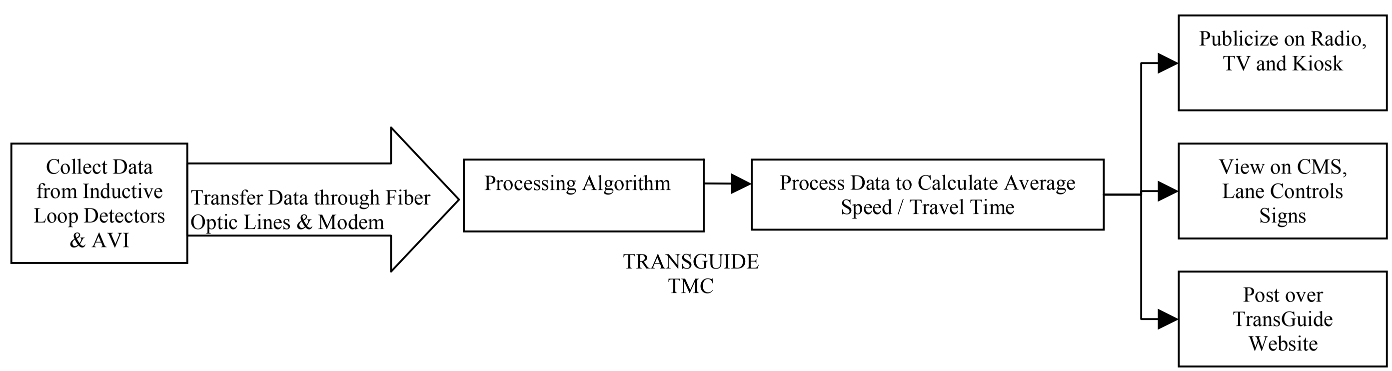


Figure 3.4 Information Flow Architecture for Travel Time and Speed Estimation, TransGuide TMC, San Antonio, Texas

3.2.2 TranStar TMC

TranStar is Houston's Traffic Management Center. It consists of several traffic agencies responsible for planning, designing, operating and maintaining transportation operation and traffic emergency management in the Houston metropolitan area, which is 5,436 square miles with a population of approximately four million. The center costs approximately $13.5 million to construct and contains a central control room, communication room, telephone switch room, and an emergency operation center along with three floors of offices for participating agencies.

TranStar utilizes groups of sensors distributed on Houston highways for traffic management. Currently, 270 CCTV cameras positioned approximately one mile apart and 153 AVI stations are used to cover 225 miles of highway. The AVI system began with the distribution of 50,000 anonymous tags. This number significantly increased to almost half a million tags with the advent of the Harris County Toll facility. The monthly cost for maintaining the AVI system in TranStar is estimated by its operators to be around $20,000. Data collected from the AVI system is transferred to the center through cable line, then processed using software that assigns different colors to different speeds on the operator's screens (Green represents "Average speed", Yellow represents "Below average", Red represents "Very slow speed", and Grey represents "No data gathered"). Since the algorithm does not generate incident alarms automatically, operators are required to continuously monitor the system. However, AID (automated incident detection) would always be challenging in Houston given the random spatial and temporal variation in traffic flow normally experienced, and the TransStar floor environment, which rivals a major stock exchange in terms of the complexity of information flow and human interaction. Certainly AID use in the past resulted in excessive false alarms because of the nature of the algorithms used.

A few vivid detectors were installed along three highways (I-288, Loop 610, and I-225) for speed estimation. The vivid detectors proved non-functional for that purpose. These are currently being used for ramp metering purposes only. Operators are optimistic that the vivid detector system might hold some promise to replace the ILD system if carefully tuned.

TranStar deployed a large number of ILD detectors (up to 800 stations), however, excessive maintenance costs render these sensors impractical in Houston's traffic conditions. Accessibility and user costs at $15.59 per user hour make the cost of replacing a malfunctioning sensor prohibitive. Additionally, maintenance funds have been sparse or non-existent for this purpose. While the high probability of failure renders the system imperfect for speed estimation, it is currently utilized for ramp metering.

Part of the TranStar mission is to help stranded motorists. For this purpose, the Motorist Assistant Program (MAP) was initiated to provide basic automotive emergency aid, i.e., for overheating, flat tires, and start jumps. The TMC receives approximately 200 daily calls and services approximately 3,600 stranded motorists a month. Additionally, TranStar deploys several weather monitoring sensors that are installed in different part of the city to collect information about bridge icing, floods, and other hazardous weather conditions that hinder the safety of motorists on highways. To improve traffic flow, TxDOT assigned 87 miles of High Occupancy Vehicle (HOV) lanes to encourage group ridership of passenger cars and buses. Cars with between 2 or more or 3 or more passengers are allowed to use HOV lanes depending on the time of the day. Furthermore, TxDOT deploys several Variable Message Signs (VMS) to communicate information to travelers. Since 1989, the MAP has helped more than 100,000 stranded motorists. The MAP program is a joint effort of the following agencies:

- Metropolitan Transit Authority of Harris County
- Texas Department of Transportation
- Harris County Sheriff's Department
- Houston Automobile Dealers Association, and
- A Houston Cellular Phone Company.

Site visits and interviews with operators have enabled the research team to model the flow of information and the TMC system architecture. Figures 3.5 to 3.8 depict a schematic representation of the information flow and architecture in TranStar, for the purposes of incident detection, lane closure, speed estimation, and special events planning.

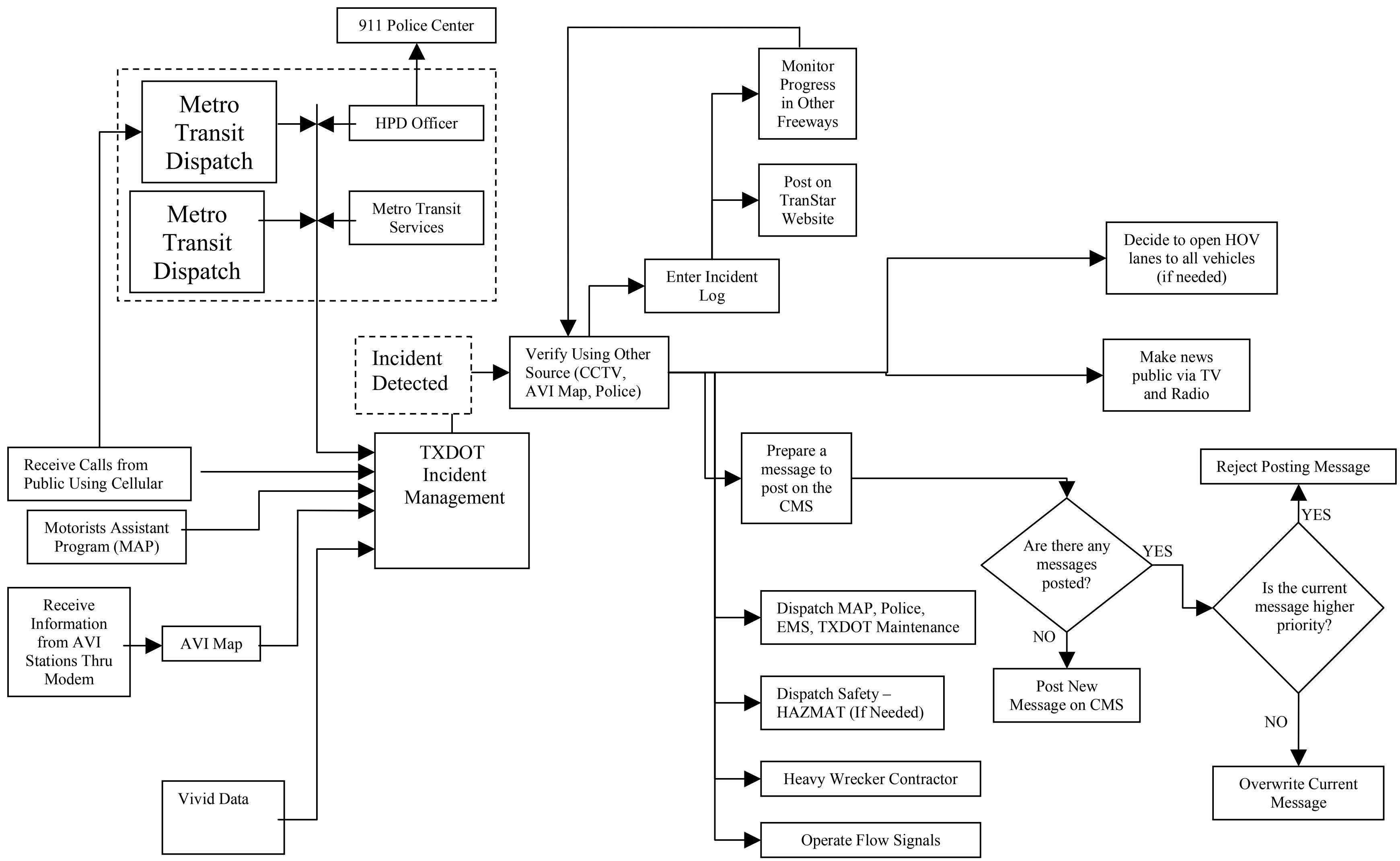
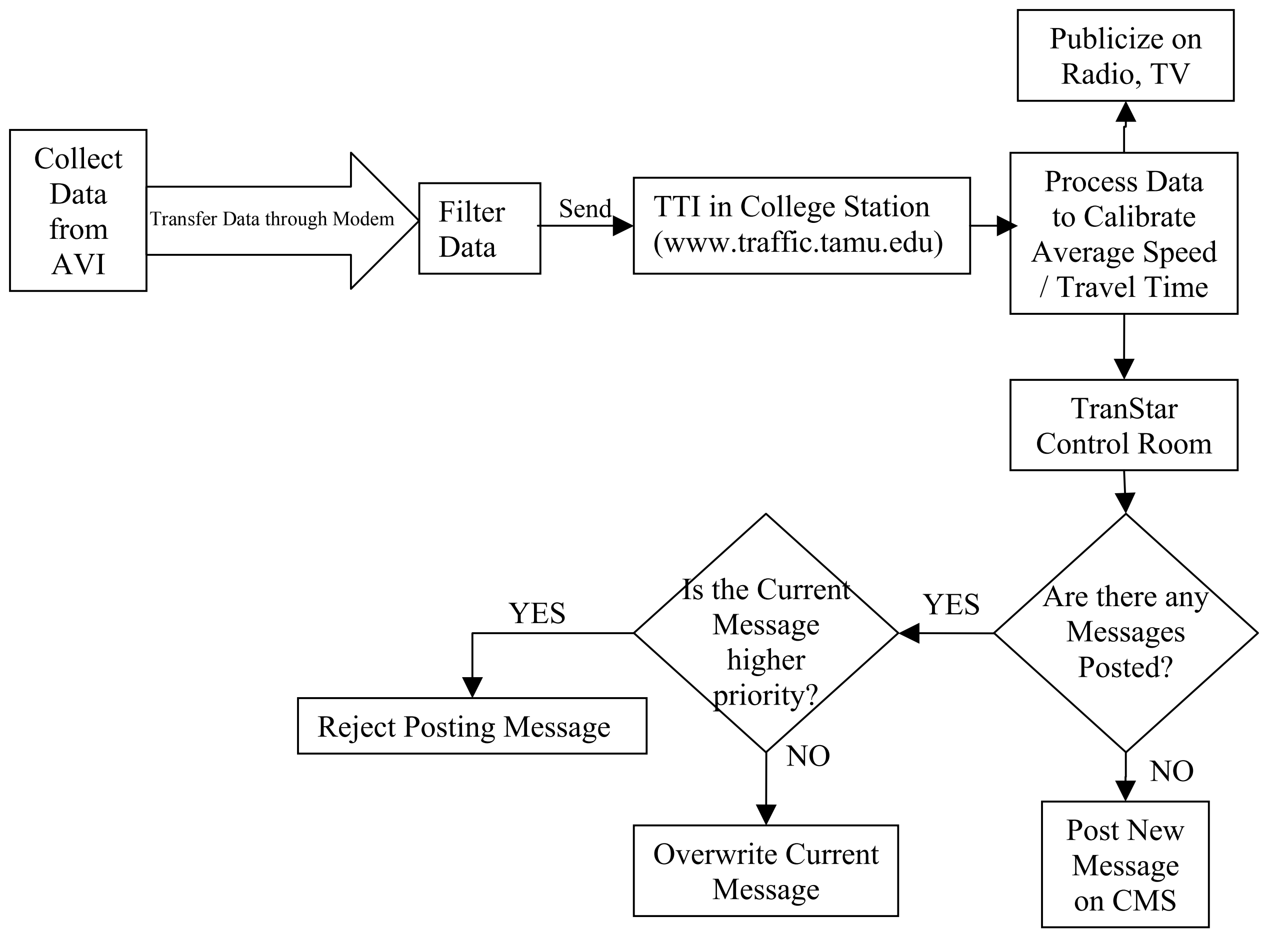


Figure 3.5 Information Flow Architecture for Incident Detection, TranStar TMC, Houston, Texas



Messages Priority:

1. Incidents
2. Travel Time
3. Special Events
4. Public Information

* **Note**: if travel time is more than 60 minutes for a certain segment of the freeway, a message of an incident is posted instead.

Figure 3.6 Information Flow Architecture for Travel Time and Average Speed Estimation, TranStar TMC, Houston, Texas

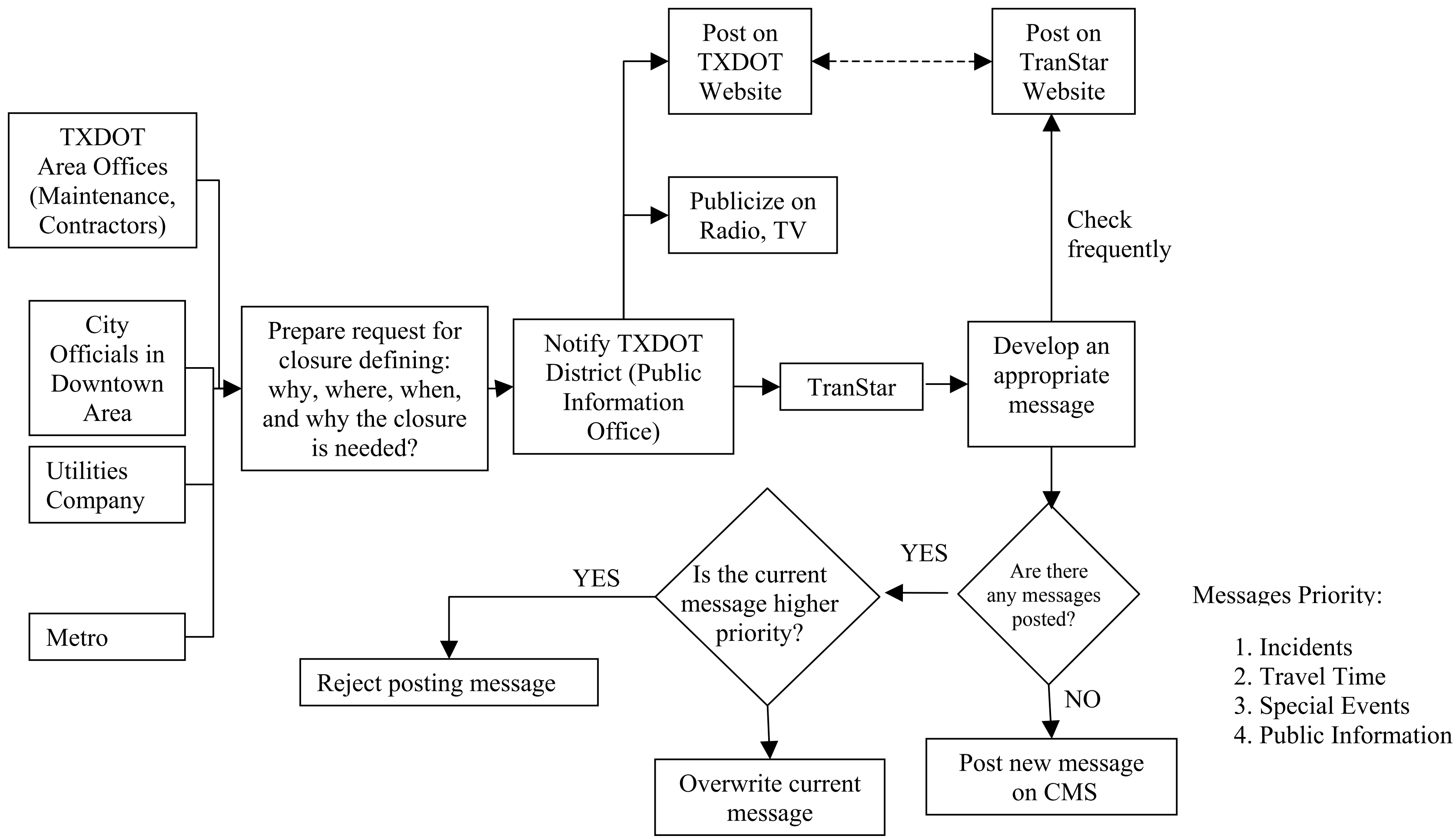


Figure 3.7 Information Flow Architecture for Lane Closure, TranStar TMC, Houston, Texas

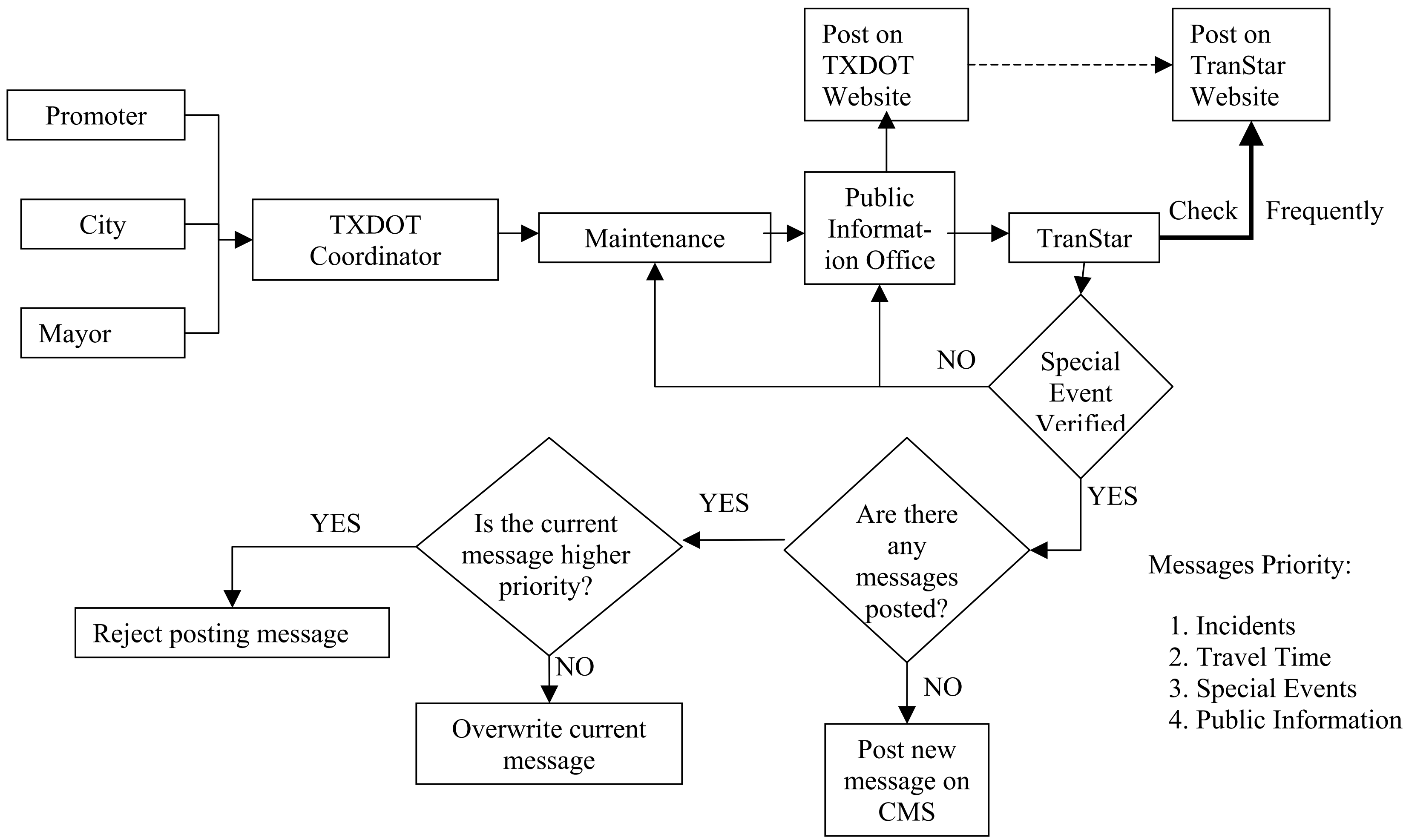


Figure 3.8 Information Flow Architecture for Special Events, TranStar TMC, Houston, Texas

3.2.3 TransVision TMC

TransVision, which started operation in 1986 to improve traffic management in the Fort Worth area, is Fort Worth's Traffic Management Center. The $8.4 million TransVision center has 29,622 square feet of space. The system has inductive loop detectors that are distributed half a mile apart and, in some instances, the density is greater. Following a system analysis focused on the high maintenance costs of loops by the center's engineers, a recommendation was made to exchange the loop system with microwave sensors.

Unlike the TransGuide and TranStar TMCs which were primarily designed with the aid of outside professional consultants, the TMC engineers designed the TransVision TMC in-house. Currently, the system does not provide or support AVI services. This may change as plans for future toll systems may include AVI services. It must be noted that one of the main reasons for not currently implementing a toll system is the nature of the Fort Worth-Dallas Metropolitan area, which consists of small-dispersed cities.

ILDs are mainly used for ramp metering (i.e, entrance ramps) in TransVision. Several sources of information are used to gather information about traffic on Fort Worth's highways. These include:

- Four police patrols covering approximately 300,000 miles annually
- Two helicopters owned by local TV stations
- Sixty-six video cameras, and
- One thousand four hundred and ninety-five traffic sensors.

The following components of the system facilitate the flow of traffic and communicate information to travelers:

- Fifty variable message signs (VMS)
- Two hundred twenty-nine Lane Control Signals (LCS)
- Six satellite buildings
- Five flow signals, and
- Two kiosks.

The information flow architecture at TransVision TMC is characterized by the fact that no sensors are deployed to collect travel time or speed. Figures 3.9, 3.10, and 3.11 illustrate the information flow architecture for TransVision.

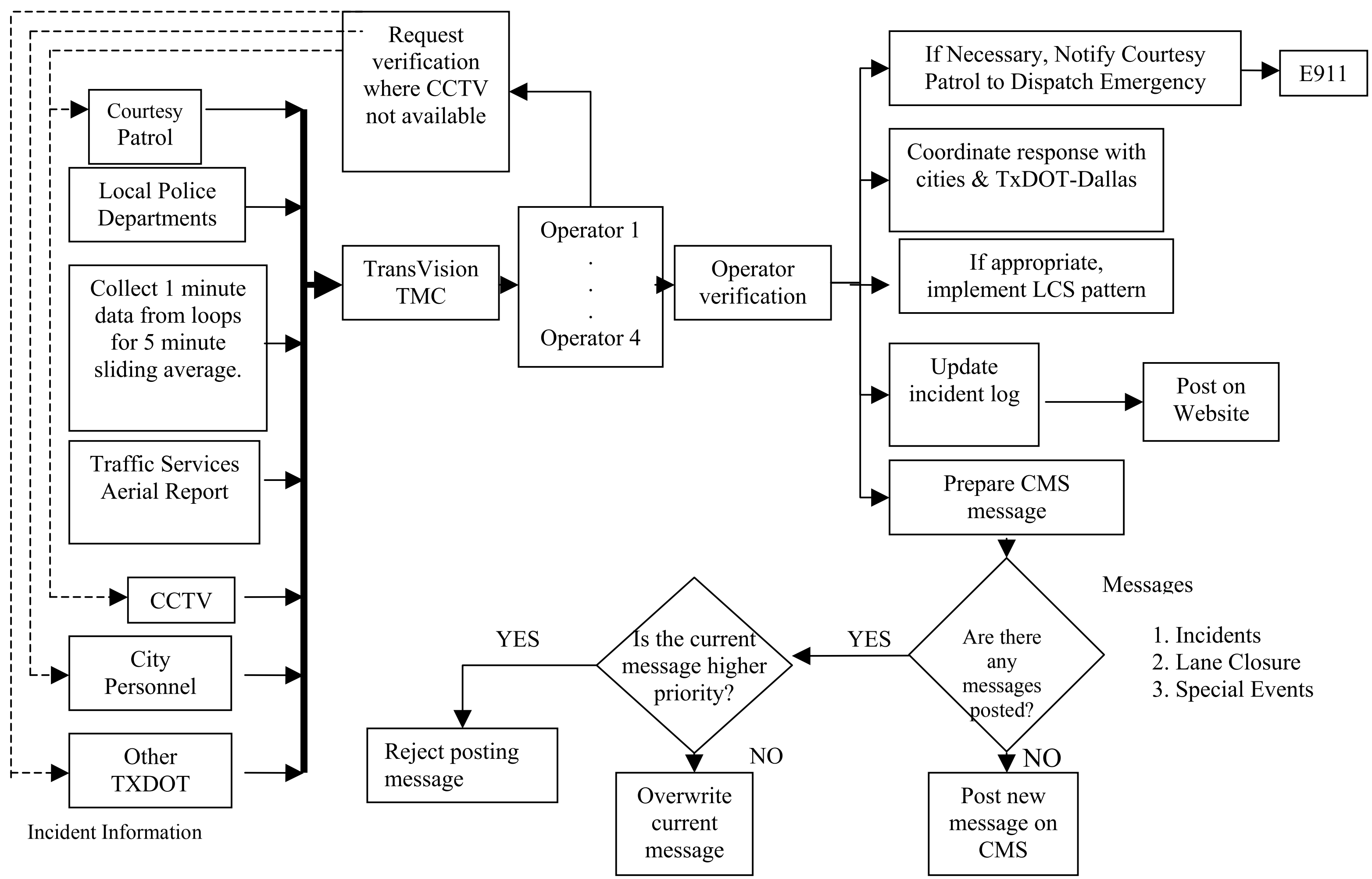


Figure 3.9 Information Flow Architecture for Incident Detection, TransVision TMC, Fort Worth, Texas

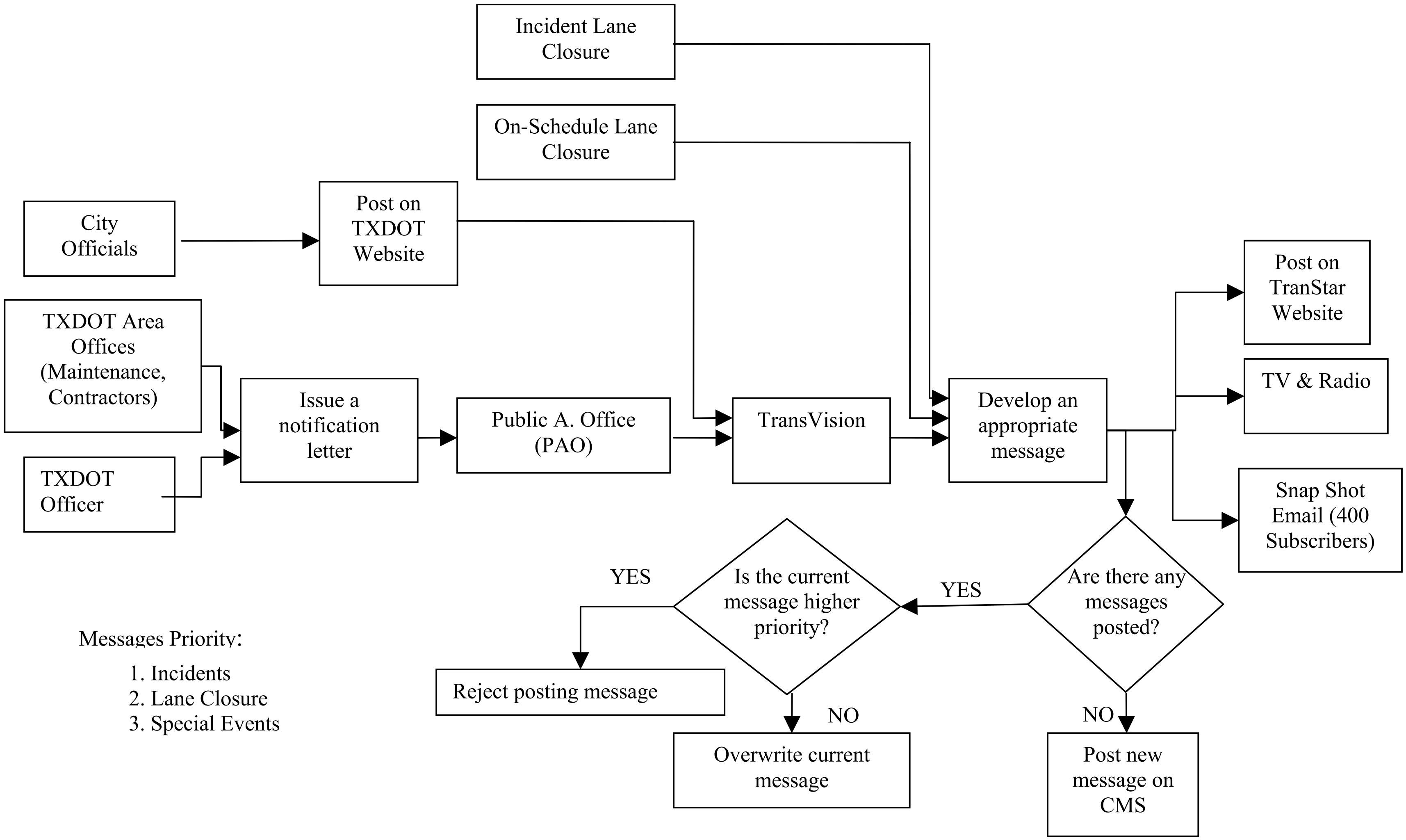


Figure 3.10 Information Flow Architecture for Lane Closure, TransVision TMC, Fort Worth, Texas

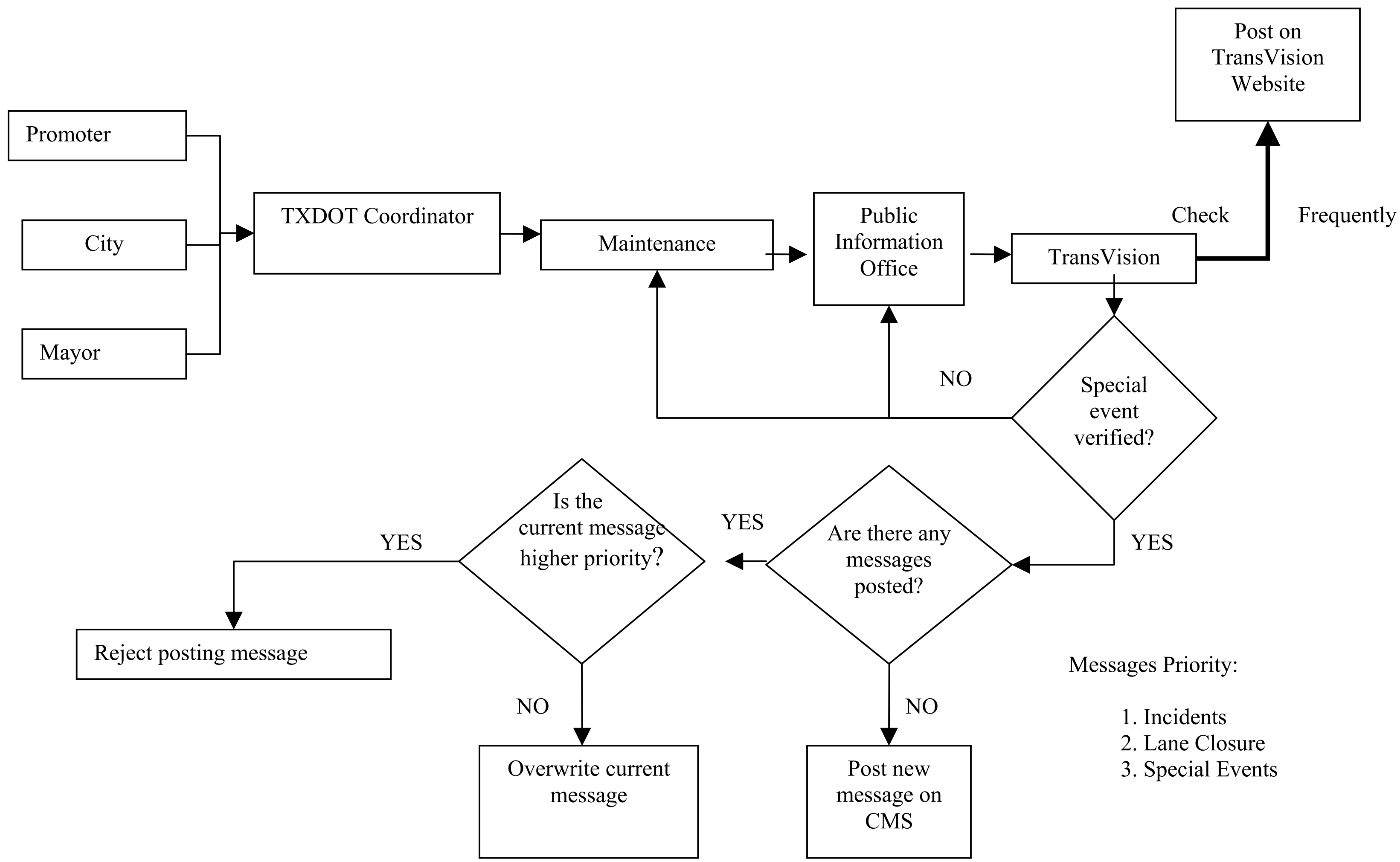


Figure 3.11 Information Flow Architecture for Special Events, TransVision TMC, Fort Worth, Texas

4. Link-Based and Point-Based Traffic Sensor Characteristics and Performance

ITS is structured to provide real-time traveler information regarding expected delays, potential bottlenecks and other information that could help users to make informed decisions to avoid congested highway sections. Advanced Traveler Information Systems (ATIS) and Advanced Transportation Management Systems (ATMS) are the two major systems upon which ITS is based.

Speed and the travel time of a highway are the most important information that affects the commute decision of motorists. Informed motorists are able to make wise decisions regarding trip departure times and alternative routes to avoid delays. Travel time has typically been estimated in the past using probe vehicles. The last decade witnessed a significant increase in using Automated Vehicle Identification (AVI) technology for travel time estimation. This increase is stimulated by the advent of the automated highway toll system.

This chapter summarizes the research conducted to estimate travel time by fusing link-based and point-based speed information gathered from different sensors. On-line AVI and ILD data were extracted from the archives of San Antonio's TransGuide TMC for analysis. The highway speed is estimated based on the fundamental speed-flow-density relationship and fusion theories.

Several studies investigated the relationship between average vehicle speed, flow, and density. In 1965, Edie proposed a generalized definition for computing average speed, density, and flow. While the original effort is based on data from link-based sensors, Cassidy and Coifman (1997) extended Edie's definitions to loop data.

4.1 Study Area

San Antonio's TransGuide collects traffic data from installed side-by-side ILD and AVI systems. The study corridor under consideration is illustrated in Figure 4.1.

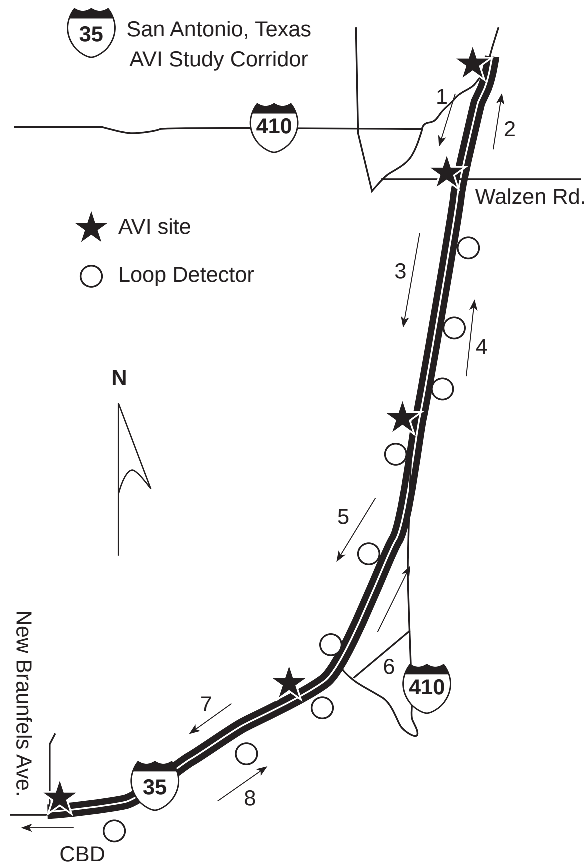


Figure 4.1 San Antonio Study Corridor

There are 52 reader sites monitoring 193 lanes throughout the metropolitan region (Haynes 2000). The Texas Department of Transportation initially distributed about 58,000 tags to San Antonio drivers. This resulted in about a 2% penetration rate during the study period. For this research, three ILDs were selected which are located on the northbound lanes of I-35 between AVI 144 and AVI 145. In this link three ILDs, L-0035N-164.412, L-0035N-164.909, and L-0035N-165.409, measured spot speed. Figure 4.2 illustrates the Corridor Specific Study Link.

TransGuide provides traffic data of ILD and AVI via their anonymous FTP site (www.transguide.dot.state.tx.us). TransGuide was identified in the fall of 1996 as one of four traffic management centers taking part in the ITS Model Deployment Initiative (MDI). The goal of this ITS MDI is to showcase various ITS technologies for the Federal Highway Administration (FHWA). The daily files are observed individually and converted to Excel spreadsheets.

The study corridor considered is a ten-mile stretch of Interstate 35 north of downtown San Antonio between New Braunfels Avenue and Randolph Boulevard. The Corridor Specific Study Link contains three ILDs and two AVI stations located in the northbound direction as shown in Figure 3.1. In this link, all the three lanes were monitored by ILD, while only the inner two lanes were monitored by the AVI.

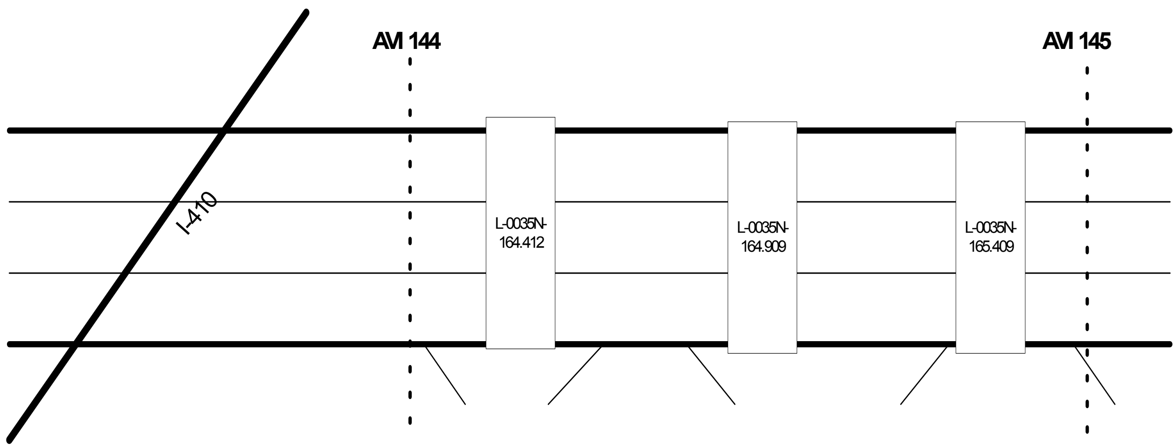


Figure 4.2 Corridor Specific Study Link

4.2 Inductive Loop Technology

Since its introduction in the early 1960s, the inductive loop detector has become the most popular detection system for traffic state sensing. The principle components of an inductive loop detector system include one or more turns of insulated loop wire wound in a shallow slot installed in the pavement, a lead-in cable from the curbside pull box to an intersection controller cabinet, and a detector electronics unit housed in the intersection controller cabinet. Loops used for freeway operate on a pulse mode where a pulse is sent every 100 or 150 milliseconds if a vehicle has been detected (Dudek, C. L. 1996). Although inductive loops are still the most widely deployed and still often considered the most reliable transportation sensor system, over 25% of all inductive loops are malfunctioning at any given time. In the early 1980's, FHWA began to explore ways of reducing the malfunction rate of traffic sensors and particularly of loops (Gibson, D. et al. 1998).

4.3 Automatic Vehicle Identification (AVI) Technology

Vehicles equipped with Automatic Vehicle Identification (AVI) transponders can be used to determine travel times between fixed points as the vehicles move along a roadway network. AVI tags have been deployed for electronic toll collection. As electronic toll collection continues to increase, the numbers of tag-equipped vehicles will increase providing travel time measurement as an auxiliary benefit. With this capability, real-time traffic data such as origin-destination pairs, travel time, and spot speeds can be collected from the vehicle while the driver obtains motorist information such as congestion delays, parking availability, and alternative route choices. There are a number of research projects being conducted in the area of commercial vehicle operations that anticipate the use of Automated Vehicle Identification (AVI), Automated Vehicle Location (AVL), and Automated Vehicle Classification (AVC) for fleet operations and regulatory uses.

Obtaining the necessary number of observations can be challenging if few probe vehicles traverse the corridor. The AVI penetration of San Antonio's I-35 route is currently approximately 2%. ILD penetration is hypothetically 100% when all lanes are equipped, however, the point data produced is limited by its nature as it is an instantaneous measure.

4.4 Data Fusion Concepts for ITS

Gold, et al. (1996) defined data fusion as "having to do with combination of complementary and sometimes competing sensor data into a reliable estimate of the environment to achieve a 'whole that is greater than the sum of its parts'." According to Linn and Hall's 1991 taxonomy of data fusion algorithms, five goal-oriented general data fusion methods are in use today (data association, positional estimation, identify fusion, pattern recognition, and artificial intelligence, Linn & Hall 1991).

The value of fusing or integrating points and link data is to complement the sources of information about the traffic state.

5. Travel Time and Traffic Speed Estimation

The objective of this chapter is to analyze and propose ways to estimate travel time and average speed by integrating link-based speed and point-based speed information from ILD and AVI, respectively. On-line data from ILD and AVI were collected from San Antonio's TransGuide from the study corridor described in the previous chapter. The data is filtered, checked for errors, and processed to be in a format suitable for analysis. Average highway speed and travel time are estimated from each individual sensor. Comparisons are made between the travel time estimates from the two sensors. Finally, the Bayesian updating procedures were used and proposed for estimating the average travel time and space mean speed based on raw estimates from each sensor.

5.1 Background

Several works have studied and discussed the relationship between average vehicle speed, flow, and density. Edie's (1965) generalized definitions for computing the average speed, density, and flow are regarded as the original and classic definitions as illustrated in Figure 5.1. These definitions are then applied to the AVI data set.

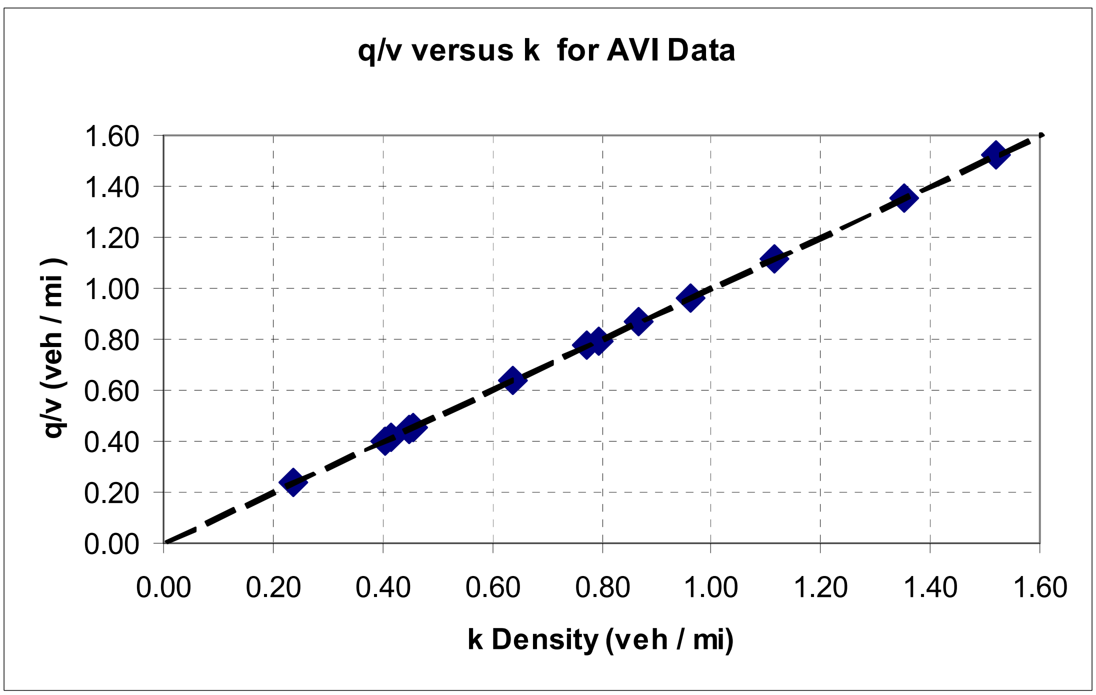


Figure 5.1 Proof of Edie's Relationship

Eisele and Rilette (2002) confirm that the most direct method to obtain the average and standard deviation of the travel time for a corridor link is by using vehicle probes that traverse the corridor link. Their study also concluded that if the link travel time is thirty minutes or more, by the time the necessary observations are made, the traffic situation might change making the variance estimates and the corresponding confidence interval inaccurate. Eisele and Rilette (2002) suggested that the simplest method to obtain an estimate of the mean corridor travel time and variance is by adding the corridor links mean travel time.

Keechoo Choi et al.(1998) researched ‘Travel Time Estimation Algorithms Using Global Positioning Systems (GPS) Probe and Loop Detector Data Fusion’. This work focused on the development of a traffic information fusion algorithm based on the voting technique, fuzzy regression, and Bayesian pooling technique for estimating dynamic link travel time in the congested network. GPS probes and loop detector data were collected over a selected study area.

Woods (1994) studied information source adequacy for traffic management strategies purposes and demonstrated that speed measurements from inductive loops were reasonably accurate at trap lengths of 20 to 78 feet. This study showed that there is an increase in the probability that vehicles will begin a lane change in a trap as its length increases and thus miss one of the detectors providing an erroneous speed value. Therefore the optimal speed trap for ILDs is estimated to be 30 feet (Woods 1994).

5.2 Data Collection and Preliminary Analysis

After downloading AVI and ILD data sets from the study corridor described earlier, the data sets were uncompressed and sorted by detector station to retain only the data associated with the link of interest. Different computer programs were developed to process the AVI and ILD data. A C++ program was developed to sort detector stations of interest during the entire day; and a Visual Basic program (Haynes 2000) was used to filter AVI match data for specified AVI stations. The programs utilized archived files from the TransGuide system to produce a standard spreadsheet for further analysis.

5.2.1 AVI Data

This section describes the format of the traffic data obtained from AVI sources. For the purposes of data fusion, the non-peak period (12:00 noon to 1:00 p.m.) and the evening peak period (5:00 p.m. to 6:00 p.m.) will be considered. Each AVI tag data contains station identification, tag identifier, and the date and time of day when the read was recorded. Direction information, however, is not recorded. The unique tag identifier should be consistent over a period of time so that tag reads at successive detector stations can be matched and link travel times can be generated. For security reasons, tag identifiers are scrambled with the UNIX crypt function using the date as the seed value. This plays a role in preventing any users of the data from tracking the anonymously assigned tags from day to day. Table 5.1 presents a sample of the AVI data.

Table 5.1 Raw San Antonio AVI Data

Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6
137	5CU1a4iKk7k9L7RJM4hdo.e8.A/UDe2/	00:00.9	3/18/2002	2D-04	0
141	ktQpmnGmMSUHcW.FBNz.vgZnMtIcX	00:06.9	3/18/2002	32-06	0
143	UbT3831Jm2.FnkfaFIvR52e8.A/UDe2/.	01:44.9	3/18/2002	17-OB	1
144	Wj191bjc9ZwGzm1JI0l.a6ZBGK7pFpd	57:26.4	3/18/2002	1A-11	1
142	efQpUCJb3IoFHhb/wy8SlEb5sDyqTC6	59:56.9	3/18/2002	15-01	0
144	rUDUMNCIvrEGefqdLvrh8oZnMtIcX06b	59:12.0	3/18/2002	1A-1D	1
147	1Hs2OE0fuCM1D9gIUP4lf.eClmuYPjp	54:01.9	3/18/2002	22-04	0
147	1Hs2OE0fuCM1D9gIUP4lf.eClmuYPjp	54:01.9	3/18/2002	22-04	0

The first column in Table 5.1 represents the station identification and the second column represents the scrambled tag identifier. For the purposes of this research, the station identifiers are reduced by one hundred (e.g. site 147 will be referred to as simply 47). In Columns 3 and 4, the time and date are recorded. The fifth column represents the strength of the read in a hexadecimal and Column 6 represents the lane of travel. The travel time computations require that the individual clocks of the AVI sites be synchronized with the system clock (Haynes 2000).

5.2.2 Inductive Loop Data

This section describes the format of the traffic data obtained from ILD sources. For the purposes of data fusion, the same periods are considered as were used for the AVI data. Loop detector stations monitor all lanes of traffic and the detectors have been paired on main lanes of travel to produce vehicle speed in addition to average volumes and occupancies. TransGuide provided the data in a format similar to the AVI data. ILDs record the pulses of individual vehicles while the data is aggregated over a specified time window. Average speed in 20-sec time intervals are computed in the field and transmitted to TransGuide. Loop sites do not report at exactly the same time; however, a rolling average is maintained within each site. TransGuide has the capability of querying the system about the state of the loop detectors. After thoroughly processing the loop data, two distinct types of errors were identified (time and data errors). It should be noted that it is not within the scope of this research to investigate the root causes of loop malfunctions and of errors in the data. Errors were corrected before the data was used for analysis. Table 5.2 presents a sample of the loop data. Each record consists of six fields: date, time, location of loop, speed, volume, and occupancy, respectively. The location of the loop is further detailed as follows: 1) the first part represents the lane designation (The character differentiates between detectors on a freeway lane (L), an entrance ramp (EN), or an exit ramp (EX). The integer corresponds to the number of the lane with lane one being the furthest inside and with the number increasing as we move towards the outside of the freeway. You might note that the main lane considered for this research is indicated by

"L"); 2) the following characters represent the highway designation and the third and final part of the detector address field corresponds to the highway milepost.

Consider the first entry in Table 5.2 as an example. The detector is monitoring travel lane 1 located at milepost 26.515 going west on Highway 410. The speed for all ramp monitoring detectors is set at –1.

Table 5.2 Sample of InductiveLoop Data

Date	Time	Lane Station	Speed	Volume	Occupancy
3/18/2002	0:07:17	L1-0410W-026.515	Speed = 71	Vol=002	Occ=002
3/18/2002	0:07:17	L2-0410E-026.515	Speed = 61	Vol=000	Occ=000
3/18/2002	0:07:17	L2-0410W-026.515	Speed = 68	Vol=002	Occ=002
3/18/2002	0:07:17	L3-0410E-026.515	Speed = 66	Vol=001	Occ=001
3/18/2002	0:07:24	EN1-0035S-160.178	Speed = -1	Vol=002	Occ=000
3/18/2002	0:07:24	L1-0035N-160.892	Speed = 61	Vol=000	Occ=002
3/18/2002	0:07:24	L2-0035N-160-892	Speed = 57	Vol=002	Occ=002
3/18/2002	0:07:24	L2-0035S-160-892	Speed = 61	Vol=000	Occ=000

5.2.3 Data Quality

AVI data has two main types of errors which are include entry duplication and direction reporting. Duplicate entries are defined as entries with similar date, time, tag identifier, and location (Khoury 2000). The AVI data was processed to remove duplicate entries before being fused with ILD data.

It is important to re-emphasize that the loop detectors monitor all lanes of traffic while the AVI readers only monitor the inner two lanes in the analysis section. The average market penetration is estimated to be 2% (Haynes 2000). With the low level of AVI market penetration experienced, losing the directional flow of tagged vehicles further reduces the size of the data sample that can be used with the detection algorithms.

5.3 AVI-Based Average Speed

Edie (1965) defined average speed, density and flow in time and space as illustrated in Figure 5.1. The Visual Basic Program referred to earlier was used to match AVI tag reads (Haynes 2000). During each time window, every match is confirmed if it is within the study corridor. The sum of the individual travel times and distances traveled by all vehicles on the link are 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 a time window, the location is stored and the vehicle will resume for the stored location for the next time window. The flow, volume and density computations were tested to guarantee proper calculation according to the definitions defined by Edie (1965). The average speed in a Region A is measured by using the following equation (5.1).

$$V = \frac{\sum_{j=1}^{n} x_j}{\sum_{j=1}^{n} t_j} \qquad \text{(Eq.5.1)}$$

Where:

$\sum_{j=1}^{n} x_j$ represents the total distance traveled by all trajectories in Region A

$\sum_{j=1}^{n} t_j$ represents the total time spent by all trajectories in Region A.

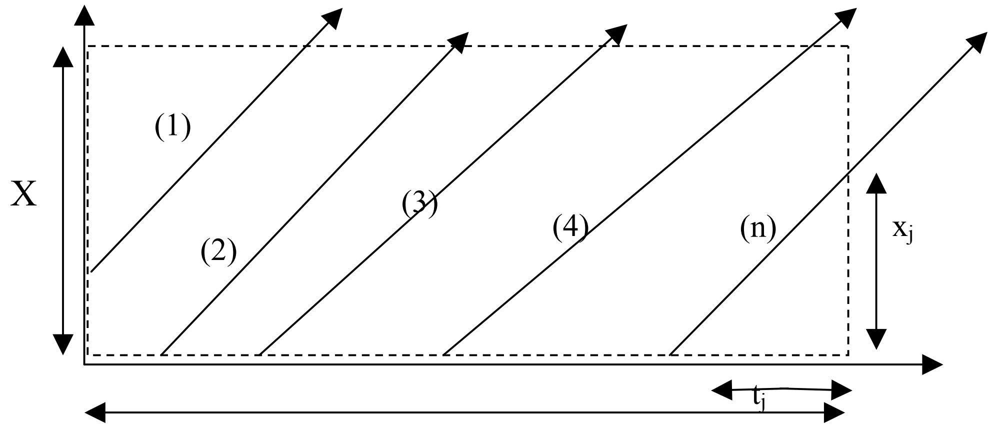


Figure 5.2 Space Diagram with n Trajectories

t_j = time a trajectory traveled with in Region A.

x_j = distance a trajectory traveled within Region A.

T = period of measurement

X = distance between two AVI stations.

This rectangular region in space and time includes *n* vehicle trajectories and each jth trajectory spends time t_j while traveling a distance x_j. For a spatial AVI system, accurate distance between AVI was given and individual travel time must be known to capture vehicles' speeds. As shown in Equations 5.2 and 5.3, the travel time of the vehicle on the given link is measured based on the real time AVI data.

$$TT_i = T_{i,up} - T_{i,dn} \qquad \text{(Eq. 5.2)}$$

Where:

TT_i = travel time of vehicle I

$T_{i,up}$ = time vehicle i passes the upstream detector

$T_{i,dn}$ = time vehicle i passes the downstream detector

Speed is likewise computed as:

$$U_i = \frac{L_j}{TT_i} \qquad \text{(Eq. 5.3)}$$

U_i = speed of vehicle i

L_j =length of link j

It is important to emphasize that the implementation described here is limited to real-time data only; and could not be replaced by historical data. For this reason, strict measurements have been followed to estimate traffic parameters.

Figure 5.3 outlines the AVI implementation procedure in a form of a theoretical time-space diagram. The dotted lines represent the vehicle trajectories. Each vehicle speed trajectory is calculated by matching upstream and downstream AVI tag reads (Haynes 2000). Using a five-minute average moving window provides better results due to the low penetration of the AVI system. The number of AVI tagged vehicles in the study corridor during peak hours is found to be significantly higher than during non-peak hours.

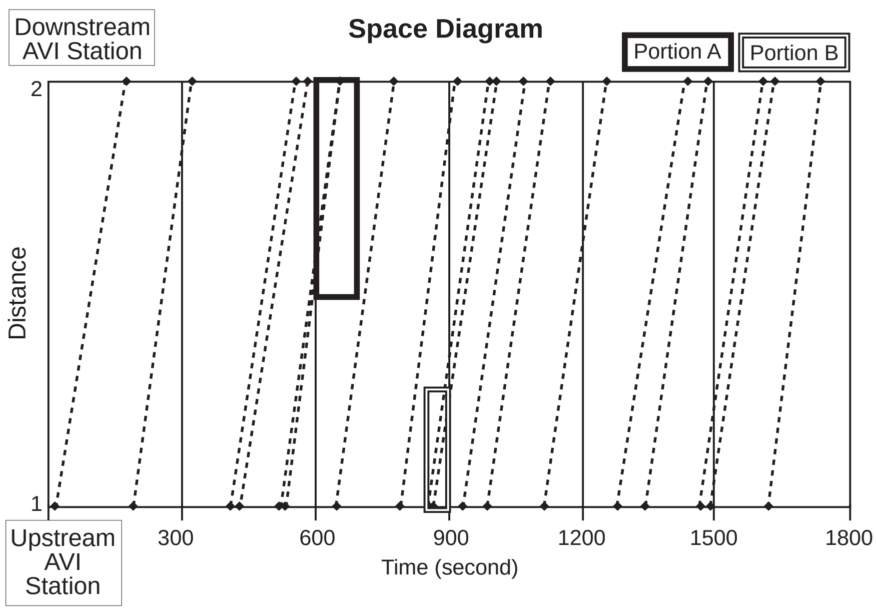


Figure 5.3 Proposed AVI Time-Space Diagram

To reliably estimate the average speed based on the AVI system; it is important to consider the contribution of all AVI tagged vehicles including the vehicles that did not enter and exit the link within the five minutes moving window as illustrated by Portions A and B in Figure 5.3. After defining and implementing Edie's traffic state definitions, it is important to ensure that the definitions are properly applied.

5.4 ILD-based Average Speed

The ILD average speed is calculated using multiple moving average windows: 1 minute, 3 minutes, 5 minutes, and 7 minutes. Figure 5.4 illustrates four-trend lines that represent the link average speed during off-peak hours. The standard deviation of the speed is found to be smaller when the average speed is calculated using larger time windows. The results of the off-peak hours are shown in Figures 5.4 and 5.5 while the results of peak hours are shown in Figures 5.6 and 5.7. Typically, congestion developed on highways during peak hours causes the frequent stop-and-go phenomena. Hence, the average speed during peak hours is expected to be lower than that during off-peak hours. It could be noticed from Figures 5.4, 5.5, 5.6, and 5.7 that the speed fluctuates less when increasing the moving average window regardless of the time of day.

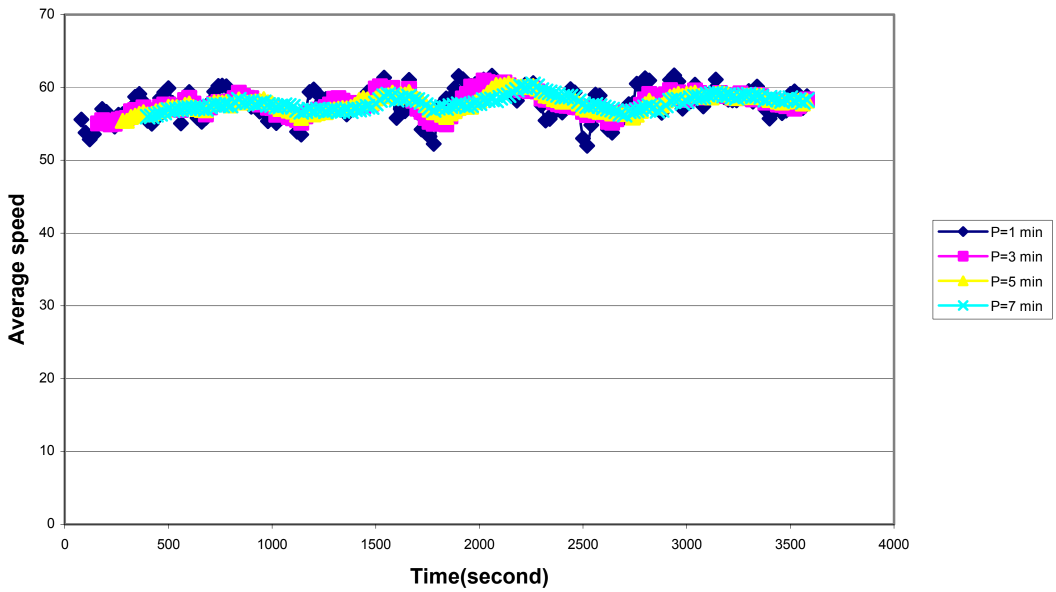


Figure 5.4 Average Speeds at ILD Station 149.412, Off-Peak Hour

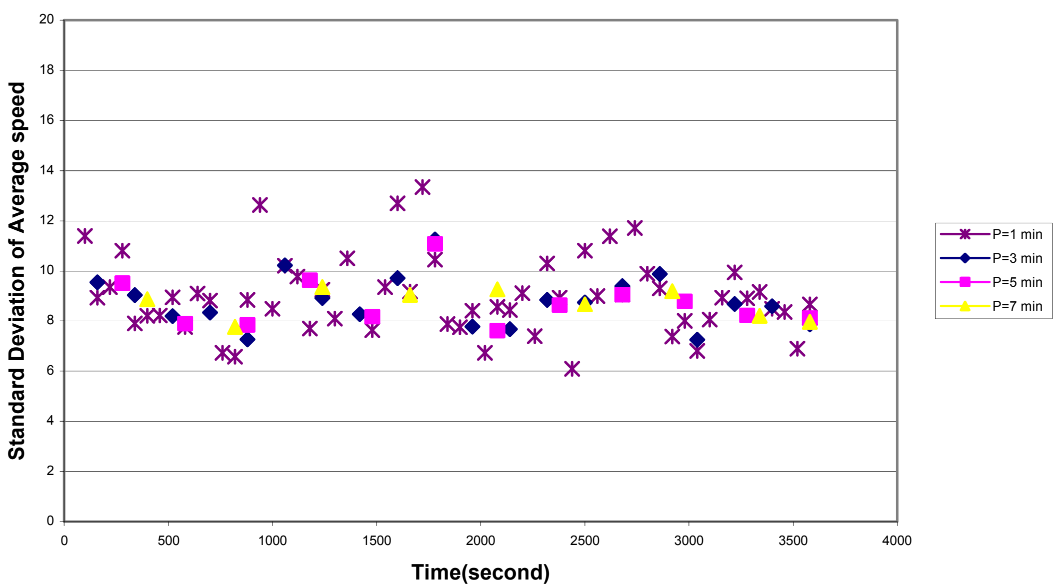


Figure 5.5 The Standard Deviation of ILD Station 149.412, Off-Peak Hour

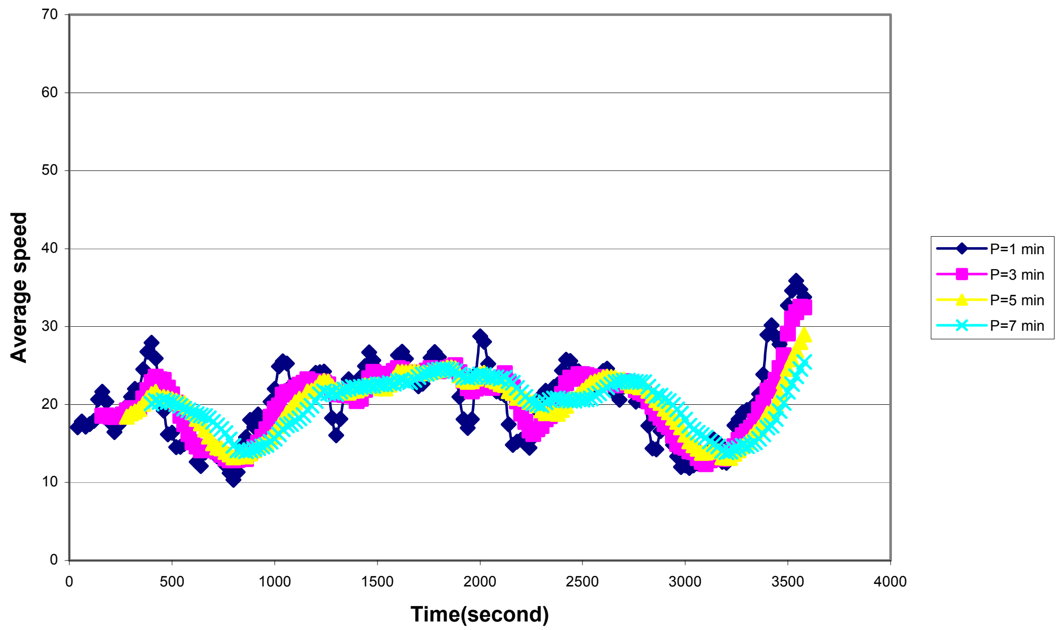


Figure 5.6 Average Speeds at ILD Station 149.412, Peak Hour

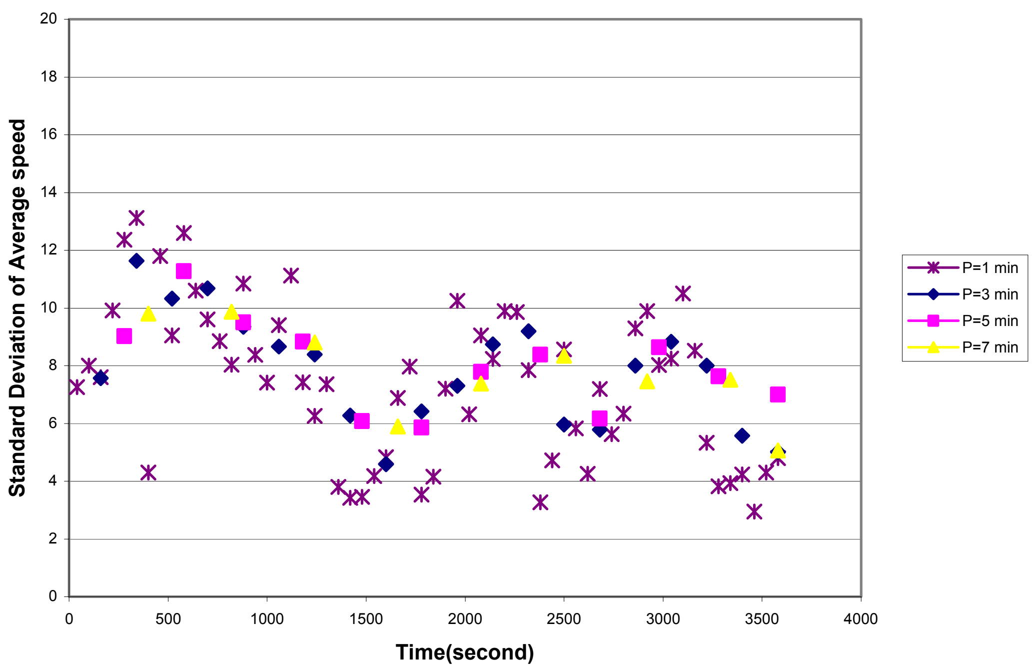


Figure 5.7 The Standard Deviation of ILD Station 149.412, Peak Hour

5.5 AVI-Based and ILD-Based Speed Comparison

Unlike the ILD sensors which are installed on all traffic lanes in the study corridor, the AVI stations are deployed to monitor only the inner two traffic lanes. Figures 5.8 and 5.9 compare the AVI and ILD systems' speed measurements. Figure 5.8 takes into account the ILD data of only the inner two lanes of the I-35 study corridor, while Figure 5.9 uses the average speed from the ILD data of the three lanes. Figures 5.8 and 5.9 demonstrate that the average speed based on three lanes is lower than that from the inner two lanes. This result supports the real world situation where large and slower vehicles tend to use the rightmost lanes. This result is important when performing link-based and point-based integration. For speed and travel estimation, a recommendation could be reasonably made to use only the inner two lanes of ILD data for fusion purposes, since the 3rd lane is often transitional due to the presence of on and off ramps.

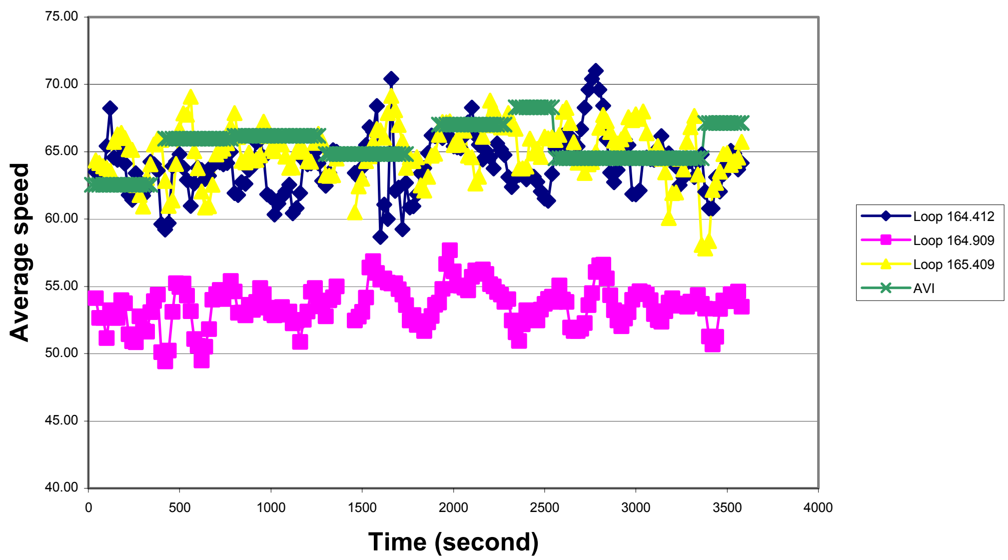


Figure 5.8 AVI vs the Inner Two Lanes of ILD

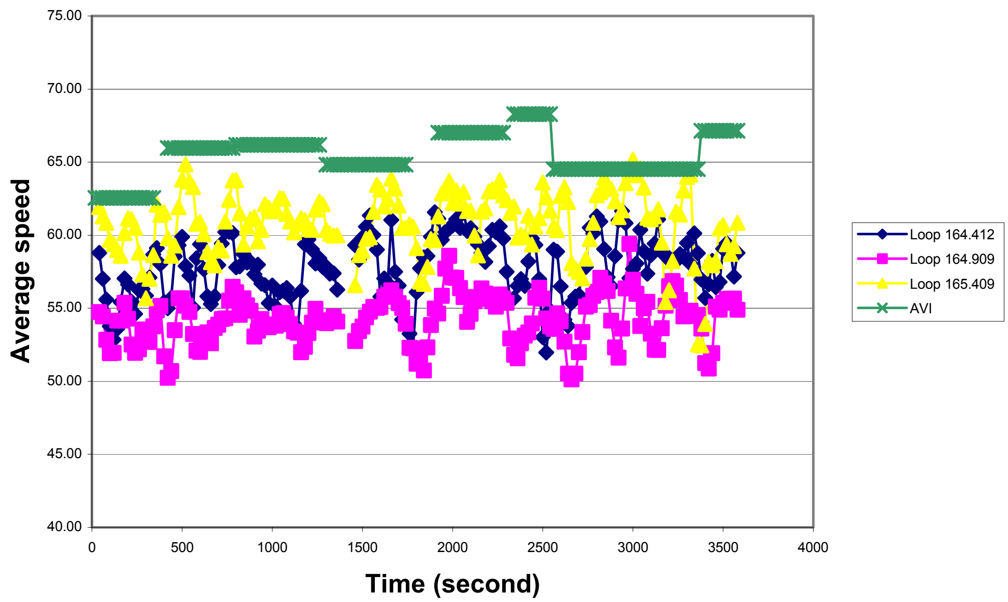


Figure 5.9 AVI vs the Three Lanes of ILD

Table 5.3 Results of Average Speed (Non-Peak Time)

	Average Speed			
Time slot (second)	**ILD 164.412**	**ILD 164.909**	**ILD165.409**	**AVI**
0-20	63.31	52.20	63.89	60.32
20-40	63.47	52.29	63.75	60.60
40-60	63.15	52.37	63.88	60.65
60-80	63.49	52.15	64.13	60.70
80-100	63.55	52.59	64.10	60.91
100-120	62.11	51.73	64.30	61.14
120-140	62.08	51.61	63.89	61.39
140-160	62.27	51.85	63.44	61.60
160-180	62.35	51.92	63.50	61.71
180-200	62.34	52.06	63.75	61.76
200-220	62.42	52.02	63.72	61.56
220-240	62.41	52.19	64.02	61.31
.	.	.	.	.
3580-1600	62.47	62.47	62.47	62.47

Table 5.3 represents the average speed of ILDs and AVI during off-peak period (12:00 noon -1:00 p.m.) on March 18, 2002. The ILD average speeds shown in this table are based only on data from the inner two lanes. Average speeds of the ILD 164.412 are lower than those of the ILD 164.909 and the ILD 165.409. This could be justified by the presence of a number of exit and entrance ramps as well as the local highway geometry. This reality, found on most freeways, reflects the weaknesses of using a single sensing system to estimate the speed and travel time. Accordingly, it supports the argument for integration and fusion. Similar steps were followed to calculate the average speed of the peak hour (5:00 p.m.-6:00 p.m.). As seen from the results of average speed, vehicles passing at ILD 164.412 are slower than other locations. A critical reason of this result is that a lot of vehicles merged from I-410 ahead of this ILD station. From Table 5.3 and 5.4, point speed data is not sufficient to estimate the link average speed, or travel time.

Table 5.4 Results of Average Speed (Peak Time)

	Average Speed			
Time slot (second)	**ILD 164.412**	**ILD 164.909**	**ILD165.409**	**AVI**
0-20	23.03	41.86	57.98	47.82
20-40	23.65	41.99	58.19	47.67
40-60	24.16	42.45	58.47	47.54
60-80	24.91	42.21	58.33	47.32
80-100	25.67	41.71	57.95	47.03
100-120	26.21	41.18	57.52	46.72
120-140	26.43	41.18	56.63	46.40
140-160	26.91	41.26	55.90	46.08
160-180	26.41	41.03	55.63	45.74
180-200	26.59	40.87	55.75	45.36
200-220	25.86	41.14	55.46	44.92
220-240	25.23	41.50	55.79	44.48
…..	…..	……	……	……
3580-1600	20.55	40.17	55.95	42.77

Figures 5.8 and 5.9 illustrate the trends of ILD and AVI sensor data showing a significant difference during off-peak hour (12:00 noon - 1:00 pm) and peak hour (5:00 p.m. - 6:00 p.m.), when computing space mean speed as described earlier. To calculate the space mean speed using the ILD system, it is assumed with an acceptable level of accuracy that the speed of any vehicle passing through an ILD station could be assumed constant over a distance L. Assume that the distance between the current sensor and preceding sensor is X and the distance between the current sensor and the succeeding sensor station is Y, then the value of L could be calculated as follows:

$$L_i = \frac{X_i + Y_i}{2} \quad \text{(Eq. 5.4)}$$

Where:

$L_i =$ The distance over which the speed is assumed to be constant for station (i)

$X_i =$ The distance between the current and preceding sensor station

$Y_i =$ The distance between the current and the succeeding sensor station

The distance L, from equation (Eq. 5.4), is explained by Figures 5.10 and 5.11 for off-peak and peak traffic.To reliably compare the AVI and ILD speeds, it is recommended to offset the speed measured from the ILD system by a time that will allow an AVI tagged vehicle to traverse the distance between the two stations.

Figure 5.10 compares the space mean speed from AVI and ILD systems during off-peak periods. The slopes of two trend lines which represent the first ILD space mean speed and third ILD space mean speed are usually higher than ILD space mean speed and are higher than second ILD space mean speed for the small section studied. Each section in the field would differ in its characteristics.

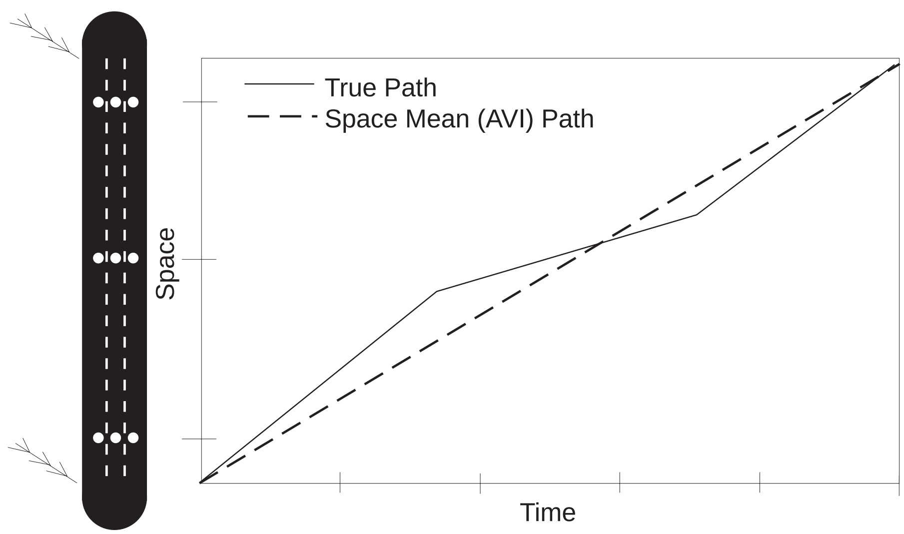


Figure 5.10 Measuring ILD Space Mean Speed during Off-Peak Hour

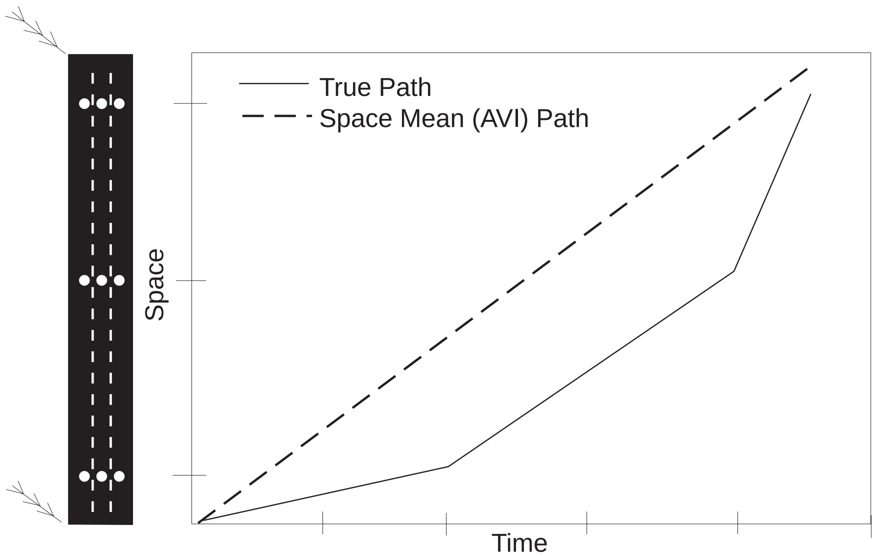


Figure 5.11 Measuring ILD Space Mean Speed during Peak Hour

Figures 5.12 and 5.13 represent the result of space mean of ILD and AVI during each selected study time period.

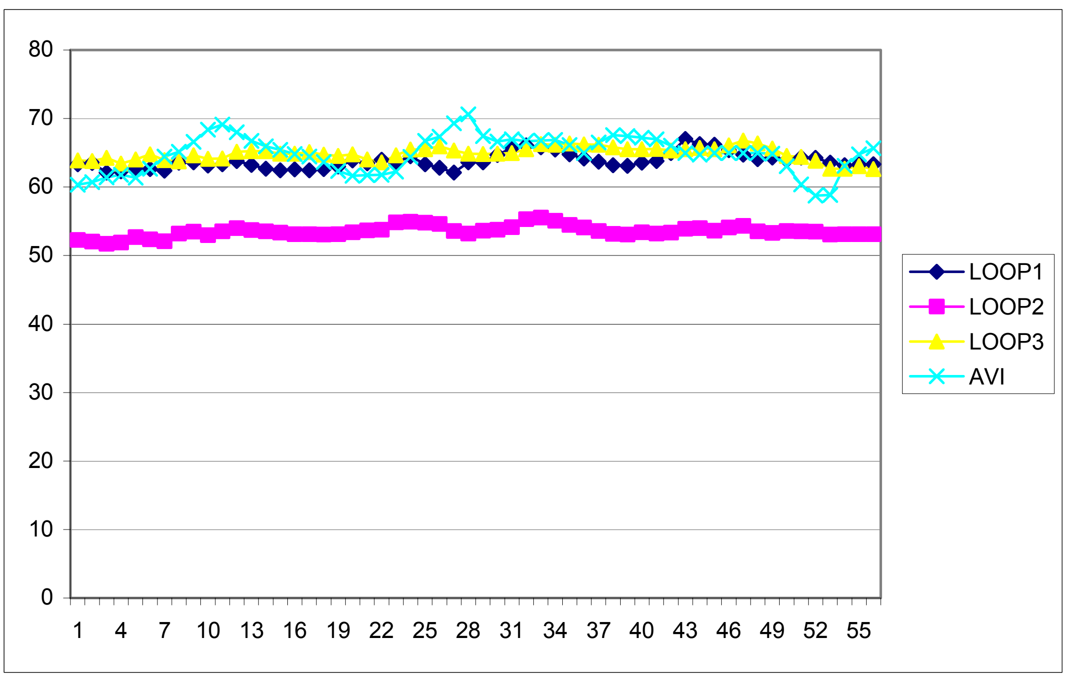


Figure 5.12 Space Mean Speed of AVI and ILD during Off-Peak Hour

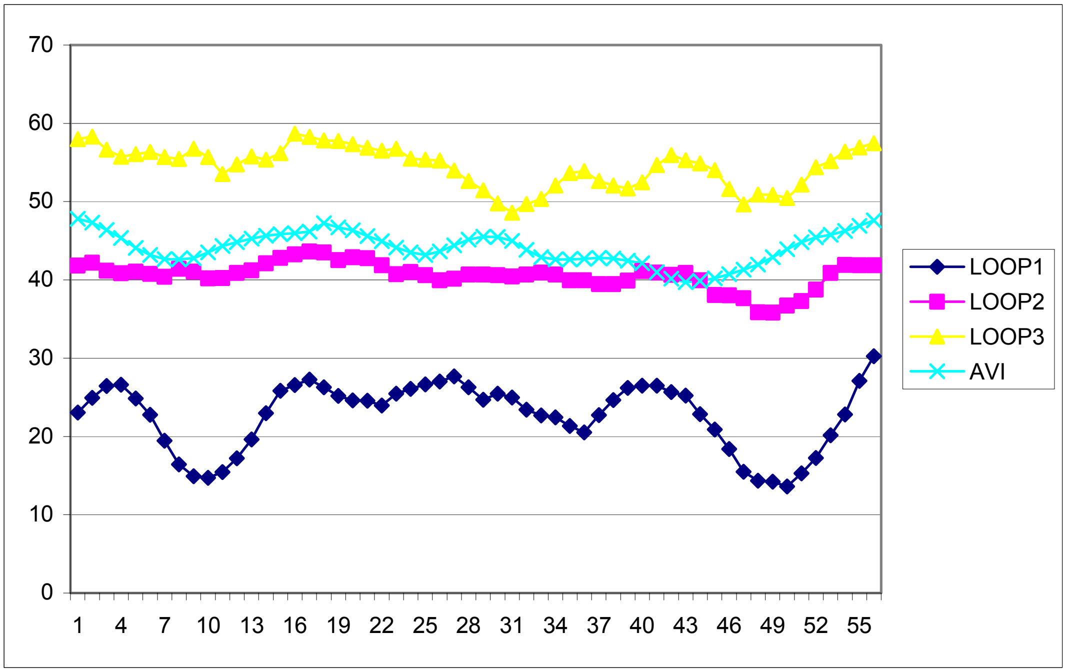


Figure 5.13 Space Mean Speed of AVI and ILD During Peak Hour

5.6 AVI-Based and ILD-based Average Speed Integration

5.6.1 Bayesian Updating

Mahmassani and Sinha (1981) investigated the adequacy of using Bayesian updating as cross-classification technique for household trip generation analysis. Their study concluded that Bayesian updating provides a useful tool for updating trip generation rate and improves the accuracy in reflecting the trip-making behavior of households. The Bayesian updating method will be studied in this research to better estimate the highway speed based on ILD and AVI data. Bayesian updating could be used to update independent and sequentially incoming data based on the new data and prior information. This updated information is called the posterior information. Bayes' theorem is simply expressed as follows:

$$\begin{bmatrix}\textbf{Posterior probability}\\ \textbf{of parameter } \boldsymbol{\theta}\textbf{,}\\ \textbf{given the sample}\\ \textbf{outcome}\end{bmatrix} = \begin{bmatrix}\textbf{Sample Likeihood,}\\ \textbf{given } \boldsymbol{\theta}\end{bmatrix} \times \begin{bmatrix}\textbf{prior}\\ \textbf{probability}\\ \textbf{of } \boldsymbol{\theta}\end{bmatrix} + \begin{bmatrix}\textbf{Margianl}\\ \textbf{Sample}\\ \textbf{Likelihood}\end{bmatrix} \qquad \text{(Eq.5.5)}$$

Although Mahmassani and Sinha (1981) used the Bayesian updating approach to predict the trip time, hence, the speed for the same type of sensor, the approach could be successfully used to integrate the point and link-based data from different types of sensors provided that the data sets are collected continuously and contain the required parameters of average speed and sample variance.

To explain the Bayesian updating approach, consider the following notations for the prior data:

θ_1 = Prior Space Mean Speed

n_1 = Number of Observations

σ_1 = Variance of prior Space Mean Speed

For this research, the first data reading will be assigned as the "a priori" information. Similarly, the new calculated speed will be assumed as a priori information for the next window speed calculation. The sampling distribution of the mean is also assumed to be normal with parameters θ_s and σ_S.With both prior and sampling distributions having normal distribution with variance, the posterior distribution of space mean speed will have the following parameter:

$$\theta_2 = \left[\frac{\frac{1}{\sigma_1^2}}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_S^2}}\right]\times\theta_1 + \left[\frac{\frac{1}{\sigma_S^2}}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_S^2}}\right]\times\theta_S \qquad \text{(Eq. 5.6)}$$

$$\sigma_2 = \sqrt{\frac{1}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_S^2}}} \quad or, \sigma_2 = \sqrt{\frac{S_1^2\times S_S^2}{n_1\times S_S^2 + n_S\times S_1^2}} \qquad \text{(Eq. 5.7)}$$

θ_2 = Posterior Space Mean Speed

σ_2 = Standard Deviation of the Posterior Mean Speed

The resulting posterior distribution is also normal, with mean and standard deviation. Equation 5.6 could be used initially to update the speed measured from each sensor before speed fusion. Figures 5.14 and 5.15 below are a comparison of the actual versus the Bayesian updated AVI speeds for peak and off-peak hours, respectively. Figures 5.14 and 5.15 suggest that no significant difference is evident between the two speed estimates. Accordingly, speeds measured by the AVI system do not require further Bayesian updating before integration with ILD estimated speeds, according to the theory.

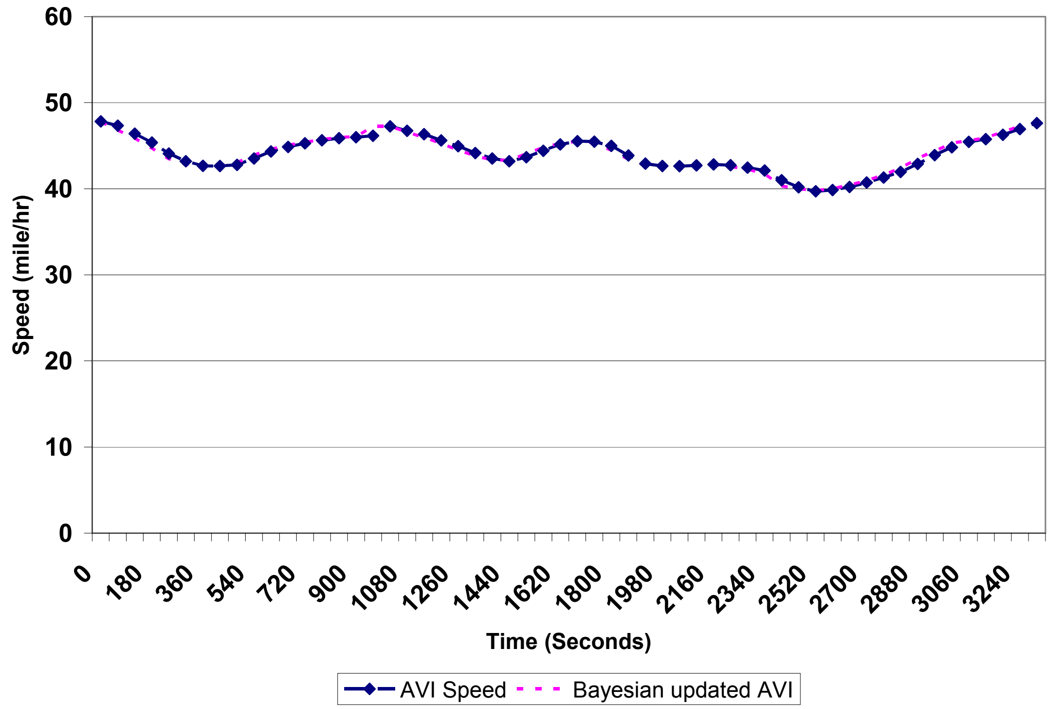


Figure 5.14 Actual vs Bayesian Updated AVI Speed, Peak Hours

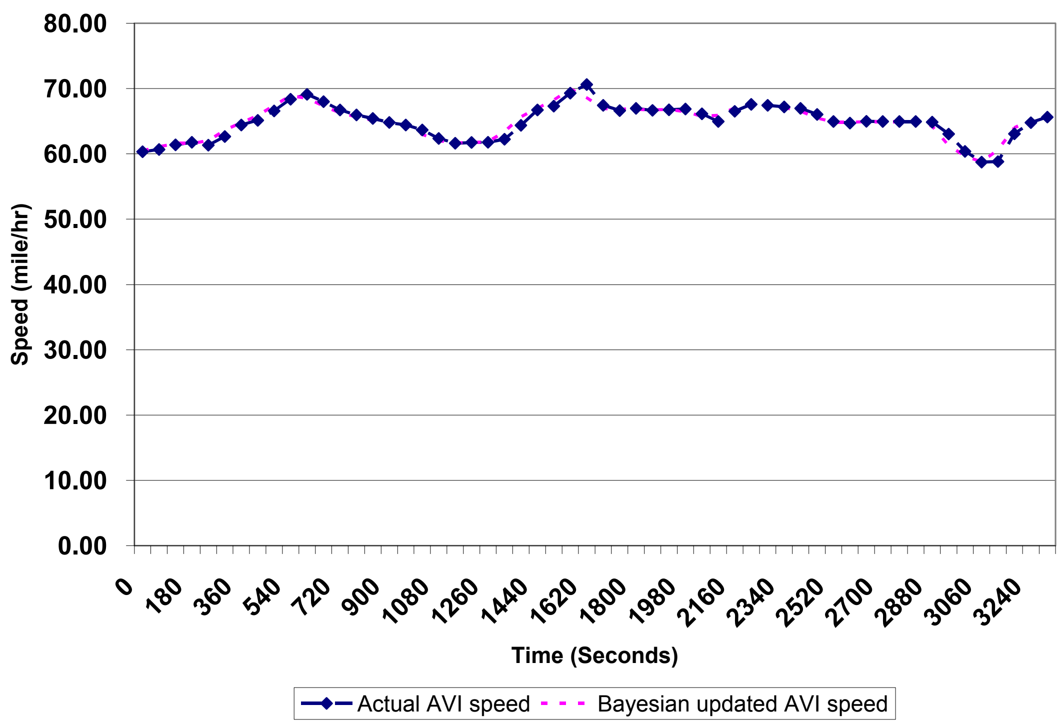


Figure 5.15 Actual vs Bayesian Updated AVI Speed, Off-Peak Hours

The speed measured by ILD sensors could also be subjected to the Bayesian updating equation to justify its use. When Equation 5.6 is used to update the ILD speeds, the results are compared to the actual ILD estimated speeds. Similarly, Figures 5.16 and 5.17 suggest that no significant difference exists between the two speed estimates. Accordingly, speeds measured by the ILD system also do not require further Bayesian updating before integration with the AVI estimated speeds.

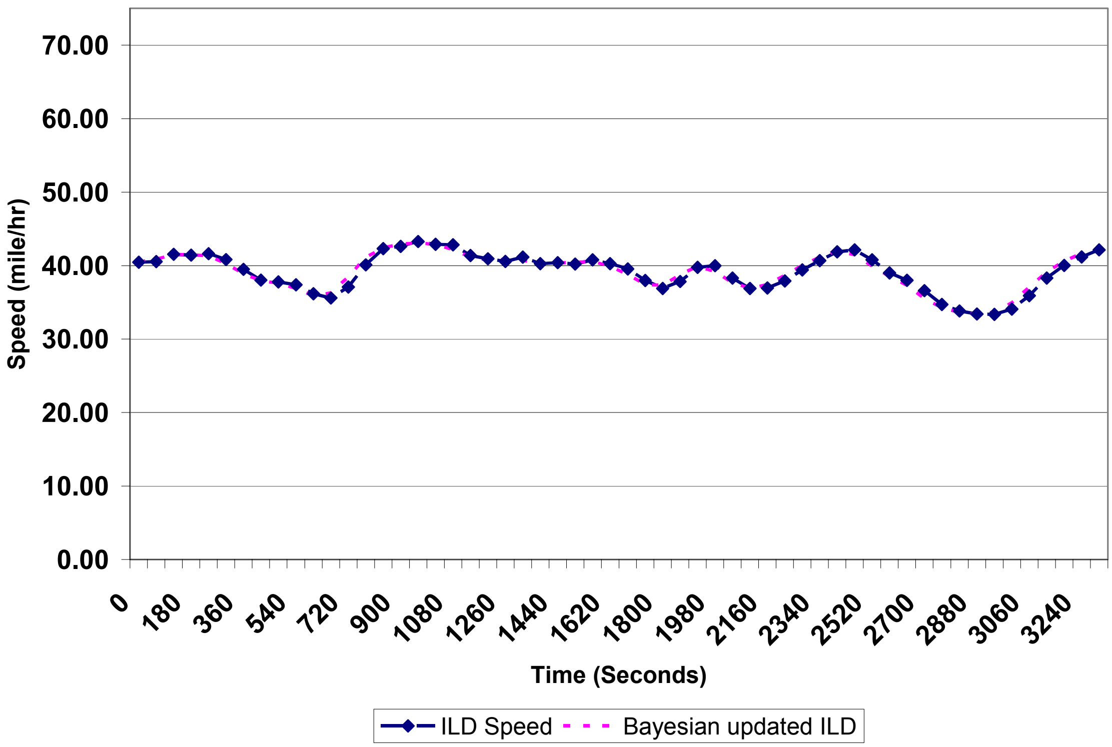


Figure 5.16 Actual vs Bayesian Updated ILD Speed, Peak Hours

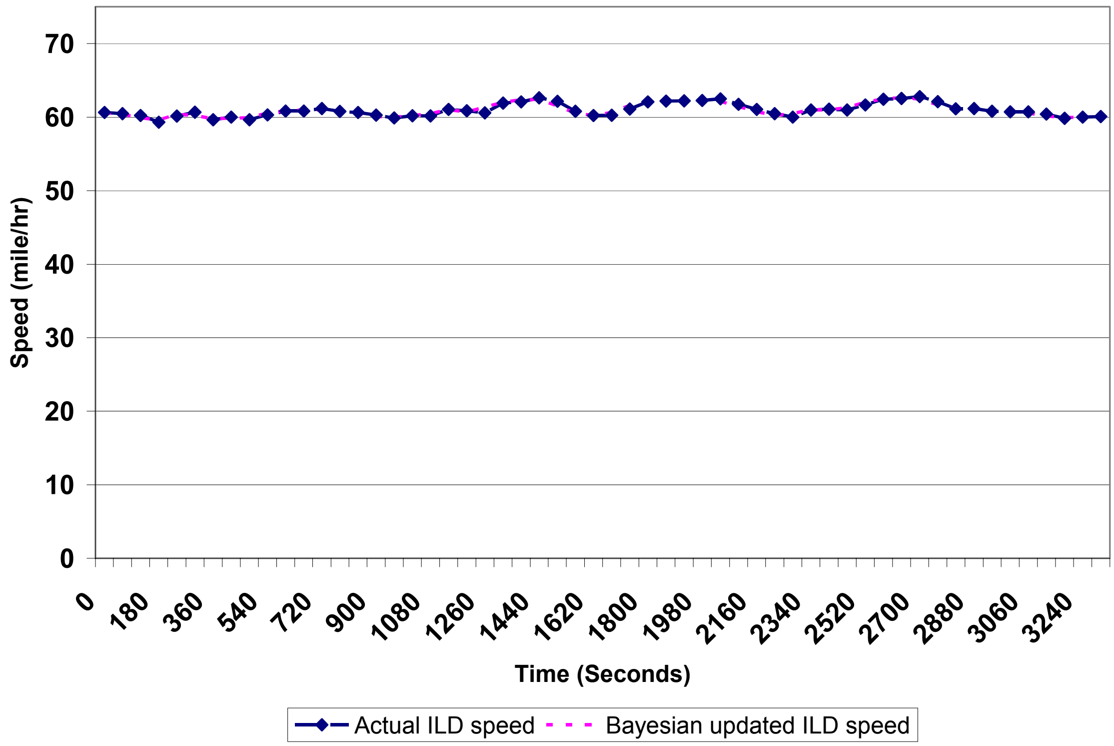


Figure 5.17 Actual vs Bayesian Updated ILD Speed, Off-Peak Hours

5.6.2 Bayesian Updating based on Accurate AVI and ILD

When both AVI and ILD systems are assumed to be hyperthically 100% accurate, the Bayesian updating could be used to calculate the integrated speed of the link. Equations 5.8 and 5.9 below are the modified versions of Equations 5.6 and 5.7.

$$\theta_{Integrated} = \left[\frac{\frac{1}{\sigma^2_{AVI}}}{\frac{1}{\sigma^2_{AVI}} + \frac{1}{\sigma^2_{ILD}}}\right] \times \theta_{AVI} + \left[\frac{\frac{1}{\sigma^2_{ILD}}}{\frac{1}{\sigma^2_{AVI}} + \frac{1}{\sigma^2_{ILD}}}\right] \times \theta_{ILD} \qquad \text{(Eq. 5.8)}$$

$$\sigma_{Integrated} = \sqrt{\frac{1}{\frac{1}{\sigma^2_{AVI}} + \frac{1}{\sigma^2_{ILD}}}} \quad or, \sigma_{Integrated} = \sqrt{\frac{S^2_{AVI} \times S^2_{ILD}}{n_{AVI} \times S^2_{ILD} + n_{ILD} \times S^2_{AVI}}} \qquad \text{(Eq. 5.9)}$$

$\theta_{Integrated}$ = Link Integrated Speed Based on Bayesian Updating and 100% Accuracy of AVI and ILD.

$\sigma_{Integrated}$ = Link Integrated Standard Deviation Based on Bayesian Updating and 100% Accuracy of AVI and ILD.

Figures 5.19 and 5.20 below show the values of the integrated speed based Bayesian updating for peak and non-peak hours, respectively. Notice that the Bayesian updated speed completely coincides with AVI speed (AVI speed curve is hard to envision, since it is exactly below the Bayesian updated curve). The reason for this complete alignment is the low value of standard deviation of AVI compared to ILD sensors, as Table 5.5 shows below.

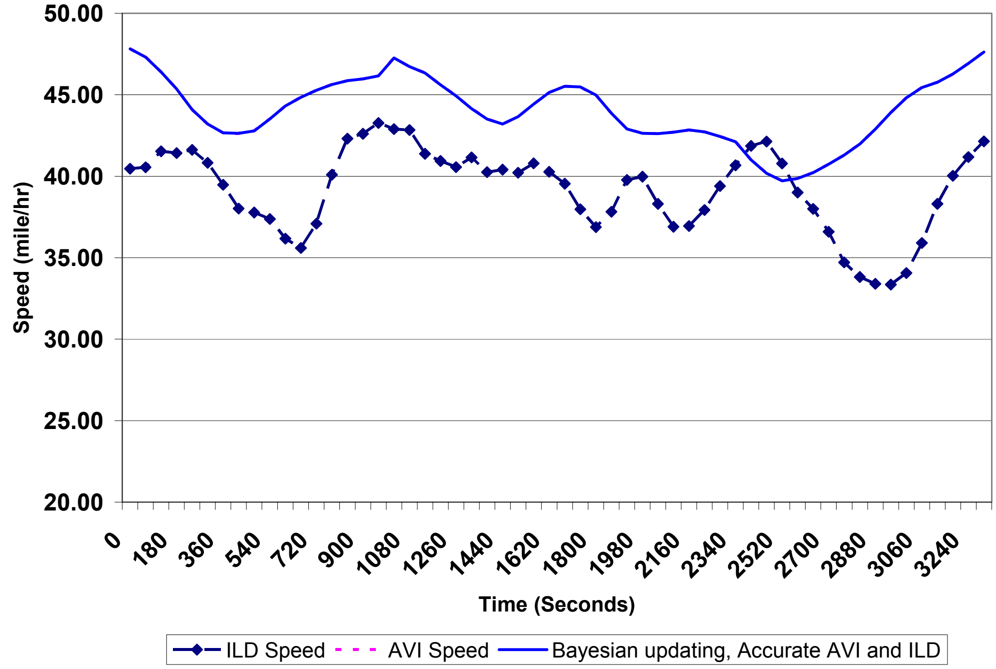


Figure 5.18 Bayesian Updating Based on Accurate AVI and ILD, Peak Hours

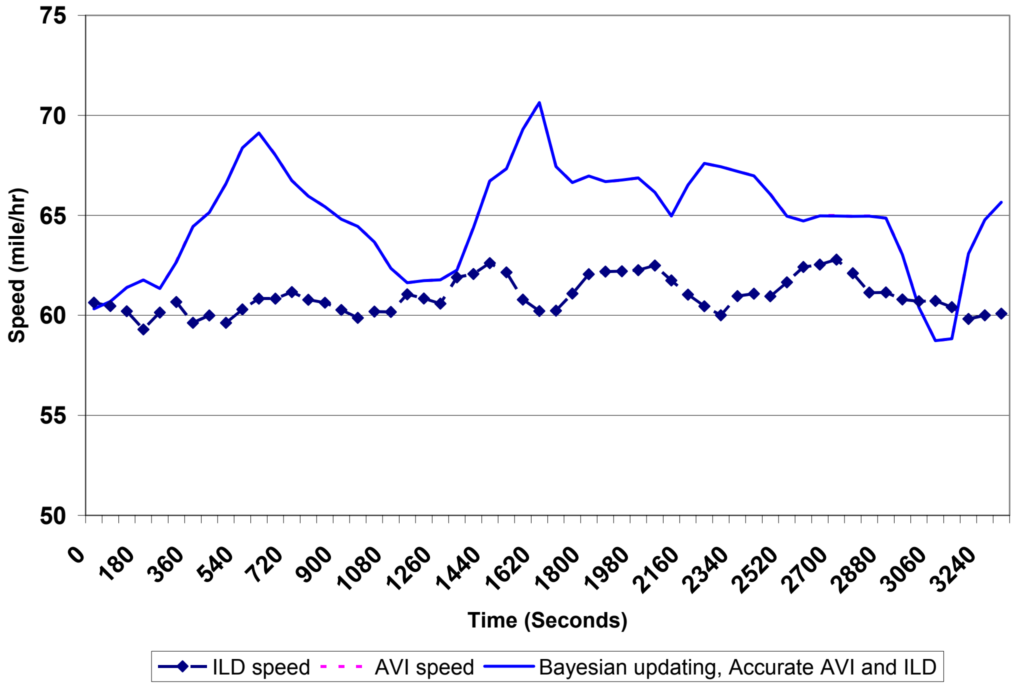


Figure 5.19 Bayesian Updating Based on Accurate AVI and ILD, Off-Peak Hours

Table 5.5 Maximum and Minimum Standard Deviations of AVI and ILD Speeds

	Peak Hours		Off-Peak Hours	
	AVI	ILD	AVI	ILD
Max	13.75	10721.10	6.18	1796.53
Min	0.52	225.05	0.87	35.42

This finding suggests that the AVI system is more reliable for speed estimation. This finding should not be taken in isolation. Other factors such as sensor accuracy, sampling frequency, and availability of data from AVI tagged vehicles should also be considered.

5.6.3 Weighted Average Method with Bayesian Updating

Inductive loops and AVI systems, as with most electronic sensors, suffer from inherent measurement errors. To better estimate traffic speed and travel time of a freeway, the effects of these errors have to be considered in addition to variations in the signal.

The accuracy of ILD sensors to measure speed and to count traffic has been studied by Woods et al. (1994). Figure 5.20 shows the expected error in speed for identical loops and varied trap length (Woods et al. 1994). Although the study by Woods et al. was comprehensive and different ILD configurations were investigated, only Figure 5.20 will be used in this study; since the deployed ILD sensors in San Antonio Study Corridor are identical. Identical ILD sensors provide more accurate speed measurements than unidentical ILDs. Figure 5.20 shows that for speeds less than 60 mph, the average error of ILD sensors for all trap lengths is less than 1.5 mph, while at 80 mph, the average error increases to 4.5 miles per hour. At slow speeds, the error is not very large because the vehicles are on the loop longer and the on/off times of the detector unit are spread further apart.

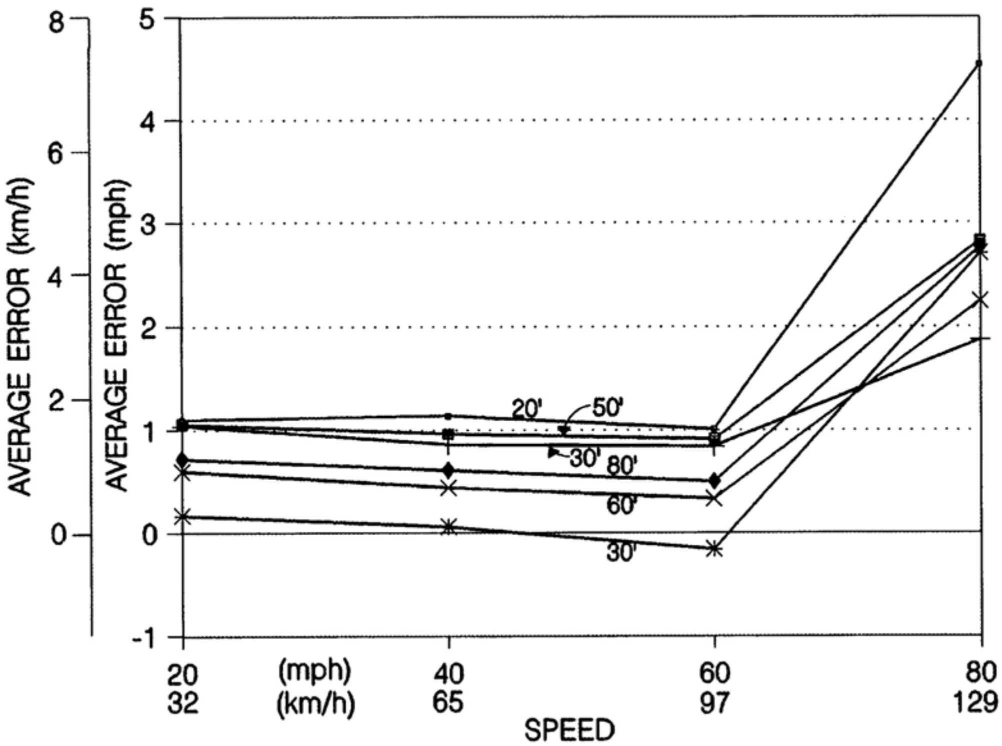


Figure 5.20 Average Errors for Different Speed Trap Lengths and Identical Detector Order (Woods et al. 1994)

The results of a study conducted by FHWA in San Antonio to estimate the accuracy of the AVI system for speed measurement are proposed to be adopted. The study was carried out with the aid of Global Positioning System (GPS) and concluded that the average accuracy of the AVI system is 98%.

The AVI more accurately measures space mean speed than ILD.

$$Estimated\ Average\,speed = \frac{\sum_{i=1}^{2} C_i\ A_i\ \ Average\,speed_i}{\sum_{i=1}^{2} C_i\ A_i} \qquad \text{(Eq. 5.10)}$$

Where:

$$Average\,speed_i = Space\ mean\ speed\ of\ \ \overline{LOOP}\ and\ AVI$$

$$C_i = Confidence\,of\ \overline{LOOP}\ \ and\ \ AVI$$

$$C_i = 1 - e_i \qquad \text{(Eq. 5.11)}$$

$$e_i = \sqrt{\frac{k^2\left(\dfrac{sd_i}{mean_i}\right)^2}{n_i}} \qquad \text{(Eq. 5.12)}$$

$$A_i = \ Accuracy\ of\ \overline{LOOP}\ and\ AVI\ in\ terms\ of\ \ speed,$$

$$for = \begin{cases} A_{\overline{LOOP}} = 80\%\ for\ non-\ peak\ period \\ A_{\overline{LOOP}} = 80\%\ for\ peak\ period \\ A_{AVI} = 98\% \end{cases}$$

$$k = normal\ \ distribution\ \ k\ \ value\ \ for\ 2 - tails\ \ (1.96\ gives\ 95\%)$$

$$n_i = sample\,size\ \ of\ \ \overline{LOOP}\ \ and\ \ AVI$$

$sd_i =$ Standard deviation of space means speed of $\overline{LOOP}\ \ and\ \ AVI$

$sd_{\overline{LOOP}}$ is the single standard deviation during 5 minutes for three Loops.

$$mean_i = space\,mean\,speed\,of\ \ \overline{LOOP}\ \ and\ \ AVI$$

$sd_{\overline{LOOP}}$ is the single space mean speed during 5 minutes for three Loops.

5.6.4 Weighted Average Method With the Use of Inverse Accuracy Factor

The difference between Equations 5.10 and 5.13 is the accuracy factor. In Equation 5.13, the accuracy value of 0.98 and 0.80 for AVI and ILD, respectively, was used. Equation 5.13 is a modified version of Equation 5.10 in order to give more crediblity to the accuracy factor.

$$Estimated\ Average\,speed = \frac{\sum_{i=1}^{2} C_i\ (\dfrac{1}{1-A_i})\ Average\,speed_i}{\sum_{i=1}^{2} C_i\ \ (\dfrac{1}{1-A_i})} \qquad \text{(Eq. 5.13)}$$

$$A_i = \text{Accuracy of } \overline{LOOP} \text{ and } AVI \text{ in terms of speed},$$

$$for = \begin{cases} A_{\overline{LOOP}} = 80\% \text{ for non} - \text{peak period} \\ A_{\overline{LOOP}} = 80\% \text{ for peak period} \\ A_{AVI} = 98\% \end{cases}$$

In this scenario, the weighted average method is applied to estimate traffic parameters in Equation 5.14. The accuracy factor is included in the weighted average method.

$$\theta_{Estimated\ speed} = \frac{A_{AVI} \times \left[\dfrac{\dfrac{1}{\sigma^2_{AVI}}}{\dfrac{1}{\sigma^2_{AVI}} + \dfrac{1}{\sigma^2_{ILD}}}\right] \times \theta_{AVI} + A_{ILD} \times \left[\dfrac{\dfrac{1}{\sigma^2_{ILD}}}{\dfrac{1}{\sigma^2_{AVI}} + \dfrac{1}{\sigma^2_{ILD}}}\right] \times \theta_{ILD}}{A_{AVI} \times \left[\dfrac{\dfrac{1}{\sigma^2_{AVI}}}{\dfrac{1}{\sigma^2_{AVI}} + \dfrac{1}{\sigma^2_{ILD}}}\right] + A_{ILD} \times \left[\dfrac{\dfrac{1}{\sigma^2_{ILD}}}{\dfrac{1}{\sigma^2_{AVI}} + \dfrac{1}{\sigma^2_{ILD}}}\right]} \qquad \text{(Eq.5.14)}$$

Where:

$$\theta_{Estimated\ speed} = \text{Space mean speed of } ILD \text{ and } AVI$$

6. Modeling Sensors Integration for Incident Detection

Congested highways create potential for delays and traffic incidents. The cost of incidents and secondary incidents that occur on overcrowded highways is reflected in lost lives, damaged property, and high insurance premiums. The Federal Highway Administration (FHWA) estimated that by 2005 approximately 70% of delays on urban highways will result from traffic incidents and will cost $35 billion (Gordon et al. 1996, and Lindley 1986).

Most major U.S. cities have installed large numbers of automated traffic sensors on highways to monitor traffic and estimate speed. These sensors are an integral part of the traffic management systems. The quality of data collected by any traffic sensor is influenced by the sensor's inherent measurement accuracy, precision and repeatability as well as the density of its distribution and its sampling frequency. The rapid advancement in computing and manufacturing technology improved the performance of available traffic sensors. Although Inductive Loop Detectors (ILDs) are considered the most mature traffic sensor, a new set of sophisticated sensors are evolving. These sophisticated sensors include Automated Vehicle Identification (AVI), Video Image Processing (VIP), Infrared, Acoustic, Laser Sensors, and the latest cellular phone location technology. These automated traffic-sensing systems are mostly coupled with visual, non-automated technologies such as: Close Circuit TVs (CCTV), Police Patrol (PP), and cellular phone reports from motorists.

Generally, traffic sensors have limited reliability as was explained in Chapter 5. Most traffic sensors perform poorly because of the environment in which they are installed and operate, and because of their inherent systematic and random errors. For this reason, traffic management centers tend to deploy multiple side-by-side traffic sensors to reduce the number of missed incidents and reduce false alarms, as well as to increase detection reliability.

Several studies investigated the application of data fusion concepts in incident detection. The ultimate goal of all these studies was to acquire the highest performance possible by exploiting redundant and complementary information from different sensors. Zhou (2000) evaluated the performance of three typical automated incident detection algorithms and developed a fusion method to improve the performance of incident detection. The method was based on Dempster-Shafer Fusion Theory. The proposed fusion method was used to fuse incident detection of the California # 8, McMaster, and DELOS detection algorithms based on traffic and incident data collected from the San Antonio Network. The proposed fusion method showed superior detection performance better than when applying detection algorithms separately. Fused algorithms were able to detect up to 80% of traffic incidents at a low 0.12 % false alarm rate.

The study conducted by Khoury (2000) reviewed automatic incident detection technologies deployed in San Antonio freeways and managed by TransGuide. Traffic and incident data collected from the San Antonio Network were used to compare the performance of Inductive Loop Detectors (ILD) and Automatic Vehicle Identification (AVI) for automated incident detection. In this study, the California #8 and the Texas algorithms were calibrated an (UCL) algorithm and the Texas algorithm were calibrated and tested using the AVI data collected. When traffic and incident data from the San Antonio network are processed by the four different algorithms, the California #8 algorithm applied to ILD data performed best in terms of Detection Rate (DR) and False Alarm Rate (FAR).

Investment on transportation systems is considerable and sometimes risky due to potentially high and irreversible costs of mistakes after construction. An incident detection system is an important part of any transportation management system and requires careful and informed investment decision-making. Providing a modeling technique that would enable traffic planners to choose the best investment of traffic sensors for incident detection and other TMC applications is of paramount importance.

This chapter proposes a modeling technique that would utilize the Monte Carlo Simulation Model to simulate the combined performance of deployment levels of multiple sensor types to detect traffic incidents. The proposed technique can be used to predict the integrated performance of detection sensor deployment plans based on priori information.

6.1 Measures of Effectiveness for Incident Detection

The objective function of incident detection is to minimize the time-to-detect, false alarm rate, and incident duration while maintaining a high detection rate. This objective function is written in Equation 6.1:

$$\text{Max }(Z) = -\beta 1\ (TTD) - \beta 2\ (FAR) + \beta 3\ (DR) - \beta 4\ (ID) \qquad \text{(Eq. 6.1)}$$

TTD = Time-to-Detect
FAR = False Alarm Rate
DR = Detection Rate
ID = Incident Total Duration,

The length of any incident is divided into three phases (detection, clearance and traffic restoration). The time to clear any incident depends mainly on the method used and the severity of the incident. Unfortunately, the performance indicators of incident detection are contradicting, e.g. detecting most incidents is advantageous but usually comes at the expense of a higher false alarm rate. In this study, modeling the fused performance of different incident detection sources gradually evolved from using simple arithmetic equations and concluded with a robust Monte Carlo simulation model.

6.2 Arithmetic Model

To explain this simple model, consider a highway network with AVI, Loops and Closed-Circuit TV (CCTV) systems deployed to detect incidents. Hypothetically, assume that the Time-to-Detect of each sensor follows a normal distribution with the AVI system detecting incidents at 6 minutes average and 2 minutes standard deviation, the ILD system detecting incidents at 5 minutes average and 1.5 minutes standard deviation, and the CCTV system detecting incidents at 4 minutes average and 1 minute standard deviation. The probability of detecting an incident within (t) minutes could be estimated based on the probability of detection by any of the three sensors, or detection by any two sensors, or by all the three sensors. For independent sensors, and when t equals to 3 minutes, the first case could be expressed using the following probability formula:

When t = 3 minutes, then:

P (TTD ≤ 3 minutes) = P (AVI TTD ≤ 3 min) + P (Loops TTD ≤ 3 min) + P (CCTV TTD ≤ 3 minutes) - P (AVI & Loops TTD ≤ 3 min) - P (AVI & CCTV TTD ≤ 3 min) - P (Loops & CCTV ≤ 3 min) + 2 (AVI, Loops & CCTV ≤ 3 min).

To calculate P (X ≤ X1) given the mean is μx and standard deviation is σx use the equation below

$$P(X \le X1) = \Phi(\frac{X_1 - \mu_x}{\sigma_x}) \quad \text{(Eq. 6.2)}$$

Then,

Table 6.1 Probability of Detection Time for Different Cases

Sensors	CCTV	Loops	AVI	CCTV & Loops	CCTV & AVI	AVI & Loops	All Sesnsors
P (TTD< 3 min)	0.1586	0.0912	0.0668	0.2353	0.21486	0.1519	0.2864
P (TTD < 3.4 min)	0.2743	0.1431	0.0968	0.3781	0.34451	0.226	0.4383
P (TTD < 3.6 min)	0.34458	0.1753	0.1151	0.4595	0.42	0.2702	0.5217

P (TTD ≤ 3 minutes) = (0.1586) + (0.0912) + (0.0668) – (0.1586 x 0.0912) – (0.0912 x 0.0668) – (0.1586 x 0.0668) + 2 (0.1586 x 0.0912 x 0.0668).

= 0.2873

= 28.73 %

The following graph contains the normal distribution curves for each sensor's Time-To-Detect.

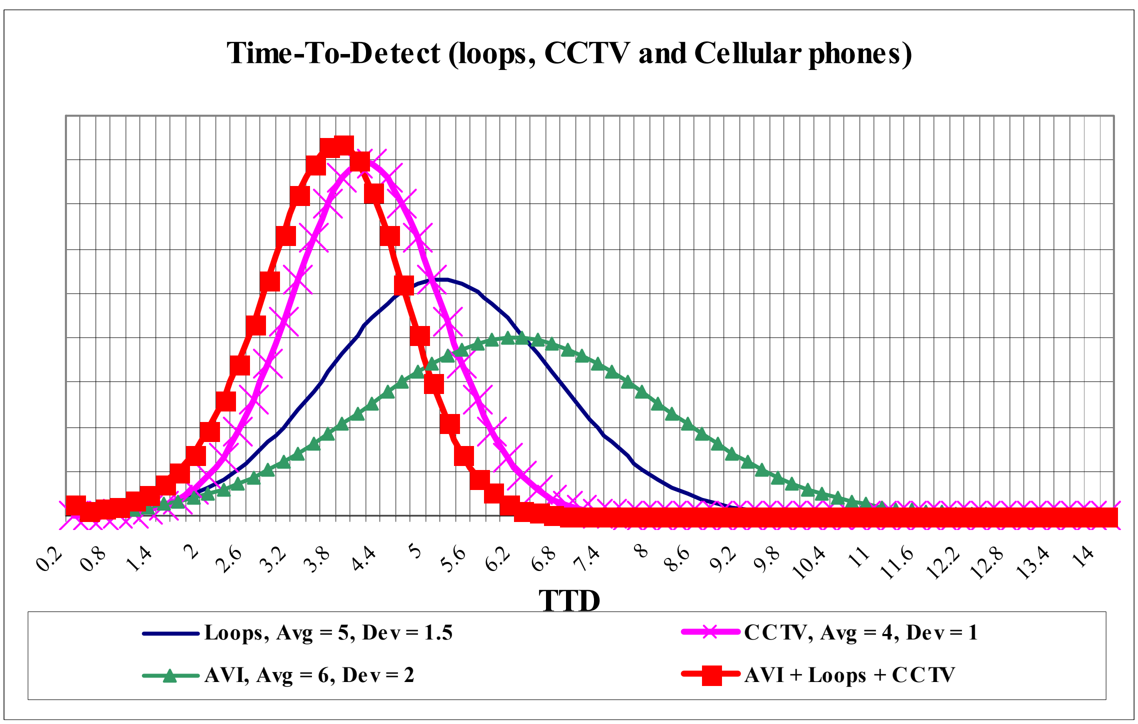


Figure 6.1 TTD Curves for Loops, CCTV, Cellular Phones, Fused Performance

From Table 6.1 and by using interpolation, the mean time-to-detect (the average time at which incidents will be detected 50% of the time) for the fused performance curve could be calculated.

P (TTD ≤ 3.4 min) $\longrightarrow$ 44.22 %

P (TTD ≤ 3.6 min) $\longrightarrow$ 52.87 %

The TTD corresponding to 50% ≈ ≤ 3.5 minutes while the average time to detect the fused combination is 3.5 minutes compared to 4, 5 and 6 minutes intervals for individual sensors. The calculations above are based on the theoretical assumption that each sensor's incident detection rate is 100% perfect and each sensors' detection performance is completely independent.

In practice, some incidents are missed by some or all sensors. The distribution that represents the case scenario where less-than-perfect detection is present could easily be drawn based on the original 100% detection rate. To draw this new distribution curve, multiply the probability of detecting incidents below certain time (t) by the DR of that sensor.

For example, if 30 incidents were detected within 4 minutes at the ideal 100% detection rate, then the number of incidents that will be detected within the same time frame at 80% detection rate is equal to 0.8 * 30 = 24 incidents. This is based on the assumption, although not proven, that missed incidents are uniformly distributed along the detection time. Figure 6.2 illustrates a comparison between 100% and 75% detection rate.

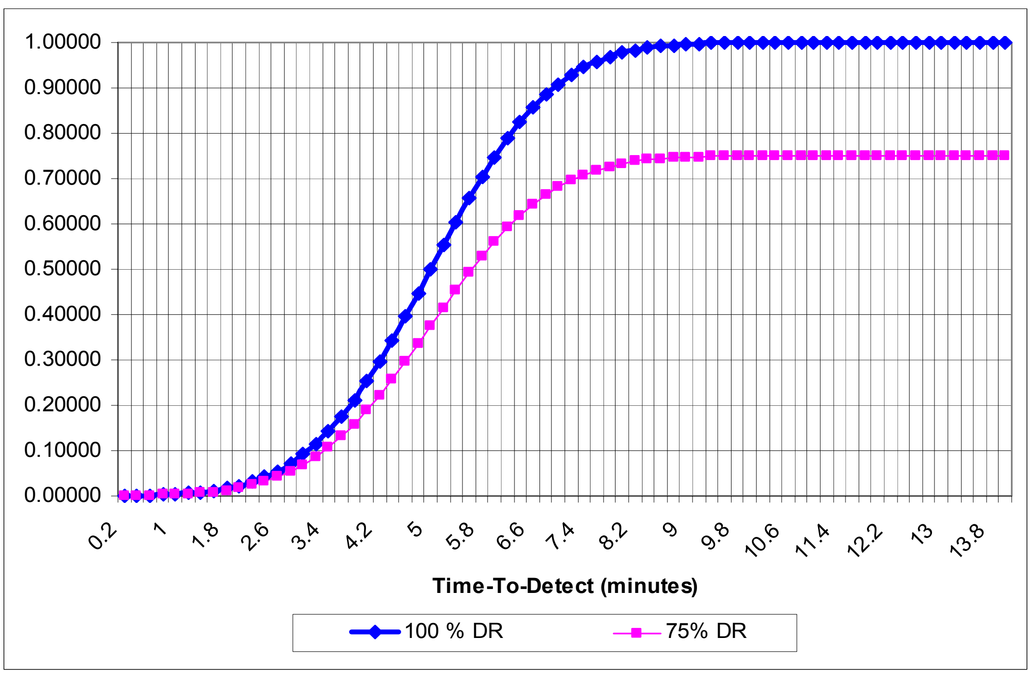


Figure 6.2 Time to Detect Incidents at 100% vs 75% Detection Rates

Similarly, the following scenario has been designed to explain the effect of less-than-perfect detection on the overall fused performance. Hypothetically, assume that the time-to-detect by AVI, ILD and CCTV is as follows:

AVI: Average TTD = 6 min, STDV = 2, DR = 55%

ILD: Average TTD = 5 min, STDV = 1.5, DR = 70%
CCTV: Average TTD = 4 min, STDV = 1, DR = 85%

When running 1000 incidents through the three sensors and assuming mutual independence (which in practice is not the case), the probability of joint detection is calculated as:

$$P(DR) = DR_{AVI} + DR_{ILD} + DR_{CCTV} - DR_{AVI} * DR_{ILD} - DR_{ILD} * DR_{CCTV} - DR_{AVI} * DR_{CCTV} + 2 * DR_{AVI} * DR_{ILD} * DR_{CCTV} \quad \text{(Eq.6.3)}$$

P(DR) = 0.85 + 0.7 + 0.55 - 0.85*0.7 - 0.7*0.55 + 0.85*0.55 + 0.85*0.55*0.7 ≈ 98%.

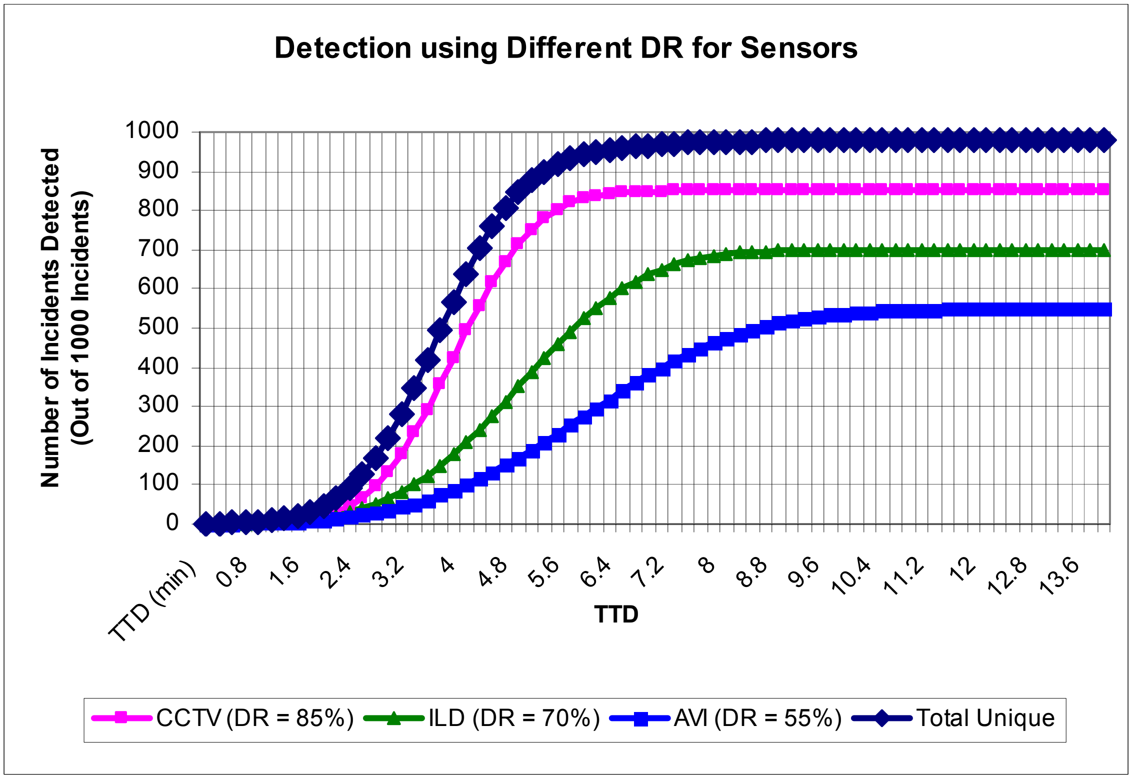


Figure 6.3 Individual vs Combined Sensor Performance

6.2.2 Detection Based on First and Second Alarms

The high number of false alarms at the Traffic Management Centers generated when automated incident detection is in use causes frustration to the operators. Waiting for a second alarm to fire before verifying incidents could substantially reduce the probability for false alarms. Utilizing this concept, two different scenarios will be considered. The first scenario involves incidents verified by operators as soon as the first AID alarm goes off. The second scenario waits for a second AID alarm before verifying incident occurrence. Verifying incident presence just after the first alarm results in a higher detection rate coupled with a high false alarm rate. Similarly, waiting for a second or corroborating alarm substantially reduces the probability of false alarms and at the same time allows many minor incidents to go undetected. Consider the numerical example mentioned above, the performance of the three sensors based on first alarm and second alarm is shown in Figure

6.4. Notice that when detecting at the first alarm, Equation 6.3 is used, while Equation 6.4 will be used for calculation at second or more alarms.

$$P(DR) = P(CCTV \cap ILD) + P(ILD \cap AVI) + P(AVI \cap CCTV) - 2 * P(CCTV \cap ILD \cap AVI) \quad \text{(Eq.6.4)}$$

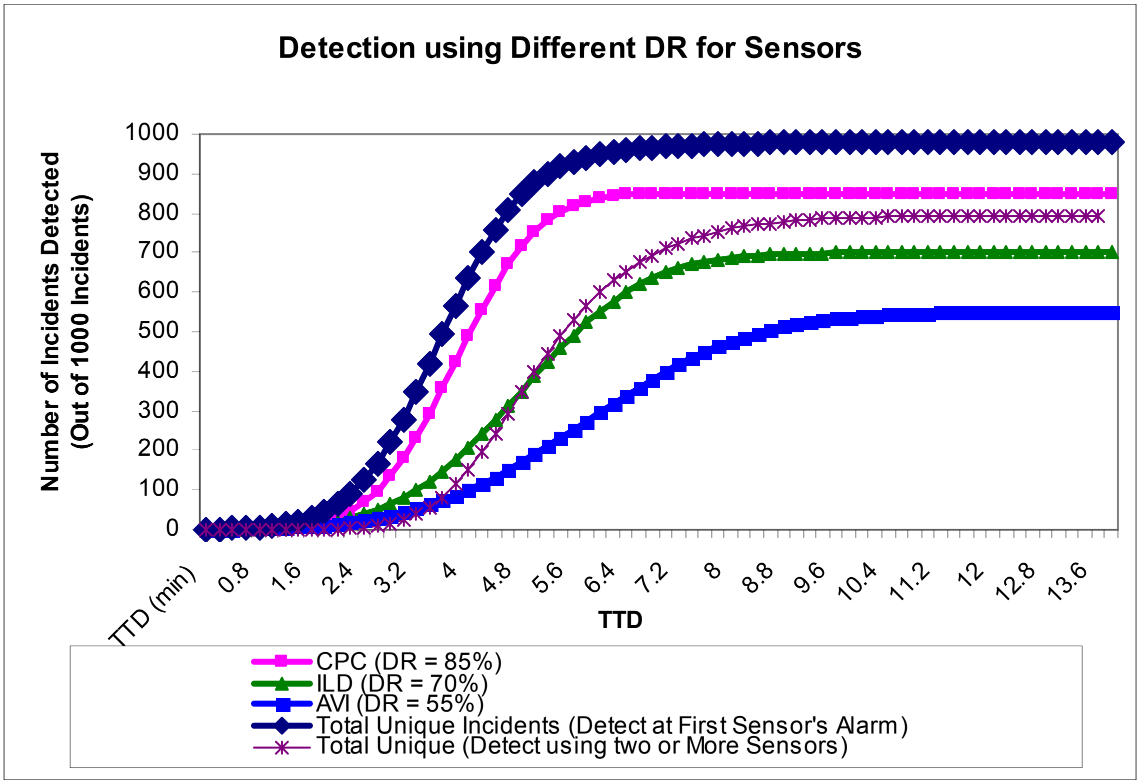


Figure 6.4 Number of Incidents Detected at First vs Two or More Sensors

6.2.3 Incorporation of False Alarms

False alarms could be best visualized as virtual "unreal" incidents that resemble the situation of real incidents. These virtual incidents are detected by AID algorithms and respond by firing an alarm. As the sensor's sensitivity level is increased, so also is the resulting detection rate of both real and unreal incidents. Similar to the "real" incident detection scenario; the joint false alarm rate calculations could also be subject to the first/second alarm scenario that was explained earlier. Equations 6.5 and 6.6 calculate the joint false alarm rate based on first and second alarm scenarios, respectively.

P (FARCCTV U FARILD U FARAVI) = P (FARCCTV) + P (FARILD) + P (FARAVI) – P (FARCCTV ∩ FARILD) – P (FARCCTV∩ FARAVI) – P (FARILD ∩ FARAVI) + P (FARCCTV ∩ FARILD ∩ FARAVI) (Eq.6.5)

P (FARCCTV U FARILD U FARAVI) = P (FARCCTV ∩ FARILD) + P (FARILD ∩ FARAVI) + P (FARAVI ∩ FARCCTV) – 2 x P (FARCCTV ∩ FARILD ∩ FARAVI) (Eq.6.6)

6.2.4 Incorporation of Sensors Correlation

A specific incident can be detected by multiple sensors and, in practice, lead to some degree of sensor correlation. The higher the number of incidents detected by any two sensors, the higher the degree of correlation between the two sensors. Although deploying multiple sensors at the same highway link improves the overall detection effort, a group of incidents still can go undetected as depicted in Figure 6.5. Applying simple arithmetic equations does not properly address sensors correlation. Furthermore, two separate simple models are required to predict the detection rate and false alarm rate. The Monte Carlo Model has the capability to correlate each sensor's input and develop a single unified model that encompasses both detection rate and false alarm rate.

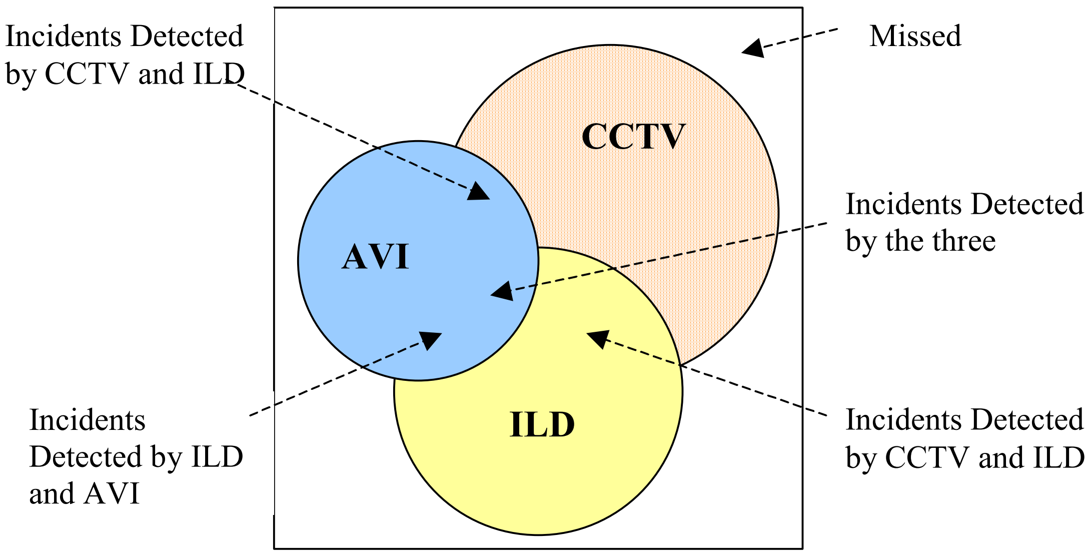


Figure 6.5 Detection Zones for CCTV, ILD, and AVI

6.3 Monte Carlo Model

The Monte Carlo Simulation Model in an Excel environment is able to handle incident detection sensors that are correlated and also incorporate different detection rates and false alarm rates. Utilizing this technique works particularly well when the underlying probabilities are known but the results are difficult to determine. Monte Carlo Simulation Model is essentially a numerical integration tool for conducting "what if" experiments numerically.

Consider the following response function: $Y = g(\vec{X})$ where Y is the response of interest and $\vec{X} = \{X_1, X_2, ..., X_n\}$ is a vector of input variables with joint probability density function $f_{\vec{x}}(\vec{X})$. The cumulative distribution function for Y is given by the following

$$F_Y(y) = P(Y \le y) = \int ... \int f_{X1,...,Xn}(x_1, ..., x_n) dx_1 .... dx_n \qquad \text{(Eq.6.7)}$$

$$= \int_{-\infty}^{\infty} .... \int_{-\infty}^{\infty} I[g(\overrightarrow{X}) \leq y] f_{x1,....,xn}(x_1,....,x_n) dx_1 ....dx_n$$

Where $I[g(\overrightarrow{X}) \leq y] = \begin{cases} 1 & g(\overrightarrow{X}) \leq y \\ 0 & g(\overrightarrow{X}) > y \end{cases}$

We can obtain an estimate for FY(Y) by simulating realizations of $\overrightarrow{X}$ (the kth realization will be denoted $\vec{x}$) many times (N times to be specific), and then counting the number of realizations that give $g(\vec{x}_k) \leq 0$

$$F_Y(y) \approx \frac{1}{N} \sum_{K=1}^{N} I[g(\overrightarrow{X_k})]$$

The mth moment of Y (e.g. the expected value of Y is the first moment, or m = 1) is given by the following

$$E(Y^m) = \int_{-\infty}^{\infty} .... \int [g(\vec{x})^m] f_{x_1,....,x_n}(x_1,.....,x_n) dx_1 ....dx_n \qquad \text{(Eq. 6.8)}$$

We can obtain an estimate for $E(Y^m)$ by simulating $g(\vec{x})^m$ N times, and then taking the average value of $g(\vec{x}_k)^m$

$$E(Y^m) \approx \frac{1}{N} \sum g(\overrightarrow{x_k})^m \qquad \text{(Eq. 6.9)}$$

6.3.1 Potential Scenarios of Incidents Detection

There are several scenarios that should be covered when modeling the performance of fused incident detection. These include first vs. second or more alarms, correlated vs. independent (non-correlated) sensors, and ideal 100% vs. less than perfect detection rate.

6.3.2 Monte Carlo Model Initiation

As stated earlier, Monte Carlo simulation model uses probabilistic distributions as an input. In this model, the sensors' Time-to-Detect (TTD) is based on Normal distribution. To explain the different phases of the model hypothetical values will be used. Assume that the Time-to-Detect (TTD) for CCTV is N (4 min, 1 min), for ILD is N (5 min, 1.5 min), and for AVI is N (6 min, 2 min). Since incidents' TTD must always be positive, then TTD should not be represented using Normal distribution. Initial runs of the model using normally distributed TTD resulted in a negative TTD. When the distribution of Time-to-Detect has been changed to Lognormal distribution; better "positive" results of TTD are found. Consequently, the mean and standard deviation of TTD are changed to Lognormal parameters using the following equations:

Coefficient of Variance for Normal Distribution = C. O. V. = $\dfrac{\sigma}{\mu}$

Variance of Lognormal distribution = ξ2 = Ln (1+c.o.v2

Mean of Lognormal Distribution = λ = Ln (μ) – 0.5 ξ2

When using the hypothetical values of TTD mean and standard deviation proposed in the arithmetic model, the values of λ, ξ could be calculated. Table 6.2 contains the mean and standard deviation for Normal and Lognormal distributions:

Table 6.2 Hypothetical Values of TTD for CCTV, ILD, and AVI

Parameter	Values for CCTV	Values for ILD	Values for AVI
Mean of Normal Dist.	4.00	5.00	6.00
Standard Deviation of Normal Dist.	1.00	1.50	2.00
Mean of Lognormal Dist.	1.36	1.57	1.74
Standard Deviation of Lognormal Dist.	0.25	0.29	0.32

6.3.3 Steps of Development of Monte Carlo Simulation Model

This section details the steps for developing a Monte Carlo Simulation Model. The general rule for each step is stated along with the specific example at hand. The steps are ordered systematically from initiation to performance analysis as follows:

1. Generate vector $\overrightarrow{u_k}$ of statistically independent and uniformly distributed random numbers between 0 and 1. For our example, u1, u2 and u3 represent the random numbers generated as in Table 6.1. Also, S1, S2 and S3 are the values of X_i that correspond to the probability values u1, u2 and u3, respectively. In Excel, the value of S_i could be calculated using

$$S_i = NORMSINV(u_i)$$

2. Transform $\overrightarrow{u_k}$ to $\overrightarrow{x_k}$ using transform matrix $x_k = F_x^{-1}(u_k)$

3. Use the correlation matrix to develop multivariate joint distribution. Cx represent the correlation matrix:

$$C_x = \begin{bmatrix} COV(X_1, X_1) & \mathrm{K} & COV(X_1, X_n) \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ COV(X_n, X_1) & \mathrm{K} & COV(X_n, X_n) \end{bmatrix} \qquad \text{(Eq. 6.10)}$$

When the CCTV, ILD and AVI sensors are completely independent, then the correlation matrix could be written simply:

Correlation matrix =

1	0	0
0	2.25	0
0	0	4

The values of the three variables (Xn1, Xn2, and Xn3) after incorporating the correlation matrix could be calculated as:

$$X_{n1}, X_{n2}, X_{n3} = TRANSPOSE\{MMULT\{MatrixA, TRANSPOSE(S_1 : S_3)\} + \mu_1 : \mu_3\}$$

4. Transform variables distribution from standard normal to the intended distribution (Lognormal, beta, gamma, etc). In our specific case, the Normal distribution is transformed to Lognormal distribution by applying the following formula:

$$X_1 = EXP(NORMSINV(\xi_1 * NORMDIST(\frac{X_{n1} - \mu_1}{\sigma_1}) + \lambda_1) \qquad \text{(Eq. 6.11)}$$

5. Apply variables governing rules and drive output. Several governing rules used in the example include:

a. Detect at first alarm ≡ Minimum TTD, in Excel: MIN(X1: X3)

b. Detect at second alarm ≡ Second Largest TTD, in Excel: Largest(X1: X3, 2)

Table 6.3 contains numerical values of the model outputs. The results illustrate outputs of performing 10 runs when each sensor was represented by 1,000 realizations (random variables). [Excel performance is low when attempting to run 10,000 realizations instead of 1,000.]

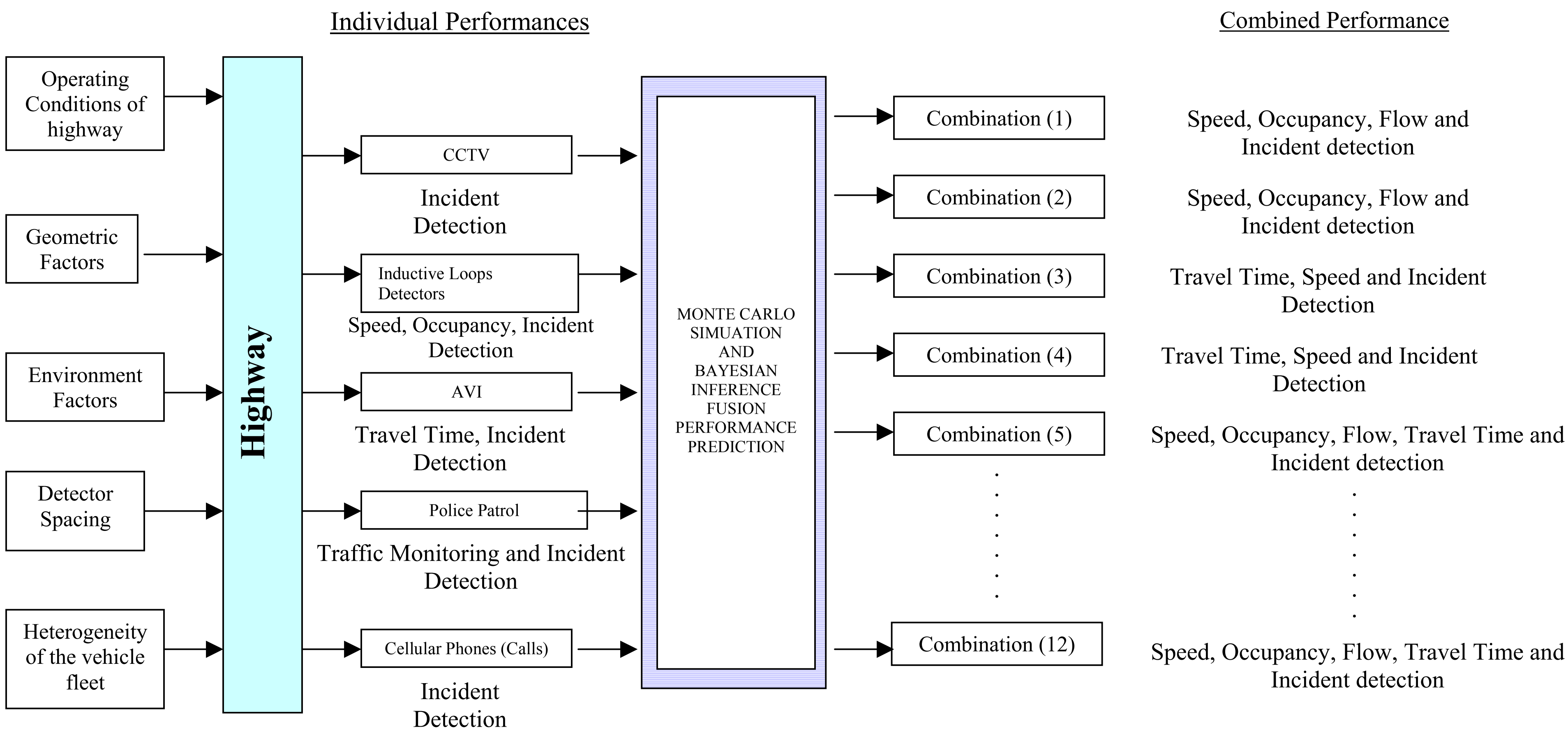


Figure 6.6 Schematic Data Flow from Traffic Sensors and Their Combined Performances

Table 6.3 Sample of Monte Carlo Simulation Calculations in Excel Format (Continues on Next Page)

Definitions & Equations:

u1 to u3	Random Variables
S1	NORMSINV(u1)
XN1 to XN3	TRANSPOSE(MMULT(Matrix A, TRANSPOSE(S1:S3)) + μ1:μ3)
X1	EXP(NORMSINV(NORMSDIST((XN1-μ1)/σ1))*ξ1+λ1)
Y	Min (X1, X2, X3)

No.	u1	u2	u3	S1	S2	S3	XN1	XN2	XN3	X1	X2	X3
1	0.3210389	0.502466	0.929143	-0.464796	0.006181	1.469436	3.5352	5.01391	11.878	3.46094	4.802184	14.77617
2	0.910117	0.469979	0.871234	1.341476	-0.075323	1.132242	5.34148	4.83052	10.529	5.39936	4.632891	11.87119
3	0.596943	0.788229	0.405586	0.245442	0.80029	-0.238915	4.24544	6.80065	5.0443	4.12232	6.812433	4.874313
4	0.4705632	0.612183	0.45662	-0.073854	0.285012	-0.108953	3.92615	5.64128	5.5642	3.81064	5.429525	5.303401
5	0.6733137	0.825051	0.036658	0.449082	0.934787	-1.790855	4.44908	7.10327	-1.1634	4.33428	7.228081	1.779766
6	0.2319103	0.802433	0.905549	-0.73257	0.850343	1.313833	3.26743	6.91327	11.255	3.24011	6.964249	13.35646
7	0.6047365	0.328707	0.446356	0.265627	-0.443485	-0.134874	4.26563	4.00216	5.4605	4.14285	3.939542	5.214905
8	0.8705139	0.528592	0.516844	1.128824	0.071732	0.042233	5.12882	5.1614	6.1689	5.12393	4.942817	5.85032
9	0.1322823	0.356014	0.621156	-1.115667	-0.369135	0.308518	2.88433	4.16945	7.2341	2.94846	4.070655	6.95433
10	0.5813026	0.184652	0.677967	0.205227	-0.897778	0.462022	4.20523	2.98	7.8481	4.0817	3.225284	7.683055
11	0.5271601	0.450992	0.402289	0.068133	-0.123156	-0.247426	4.06813	4.7229	5.0103	3.94622	4.536331	4.847456
12	0.0960302	0.323637	0.648055	-1.304509	-0.457553	0.380075	2.69549	3.97051	7.5203	2.8145	3.915213	7.28501
13	0.761922	0.047724	0.907511	0.712499	-1.667335	1.325584	4.7125	1.2485	11.302	4.62471	2.298263	13.45875
14	0.8785025	0.984858	0.503409	1.167534	2.166359	0.008544	5.16753	9.87431	6.0342	5.173	12.43214	5.72376
15	0.1872346	0.041873	0.444328	-0.888133	-1.729354	-0.140006	3.11187	1.10895	5.44	3.11835	2.236348	5.197561
16	0.9531038	0.644011	0.042727	1.675723	0.369201	-1.719882	5.67572	5.8307	-0.8795	5.86252	5.634583	1.863686
17	0.8321311	0.571088	0.866543	0.962621	0.179145	1.110198	4.96262	5.40308	10.441	4.91848	5.182221	11.70252
18	0.5314881	0.955887	0.979317	0.079011	1.704832	2.039848	4.07901	8.83587	14.159	3.9568	10.14576	21.39847
19	0.0870177	0.812562	0.387288	-1.359351	0.887379	-0.286394	2.64065	6.9966	4.8544	2.77675	7.078753	4.726366
20	0.7703072	0.398489	0.771344	0.739859	-0.25726	0.743281	4.73986	4.42116	8.9731	4.65597	4.276209	9.222133
21	0.5821963	0.961486	0.961017	0.207516	1.768191	1.762611	4.20752	8.97843	13.05	4.084	10.43281	17.87389
22	0.358994	0.891845	0.016433	-0.361149	1.236398	-2.133724	3.63885	7.78189	-2.5349	3.5504	8.254719	1.424607
23	0.5960583	0.099711	0.471515	0.243158	-1.283201	-0.071461	4.24316	2.1128	5.7142	4.12	2.721827	5.434067
24	0.9642196	0.812223	0.049768	1.801902	0.886116	-1.647111	5.8019	6.99376	-0.5884	6.04752	7.07482	1.953843
25	0.9786466	0.499255	0.399468	2.026564	-0.001866	-0.254725	6.02656	4.9958	4.9811	6.39147	4.785197	4.82454

Table 6.3 Samples of Monte Carlo Simulation Calculations in Excell Format (Continued)

Detect On first Alarm		**Detect On Second Alarm**	
Average TTD =	3.339125496	**Average TTD =**	4.73014001
STDEV =	0.920642636	**STDEV =**	1.478237317
P (TTD > 7 min) =	0.0010	**P (TTD > 7 min) =**	0.067
P (TTD > 10 min) =	0.0000	**P (TTD > 10 min) =**	0.01

	Y = Min (X1,X2,X3)			**Y = Second Max (X1,X2,X3)**	
Y = Min (X1,X2,X3)	**P (TTD > 7 min)**	**P (TTD > 10 min)**	**Y = 2nd Max (X1,X2,X3)**	**P (TTD > 7 min)**	**P (TTD > 10 min)**
2.949770728	0	0	4.488240661	0	0
4.124928096	0	0	5.162088391	0	0
2.858922407	0	0	3.30543541	0	0
3.378566647	0	0	3.84479897	0	0
2.133607797	0	0	5.056146823	0	0
1.80459272	0	0	2.948342645	0	0
2.108482507	0	0	3.589638547	0	0
3.003585841	0	0	3.461803146	0	0
2.510899415	0	0	3.205927864	0	0
3.298348876	0	0	4.435057777	0	0
4.107801941	0	0	4.325780061	0	0
1.979898555	0	0	5.014064759	0	0
4.431392961	0	0	4.609221966	0	0
2.301669051	0	0	2.713151117	0	0
2.651032317	0	0	5.080532876	0	0
3.188931505	0	0	6.136025329	0	0
3.725657443	0	0	5.529985765	0	0
2.784457537	0	0	2.883690248	0	0
3.762136956	0	0	4.008126891	0	0
3.04838698	0	0	5.656091086	0	0
1.997341938	0	0	2.893685032	0	0
1.504393494	0	0	3.379244959	0	0
3.779275043	0	0	3.939748663	0	0
4.116480321	0	0	5.057100929	0	0
4.598605994	0	0	5.320147066	0	0

6.3.4 Preliminary Results at Ideal 100% DR, Prior to FAR Consideration

Better performance was found when averaging the results of ten runs of independent sensors as illustrated in Tables 6.4 and 6.5. Table 6.4 was based on first alarm detection, meaning the joint time to detect is equal to the minimum of the three sensors. Table 6.4 shows that the average TTD for the three sensors was lower than any individual sensor. The standard deviation was also lower thus producing more consistent TTD values. Table 6.5 was constructed based on second alarm detection, i.e. when waiting for a confirmatory alarm before start incident verification process. Notice that the average TTD incidents from the 10 runs was higher then that of CCTV, however, this result needs to be weighted against the lower false alarm rate generated from this scenario.

Table 6.4 Simulation Results of Independent Sensors at First Alarm and 100% DR

Sets	Average TTD	STDEV (TTD)	P (TTD > 7 min)	P (TTD > 10 min)
Set 1	3.28	0.95	0.001	0
Set 2	3.27	0.97	0.002	0
Set 3	3.34	0.97	0.002	0
Set 4	3.30	0.92	0	0
Set 5	3.26	0.89	0	0
Set 6	3.28	0.96	0.001	0
Set 7	3.29	0.94	0.002	0
Set 8	3.33	0.96	0.001	0
Set 9	3.24	0.97	0	0
Set 10	3.21	0.93	0.001	0
Average	**3.28**	**0.95**	**0.1000%**	**0.0000%**

Table 6.5 Simulation Results of Independent Sensors at Second Alarm and at 100% DR

Sets	Average TTD	STDEV (TTD)	P (TTD > 7 min)	P (TTD > 10 min)
Set 1	4.64	1.36	0.059	0.004
Set 2	4.77	1.47	0.08	0.007
Set 3	4.71	1.46	0.065	0.01
Set 4	4.76	1.56	0.078	0.013
Set 5	4.77	1.56	0.087	0.01
Set 6	4.83	1.59	0.08	0.016
Set 7	4.69	1.48	0.071	0.007
Set 8	4.73	1.56	0.073	0.014
Set 9	4.75	1.44	0.073	0.005
Set 10	4.77	1.47	0.073	0.01
Average	**4.74**	**1.49**	**7.3900%**	**0.9600%**

In real world situations, sensors monitoring traffic tend to share some level of dependency that could be represented by correlation factors. To study the effects of sensors dependency on the overall performance, assume the correlation factors between different sensors in the example at hand is as follows:

R (CCTV & ILD) = 0.5
R (CCTV & AVI) = 0.4
R (ILD & AVI) = 0.3

Table 6.6 below contains results of TTD for the ten simulation runs (sets) based on the given correlation factors and assuming incidents are detected at the first sensor alarm. Table 6.7 contains the results when detecting at second sensor alarm. The simulation results in Tables 6.4, 6.5, 6.6, and 6.7 infer that correlated sensors produce higher average and standard deviation of TTD than independent sensors. It could also be noticed that more incidents are detected within 7 minutes by correlated sensors than independent sensors.

Table 6.6 Simulation Results of Correlated Sensors at First Alarm

Sets	Average TTD	STDEV (TTD)	P (TTD > 7 min)	P (TTD > 10 min)
Set 1	3.9496	1.6987	0.055	0.006
Set 2	3.9051	1.5023	0.037	0.002
Set 3	3.8605	1.6976	0.055	0.003
Set 4	3.9199	1.7236	0.045	0.007
Set 5	3.8323	1.5123	0.032	0.003
Set 6	3.8165	1.6220	0.036	0.005
Set 7	3.8757	1.6239	0.043	0.003
Set 8	3.8742	1.6504	0.053	0.001
Set 9	3.9390	1.7235	0.051	0.009
Set 10	3.9145	1.5992	0.05	0.004
Average	**3.89**	**1.64**	**4.57%**	**0.43%**

Table 6.7 Simulation Results of Correlated Sensors at Second Alarm

Sets	Average TTD	STDEV (TTD)	P (TTD > 7 min)	P (TTD > 10 min)
Set 1	4.9141	2.5482	0.142	0.041
Set 2	5.0164	2.6438	0.163	0.043
Set 3	4.9624	2.3945	0.161	0.047
Set 4	5.0456	2.4641	0.17	0.047
Set 5	4.8198	2.4273	0.149	0.039
Set 6	4.9721	2.4941	0.166	0.041
Set 7	5.0081	2.4980	0.162	0.039
Set 8	5.1203	2.4392	0.195	0.043
Set 9	4.9894	2.4196	0.157	0.047
Set 10	5.0967	2.8793	0.179	0.056
Average	**4.99**	**2.52**	**16.44%**	**4.43%**

6.3.5 Preliminary Results at Less Than 100% DR, Prior to FAR Consideration

The final scenario assumes that each sensor detects 100% of the incidents in the ideal situation. In practice, sensors tend not to detect all incidents within a reasonable time window. In such circumstances, deploying multiple sensors may not only reduce the average time to detect incidents, but also increase the number of detected incidents. To incorporate this scenario in the model, missed incidents are randomly assigned with an infinite time to detect. Table 6.8 contains the results of the simulation when considering no correlation between sensors and when the detection rates of the CCTV system is 85%, the ILD system is 70%, and the AVI system is 55%. In this scenario, the sensors jointly detected 98% of the incidents. Alternately, when detecting at second alarm, the joint performance declined to 81%, which is lower than the performance of CCTV.

Table 6.8 Simulation Results of Independent Senors at First Alarm and 85%, 70% and 55%DR for CCTV, ILD, and AVI Sensors

Sets	Average TTD	STDEV (TTD)	P (TTD > 7 min)	P (TTD > 10 min)
Set 1	3.77	1.45	0.0316	0.0071
Set 2	3.80	1.75	0.0306	0.0122
Set 3	3.74	1.52	0.0286	0.0092
Set 4	3.70	1.46	0.0235	0.0071
Set 5	3.74	1.83	0.0265	0.0071
Set 6	3.77	1.61	0.0316	0.0102
Set 7	3.75	1.47	0.0245	0.0102
Set 8	3.73	1.86	0.0286	0.0102
Set 9	3.71	1.47	0.0214	0.0071
Set 10	3.78	1.45	0.0286	0.0082
Average	**3.75**	**1.59**	**2.7551%**	**0.8878%**

Table 6.9 Simulation Results of Independent Senors at Second Alarm and 85%, 70% and 55%DR for CCTV, ILD, and AVI Sensors

Sets	Average TTD	STDEV (TTD)	P (TTD > 7 min)	P (TTD > 10 min)
Set 1	4.81	3.82	0.162244898	0.047959184
Set 2	4.93	3.72	0.175510204	0.07244898
Set 3	4.88	3.62	0.201020408	0.064285714
Set 4	4.68	3.15	0.155102041	0.051020408
Set 5	4.85	3.83	0.168367347	0.054081633
Set 6	4.78	3.59	0.165306122	0.064285714
Set 7	4.95	3.82	0.179591837	0.062244898
Set 8	4.78	3.43	0.176530612	0.059183673
Set 9	4.73	3.25	0.170408163	0.05
Set 10	4.68	3.35	0.159183673	0.052040816
Average	**4.81**	**3.56**	**17.1327%**	**5.7755%**

6.3.6 Incorporating False Alarms and Sensors Correlation

Some changes are required on the model to incorporate the false alarms and improve application of the correlation factors. While the analysis until this point was based on 1,000 observations, to incorporate the false alarm rate this number needs to be increased to 5,400 observations. Consider a freeway where incidents occurrence rate is an average of Ψ incidents per peak hour. (Note: In this study, analysis will be performed on peak hours only where the a.m. peak is defined as 6:30 a.m. to 9:30 a.m. and the p.m. peak is defined as 3:30 p.m. to 6:30 p.m. Monday through Friday.) In San Antonio's TransGuide, the data is transferred to the TMC every 20 seconds, thus equating to three slots of time in each minute. Based on these assumptions, the total number of time slots in one week will be:

N = 3 slots/min x 60 min/hr * 6 peak hrs/day * 5 days/week = 5400 Slots

Based on Table 6.3, the internal calculations of Monte Carlo simulation model will be as follows:

1. Columns 1 to 3: Function = Rand () [is a random number generator for sensors 1, 2 and 3]
2. Column 4 to 6: Function = NORMSIV (Columns 1 to 3, respectively) represent the Z value of random number generated in columns 1 to 3
3. Columns 7 to 9: Function = {=TRANSPOSE (MMULT (A- matrix, TRANSPOSE (column4: column6)) + μ1: μ3)}
4. Columns 10 to 12: Function = {=EXP (NORMSINV (NORMSDIST ((Column 7 – μ1)/STD (1)))*Log-STD (1) + mean log (1))}
5. Column 13: Function = IF (RAND () <=probability of incident occurrence, 1, 0) [1= incident occurred, 0 = no incident occurred]
6. Column 14: Function = IF (column13 = 1, IF (RAND () <=Sensor (1)'s detection rate, 1, 0), 0) [1 = incident detected by sensor (1), 0 = incident not detected by sensor 1]
7. Column 15: Function = IF (Column13 = 1, IF (Column14 = 1, IF (RAND () <=Probability of detection by sensor-2 given detected by sensor-1, 1, 0), IF

(RAND () <=probability of detection by sensor-2 given not detected by sensor-1, 1, 0)), 0)

8. Column 16: basically, assign the number 1 if an incident is detected by sensor-3 the same way column 15 was calculated, with taking both sensors 1 and 2 in consideration.
9. Column 17: Function = IF (SUM (Columns 14 to 16) =0, 0, 1) [the incident is detected by one or more sensors]

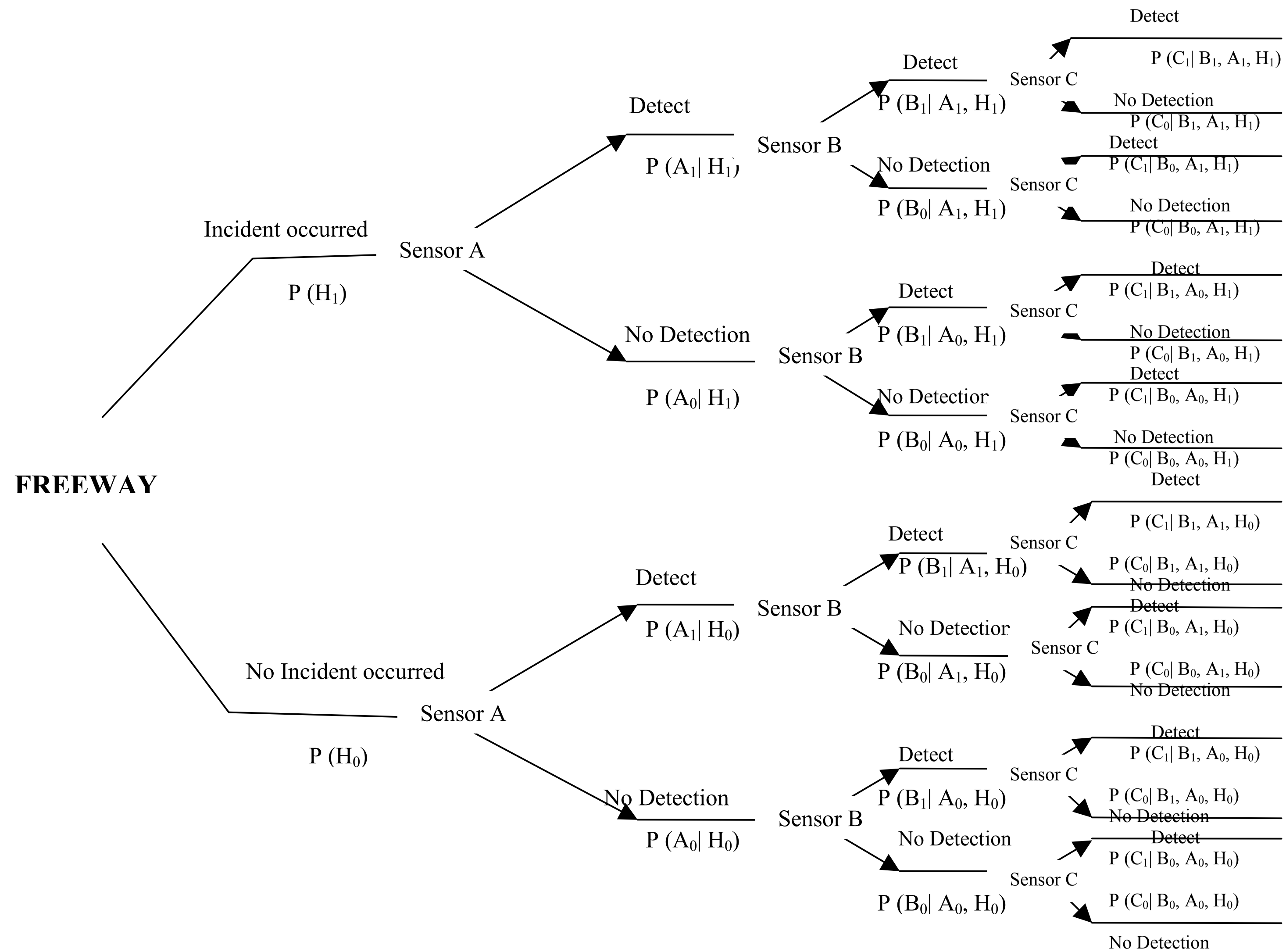


Figure 6.7 Distributions of Sensors Detection Probabilities

6.4 Monte Carlo Model Validation

To ensure the quality of Monte Carlo Simulation Model results, data from multiple sources will be used. The required data to validate the model is a set of basic characteristics of traffic sensors that include:

1. The probabilistic distribution of sensors' TTD which includes the type of distribution and its parameters.
2. The optimal threshold values of sensors DR and FAR when calibrating the sensor.
3. The degree of correlation between sensors. (Most fusion theories assume independence between sensors. This assumption is based on the fact that different sensors use different raw data and employ different decision-making rules.)

Accurately estimating each sensor parameters that the model requires is a challenging task since it is difficult to assign an exact start time for each incident. Figure 6.8 below depicts the methodology that was implemented to validate the Monte Carlo Model denoted by "Logman Model" in the figure. As illustrated in Figure 6.8, the following five major steps are required to validate the model:

Step 1: When running a stream of real incidents through individual algorithms (or sensors), the output performance resulting from each algorithm (or sensor) is gauged. The output performance should reflect sensors' (or algorithm) TTD distribution, DR, and FAR. These parameters are denoted by the symbol (Ǿ1) for different algorithm (or sensor).

Step 2: When using statistical analysis, the correlation between any pair of algorithms (or sensors) denoted by $\hat{\gamma}_{ij}$ will be measured.

Step Results from Steps 1 and 2 are then used as an input to the Logman Model. The model utilizes this input to combine performances and finds the fused performance of different combinations of algorithms (or sensors).

Step 4: In this step, data from real incidents are directly processed through the fusion algorithm while output performance is accordingly measured.

Step 5: The Logman Model is validated by comparing the consistency among the values found in Steps 3 and 4 above. The lower the variability between these two output results, the higher the confidence level of the model performance.

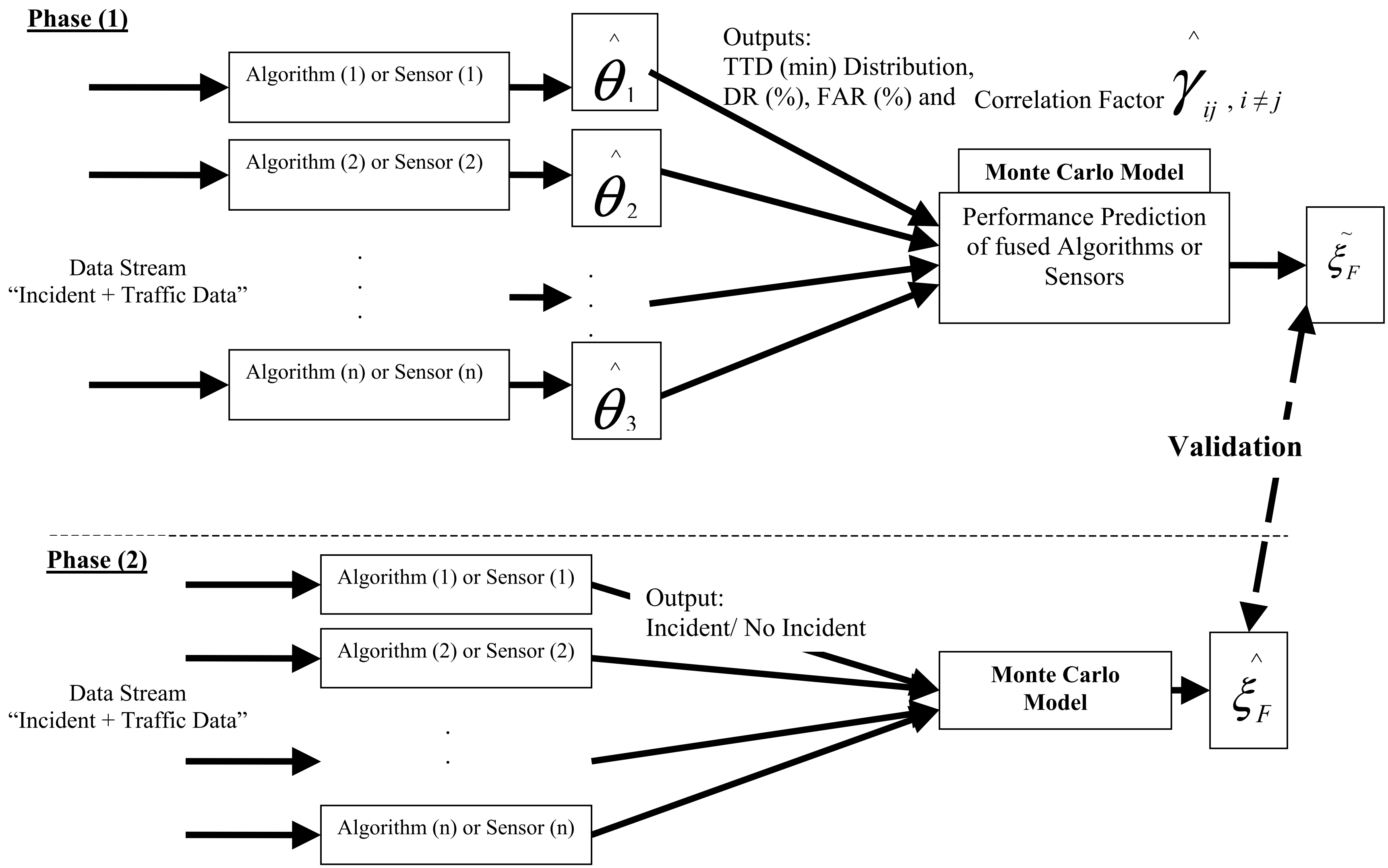


Figure 6.8 The Validation Process of Logman Model

6.4.2 The Validation Process of Logman Model

To validate the Logman Model numerically, conditional probability equations were applied to the results of incident detection by three algorithms (Cal 8, Delos, and McMaster) (Zhou 2000). In his study, Zhou (2000) processed incidents and traffic data using the three processing algorithms to investigate any potential for improved performance when fusing the algorithms. Table 6.10 below contains the results when running the incident and traffic data through the algorithms. Congestion incidents were not included in the study, only major, minor and stall incidents make up the numbers in the table. The table contains the results of detection based on varied levels of False Alarm Rate, i.e., 0.05%, 0.2%, 0.5%, and 1.0%, respectively.

6.4.3 Results of Time-to-Detect Incidents

The Time-to-Detect (TTD) of any given incident by a specific sensor at 0.05% and 1.0% FAR levels were not accessible. The TTD incidents at 0.2% and 0.5% FAR could be inferred with an acceptable degree of reliability by reconstructing the DR vs TTD graphs that Zhou produced for each level of FAR. No exact incident number could be assigned to a specific Time-to-Detect from the DR vs TTD graph, therefore, incidents' TTD were randomly assigned to the incident number by using a random number generator on the Excel spread sheet. Table 6.11 contains the assigned TTD incidents to any specific incident number based on 0.2% and 0.5% FAR levels, only.

Table 6.10 Incidents Detected by CA #8, Delos, and McMaster Algorithms (Zhou 2000)

A priori FAR	**0.05%**				**0.20%**				**0.50%**				**1.00%**			
Incident ID	**CA**	**Delos**	**MCM**	**Σ**	**CA**	**Delos**	**MCM**	**Σ**	**CA**	**Delos**	**MCM**	**Σ**	**CA**	**Delos**	**MCM**	**Σ**
1		1		1	1	1	1	3	1	1	1	3	1	1	1	3
3	0	0	1	1	1	1	1	3	1	1	1	3	1	1	1	3
4			1	1	1	1	1	3	1	1	1	3	1	1	1	3
8	0	0	1	1	1	1	1	3	1	1	1	3	1	1	1	3
9				0				0			1	1			1	1
12				0	1	1		2	1	1	1	3	1	1	1	3
14				0				0		1		1		1	1	2
15	1	1	1	3		1	1	2	1	1	1	3	1	1	1	3
16				0				0	1	1	1	3	1	1	1	3
21	1	1		2	1	1	1	3	1	1	1	3	1	1	1	3
24	1	1	1	3	1	1	1	3	1	1	1	3	1	1	1	3
25			1	1			1	1		1	1	2		1	1	2
29			1	1		1	1	2	1	1	1	3	1	1	1	3
31	0	0		0				0				0		1		1
33		1		1	1	1	1	3	1	1	1	3	1	1	1	3
35				0	1	1	1	3	1	1	1	3	1	1	1	3
41				0				0		1		1	1	1	1	3
42	0	0	1	1	1	1	1	3	1	1	1	3	1	1	1	3
44	1	0	1	2	1	1	1	3	1	1	1	3	1	1	1	3
47	1	1		2	1	1	1	3	1	1	1	3	1	1	1	3
50	0	0	1	1			1	1	1	1	1	3	1	1	1	3
53	1		1	2	1	1	1	3	1	1	1	3	1	1	1	3
58			1	1			1	1	1	1	1	3	1	1	1	3
68				0				0				0			1	1
71				0	1	1	1	3	1	1	1	3	1	1	1	3
72	0	0	1	1		1		1		1	1	2	1	1	1	3
73			1	1	1		1	2	1	1	1	3	1	1	1	3
74				0				0			1	1			1	1
81	1		1	2	1	1	1	3	1	1	1	3	1	1	1	3
83	1		1	2	1	1	1	3	1	1	1	3	1	1	1	3
84		1		1	1	1		2	1	1	1	3	1	1	1	3
92				0			1	1		1		1	1	1		2
96			1	1			1	1	1	1	1	3	1	1	1	3
97				0				0	1	1	1	3	1	1	1	3
102				0				0	1			1	1	1	1	3
104	0	0		0		1		1	1	1	1	3	1	1	1	3
108	1			1	1	1	1	3	1	1	1	3	1	1	1	3
109	1	1		2	1	1	1	3	1	1	1	3	1	1	1	3
113				0				0	1	1	1	3	1	1	1	3
No. Detected	10	8	17	24	20	23	25	29	30	34	33	37	33	36	37	39
% Detected	0.26	0.21	0.44	0.62	0.51	0.59	0.64	0.74	0.77	0.87	0.85	0.95	0.85	0.92	0.95	1.00
% Detected by 3				0.05				0.36				0.64				0.72
% Detected by 2				0.23				0.56				0.79				0.90

Table 6.11 Time-to-Detect Incidents by CA #8, Delos, and McMaster Algorithms (Zhou 2000)

A priori FAR	**0.20%**			**0.50%**		
Incident ID	**CA**	**Delos**	**MCM**	**CA**	**Delos**	**MCM**
1	-3	-7	-1	-5	-9	1
3	-7	19	-5	-9	-7	-7
4	-9	-5	7	-9	-10	-5
8	-10	-5	11	-5	17	-7
9						-9
12	-1	11		1	-1	-1
14					-10	
15		-5	-3	-7	5	-5
16				-9	-7	-7
21	-5	-7	7	7	-10	-10
24	-5	-9	1	-9	-10	-9
25			11		-9	-10
29		-10	-5	5	11	-10
31						
33	-10	-1	-3	-5	15	-5
35	-1	-7	5	-7	9	-7
41					-1	
42	-5	-5	-5	-5	-9	-9
44	-10	-10	-5	-7	-7	7
47	7	3	3	-10	-3	-5
50			1	-10	-10	-9
53	-3	-1	-7	-9	-10	-5
58			-5	-1	3	-9
68						
71	-9	-1	-5	-9	-9	19
72		-7			-10	-3
73	-7		-10	-7	21	-7
74						-5
81	-7	13	-7	-7	11	13
83	1	-7	-1	-9	-7	-10
84	11	9		-3	-7	-5
92			-3		-10	
96			-3	3	3	-10
97				-10	-1	-9
102				15		
104		27		-10	-9	-5
108	-10	-10	1	-9	-10	7
109	-5	-5	-5	-10	-5	1
113				-1	3	-5

[Note: To reduce the complexity of the calculations, the value -10 minutes in the TTD is assigned to represent the base of the calculations. All TTD values are shifted (by adding 10 minutes to each TTD) to facilitate the calculations. This process is compensated for after processing the final results are analyzed.]

6.4.4 Best Fit Probability Distribution

Given the assumption that incidents are detected when they fall within a window of 10 minutes before the incident start and end time, the TTD values in Table 6.11 contain some negative values. The probabilistic distribution of TTD for every sensor is not expected to be perfect for the following two major reasons:

1. The incident data set is reasonably small, and
2. Several incidents were assigned minus 10 minutes as TTD, which cause the distribution to start with a high value at -10, and not perfectly follow Lognormal distribution.

BestFit© 4.0 is a software package that is capable of determining the best fitting curve and parameters to any set of data. Unfortunately, when using this package to find the best fitting curve and its parameters for the incident data found in Table 6.11, the package suggest the following curves as the best fitting curves.

	0.2% FAR	0.5% FAR
Cal 8	Expon	Expon
	ExtValue	ExtValue
	InvGauss	Pareto
	Logistic	InvGauss
Delos	Expon	Expon
	InvGauss	Pareto
	LogLogistic	InvGauss
	Lognormal	
McMaster	InvGauss	InvGauss
	LogLogistic	Lognormal
	ExtValue	ExtValue
	Pearson	Expon
	Lognormal	

The first phase of the validation process for the Logman Model is to predict the performance of the model based on the probability distribution of Time-to-Detect (TTD), the conditional probability of detection by different sensors, and the level of false alarms assigned to each algorithm. This phase is schematically described in Figure 6.7. It is important to mention that the data that Zhou used is collected 6 hours a day in a two-month span [3 peak hours and 3 off-peak hours for each day of the work week (Monday through Friday)]. Capturing every 20 seconds of detection decision throughout the two-month span is useful when attempting to exactly replicate the detection process. The number of 20-seconds sets that needs to be generated in the model is overwhelming, however, and causes Excel to take extended time to recalculate each scenario. For this reason, incidents were developed and allowed to randomly distribute over only one week. This process will not affect the outcome of real incidents detection process, but will affect the results of FAR calculation, which isn't part of this validation process given the available data set. Tables 6.12, 6.13, and 6.14 represent the results of 10 run sets at 0.2% FAR, while Tables 6.15, 6.16, and 6.17 contain the results at 0.5% FAR level.

The data set shown in Table 6.11 is used to arithmetically calculate the expected output performance at different scenarios. The results of the empirical discrete validation and side-by-side performance comparison between the two validation phases are shown in Table 6.18.

Table 6.12 Simulation Results of Detection Rate by Different Sensors at 0.2% FAR

Detection Rate (%)

				Fused Sensors	
Run #	**Cal # 8**	**Delos**	**MCM**	**1st Alarm**	**2nd Alarm**
1	53.12%	62.64%	67.08%	79.56%	58.21%
2	51.95%	61.72%	66.11%	77.63%	57.17%
3	53.43%	63.73%	64.00%	77.38%	58.19%
4	52.07%	63.85%	64.12%	78.54%	57.87%
5	51.14%	61.05%	63.42%	76.38%	55.97%
6	52.48%	62.23%	65.60%	78.63%	57.36%
7	52.97%	62.63%	63.28%	77.42%	57.11%
8	50.08%	60.11%	64.22%	75.28%	55.53%
9	50.13%	60.62%	63.48%	75.90%	56.17%
10	52.56%	61.19%	65.55%	76.61%	57.33%
Average	**51.99%**	**61.98%**	**64.69%**	**77.33%**	**57.09%**
Stdev	**1.19%**	**1.26%**	**1.31%**	**1.33%**	**0.93%**

Table 6.13 Simulation Results of Average Time-to-Detect Incidents by Different Sensors at 0.2% FAR

Average TTD (min)

				Fused Sensors	
Run #	**Cal # 8**	**Delos**	**MCM**	**1st Alarm**	**2nd Alarm**
1	5.55	8.68	8.64	4.37	7.47
2	5.82	8.05	8.78	4.43	7.48
3	5.44	8.94	8.78	4.43	7.66
4	6.03	9.13	8.90	4.59	7.94
5	5.32	9.05	9.13	4.33	7.71
6	5.80	9.11	8.41	4.42	7.51
7	5.49	8.64	9.18	4.42	7.49
8	5.52	8.63	8.71	4.44	7.73
9	5.94	9.40	8.97	4.68	8.13
10	5.53	9.59	8.58	4.54	7.86
Average	**5.65**	**8.92**	**8.81**	**4.46**	**7.70**
Stdev	**0.24**	**0.44**	**0.24**	**0.11**	**0.22**

Table 6.14 St. Dev. of Time-To-Detect Incidents by Different Algorithms at 0.2% FAR

Std Dev. TTD (min)

				Fused Sensors	
Run #	**Cal # 8**	**Delos**	**MCM**	**1st Alarm**	**2nd Alarm**
1	5.16	11.10	5.19	3.37	4.86
2	4.65	8.59	5.90	3.52	5.48
3	5.17	9.77	5.42	3.74	6.55
4	5.95	9.90	5.29	3.66	5.23
5	5.28	9.86	5.14	3.45	5.19
6	4.89	10.27	6.17	3.80	6.10
7	5.08	10.37	5.48	4.03	5.00
8	6.06	11.51	5.81	4.20	8.02
9	7.12	9.40	5.77	3.70	5.57
10	5.82	10.36	5.80	3.96	5.28
Average	**5.52**	**10.11**	**5.60**	**3.74**	**5.73**
Stdev	**0.73**	**0.83**	**0.34**	**0.26**	**0.95**

Table 6.15 Detection Rate by Different Sensors at 0.5% FAR

Detection Rate (%)

Run #	Cal # 8	Delos	MCM	3 Fused Sensors 1st Alarm	3 Fused Sensors 2nd Alarm
1	77.75%	87.14%	84.04%	94.37%	79.53%
2	75.95%	87.30%	81.94%	94.83%	77.50%
3	76.97%	86.79%	83.85%	95.14%	78.62%
4	78.24%	88.55%	84.01%	95.36%	80.04%
5	75.98%	87.63%	83.71%	94.90%	79.07%
6	77.58%	86.01%	84.04%	94.08%	78.92%
7	76.24%	86.98%	83.65%	95.82%	78.33%
8	76.00%	87.21%	84.87%	94.86%	80.02%
9	76.49%	85.58%	83.84%	95.22%	77.87%
10	75.16%	87.90%	84.90%	94.72%	80.16%
Average	**76.64%**	**87.11%**	**83.89%**	**94.93%**	**79.01%**
Stdv	**0.97%**	**0.86%**	**0.81%**	**0.49%**	**0.94%**

Table 6.16 Average Time-to-Detect Incidents by Different Sensors at 0.5% FAR

Average TTD (min)

	Cal # 8	Delos	MCM	3 Fused Sensors 1st Alarm	3 Fused Sensors 2nd Alarm
1	5.00	7.47	5.30	2.91	4.68
2	4.75	7.36	6.11	2.69	4.91
3	5.21	7.36	5.63	2.62	5.00
4	4.89	7.44	5.59	2.67	4.82
5	5.12	6.96	6.07	2.80	5.00
6	4.78	8.05	5.96	2.78	4.92
7	4.92	8.29	6.04	2.78	4.96
8	5.45	7.13	5.94	2.84	4.91
9	4.66	8.23	5.57	2.76	4.95
10	5.04	7.00	5.80	2.77	4.88
Average	**4.98**	**7.53**	**5.80**	**2.76**	**4.90**
Stdv	**0.24**	**0.49**	**0.27**	**0.08**	**0.10**

Table 6.17 St. Dev. of Time-To-Detect Incidents by Different Sensors at 0.5% FAR

Std Dev. TTD (min)

	Cal # 8	Delos	MCM	3 Fused Sensors 1st Alarm	3 Fused Sensors 2nd Alarm
1	6.73	8.69	5.97	4.73	4.15
2	5.21	10.53	5.73	3.37	3.88
3	4.81	8.51	6.26	2.66	3.29
4	6.01	10.86	5.57	3.42	3.35
5	5.81	8.08	5.84	2.62	3.95
6	5.01	9.62	6.19	3.73	3.58
7	5.68	8.74	7.33	3.93	3.79
8	6.53	9.24	6.47	3.36	4.63
9	5.06	8.66	6.29	2.82	3.36
10	5.37	9.05	6.03	3.02	3.54
Average	**5.62**	**9.20**	**6.17**	**3.37**	**3.75**

Table 6.18 Results of Model Validation Process (Phase 1 vs Phase 2)

	0.2% FAR					0.5% FAR				
				Fused Performance					Fused Performance	
	CA	Delos	MCM	1st Alarm	2nd Alarm	CA	Delos	MCM	1st Alarm	2nd Alarm
Numerical Validation										
COUNT	20	23	25	29	22	30	34	33	37	31
Average TTD (min)	5.60	9.13	8.96	5.90	6.82	4.97	7.56	5.76	2.32	4.61
St.Dev TTD (min)	5.68	10.02	5.63	8.03	5.11	6.03	9.07	6.85	4.51	4.82
DR (%)	51.28%	58.97%	64.10%	74.36%	56.41%	76.92%	87.18%	84.62%	94.87%	79.49%
Performance Prediction										
Average TTD (min)	5.65	8.92	8.81	4.46	7.70	4.98	7.53	5.80	2.76	4.90
St.Dev TTD (min)	5.52	10.11	5.60	3.74	5.73	5.62	9.20	6.17	3.37	3.75
DR (%)	51.99%	61.98%	64.69%	0.773324	0.5709056	76.64%	87.11%	83.89%	94.93%	79.01%

6.4.5 Conclusions

In this study, modeling the fused performance of different incident detection sources has gradually evolved from using simple arithmetic equation and concluded with a robust Monte Carlo simulation model.

The arithmetic model based on simple probabilistic distribution equations is used to predict the combined hypothetical performance of three types of sensors. When sensors were combined, the arithmetic model predicted a better performance level versus from any individual sensor. Hypothetically, three sensors with 6 minutes, 5 minutes and 4 minutes time-to-detect provided an average overall 3.5 minutes time-to-detect. Applying simple arithmetic equations to predict the combined performance of incident sensors did not properly address sensors' correlation. Furthermore, two separate simple models are required to predict the detection rate and false alarm rate. The Monte Carlo Model has the capability to correlate and develop a single model that encompasses both detection rate and false alarm rate.

The Monte Carlo technique works particularly well when the underlying probabilities are known but the results are difficult to derive deterministically. Monte Carlo simulation is essentially a numerical integration tool for conducting "what if" experiments. Three scenarios were investigated to predict the combined performance of detection sensors: (a) first vs. second or more alarms, (b) correlated vs. independent (non-correlated) sensors, and (c) ideal 100% vs. less than perfect detection rate.

When processing a hypothetical scenario using the proposed Monte Carlo model, the average TTD for the three sensors was lower than any individual sensor. The standard deviation of the time to detect was also lower, resulting in more consistent TTD values. When waiting for a second confirmatory alarm, the average time-to-detect from the three sensors was larger than when detecting at first alarm. This model can be used by decision makers to decide the detection sensor to be deployed and whether to detect at first or second alarm. Utilizing the assumption that the average TTD for AVI is 6 minutes, ILD is 5 minutes, and CCTV is 4 minutes, these results are supported by running a numerical scenario. Based on the aforementioned hypothetical values, the model estimated the combined performance to be approximately 3.3 minutes and 4.8 minutes at first and second alarms, respectively.

Combining CCTV at 85%, ILD at 70%, and AVI at 55% at first alarm resulted in 98% detection rate compared to 81% at the second alarm. This result suggests that the combined performance at second alarm is lower than the highest performing sensor (i.e. CCTV). Please note that this result should not be taken in isolation since the false alarm rate of the combined sensors performance is lower when detecting at second alarm.

The proposed Monte Carlo model was validated using traffic and incident data from San Antonio's TransGuide. The proposed model showed higher accurate performance when processing the data from Zhou's study (2000). The results showed that the model is capable of acting as a performance prediction tool that could be utilized to decide the types of algorithms or sensors that could give the highest performance. Accurately estimating each sensor parameters that the model requires is a challenging task since it is difficult to assign an exact start time for each incident.

7. Conclusions and Recommendations

7.1 Conclusions and Recommendations

The information flow and decision-making in Texas varies from one traffic management center to another. This is primarily due to the different types of traffic sensors deployed, level of automation, and the size and demography of the metropolitan served. The expanding small size metropolitan areas in Texas could greatly benefit from the experience acquired by the large metropolitan areas to manage traffic. Investment decisions of the type of traffic sensors to be deployed in any metropolitan area should be carefully considered. For example, ILD systems seem to perform poorly and require costly and frequent maintenance in areas that have expansive soils, i.e., City of Houston. Sharing information about the performance of the existing AVI systems among Texas cities (i.e., Austin and Dallas-Fort Worth area) can be of great benefit when considering future toll systems. The types of incident detection sensors and methods currently deployed in Texas major cities are diverse, thus conducting Benefit-Cost Ratio studies to justify further investment decisions for incident detection is important.

The data obtained from TransGuide for ILD and AVI is shown to be useful for estimating traffic parameters. Even at low penetration levels of AVI, obtaining reliable travel time and space mean speed information is possible. AVI speed data is available for comparison with data calculated from ILD sensors in the study corridor. One of the benefits of the AVI systems is its capability to directly measure travel time and calculate average speeds.

Significant differences are found among the speeds recorded by different ILD stations on the study corridor. The average speed of the ILD at the milepost 164.909 was lower than that of mileposts 164.412 and 165.409 during the non-peak period. Estimating the average speed of a link by simply averaging the speed of the three ILD sensors could be misleading, therefore, careful consideration of the local highway geometry is important to reliably estimate link speed. Exit and entrance ramps cause fluctuation between speed measurements. When ILD sensor readings are affected by local geometry, construction and maintenance delays, or are not representative of the overall flow of traffic, it is recommended to measure the speed of ILD sensors separately and use engineering judgment.

The AVI system is capable of estimating highway travel time with high accuracy. Low penetration of AVI tagged vehicles or penetration fluctuation throughout the day can lower the creditibility of the AVI system. The AVI system is not currently reliable enough to be implemented for automated incident detection due to the low penetration levels. This is particularly true for the San Antonio Network. In contrast, the ILD system is very reliable in measuring traffic volume and has reasonable potential to automatically detect incidents. Deploying the AVI and ILD systems in the same link provides a better overall estimate of traffic parameters and incident detection. Table 7.1 summarizes the conclusions for performance potentials of AVI and ILD when deployed separately versus jointly to measure traffic parameters and to detect incidents at low AVI penetration rate. Where AVI penetration is dense, there is the potential for better estimation of traffic flow parameters than with ILDs, but their respective performance for AID depends largely on density of loops or AVI readers. While the fused performance of point-based (ILD) and link-based

(AVI) systems for AID is demonstrated to be better than that of any system alone, the improvement in performance does not justify investment in a second parallel system. This is an important factor when making decisions regarding deployment and the use of parallel link and point based systems.

Table 7.1 Performance Potential of AVI and ILD, Working Separately and Jointly

	Travel Time	Speed	Volume	AID
AVI	●	⊙	○	○
ILD	○	○	●	●
AVI & ILD	●	⊙	●	●

○ = Low Performance
⊙ = Medium Performance
● = High Performance

7.2 Future Work

The major advantage of AVI (link data) is the ability to directly measure travel time and derive average speed information. The benefit of ILD (point data) is the ability to directly measure occupancy.

The introduction of wireless location technology via cell phones and GPS systems will increase the potential for tracking probe vehicles through a network. Vehicles tracked in such a way provide the idea source of information because they can be used to acquire both point and link data.

Research should be conducted to further model the combined performance of point, link, and probe systems at varying levels of deployment in order to estimate 1) the Benefit-to-Cost (B/C) ratio of marginal investments when one system is already in place, 2) the B/C ratio of any particular approach, and 3) the B/C ratio of investing in a complete new combined system.

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