AN INCIDENT DETECTION ALGORITHM BASED ON A DISCRETE STATE PROPAGATION MODEL OF TRAFFIC FLOW

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To:

My mother Kajal and my father Durgadas Guin

whose love and support made this possible.

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LIST OF ABBREVIATIONS

- AASHTO : American Association of State Highway and Transportation Officials
- ACGNN : Adaptive Conjugate Gradient Neural Network
- AIDA : Automatic Incident Detection Algorithm
- ARIMA : Auto-Regressive Integrated Moving Average
- ARMA : Auto-Regressive Moving Average
- ATMS : Advanced Traffic Management System
- ATR : Automatic Traffic Recorders
- CB : Citizen Band
- CCTV : Close Circuit TV
- CLDU : Committee Decision Logic Units
- CUSUM : CUmulative SUM
- DCUSUM : CUmulative SUM of Differences
- DELOS : DEtection LOgic with Smoothing
- DOCC : Downstream Occupancy

- DOCCTD : Relative Temporal Difference in Occupancies
- DOT : Department of Transportation
- DSPM : Discrete State Propagation Model
- DSPMID : Discrete State Propagation Model Incident Detection
- DWT : Discrete Wavelet Transform
- FHWA : Federal HighWay Administration
- FIR : Finite Impulse Response
- GA : Genetic Algorithms
- GLR : Generalized Likelihood Ratio
- HIOCC : HIgh OCCupancy logic
- IDWT : Inverse Discrete Wavelet Transform
- IIS : Incident Innovations Signatures
- ITS : Intelligent Transportation Systems
- LDA : Linear Discriminant Analysis
- LOESS : LOcally weighted polynomial regrESSion
- LWR : Lighthill-Whitham-Richards

- MAPE : Mean Absolute Percentage Error
- MIPA : M-Interval Polynomial Approximation
- MLF : Multi-Layer Feed-forward
- MM : Multiple Model
- mph : miles per hour
- OCCD : Spatial Difference in Occupancy
- OCCDR : Relative Spatial Difference in Occupancies
- PATREG : PATtern REcoGnition logic
- PNN : Probabilistic Neural Network
- RADAR : RAdio Detection And Ranging
- RBFNN : Radial Basis Function Neural Network
- RMSE : Root Mean Squared Error
- SND : Standard Normal Deviate
- SVM : Support Vector Machine
- TDNN : Time Delay Neural Network
- TMC : Traffic Management Centers

- TTI : Texas Transportation Institute
- vph : vehicles per hour
- VTLU : Vote Taking Logic Unit

SUMMARY

This dissertation presents a methodology for detecting incidents on freeways using traffic operations data. The methodology is based on the hypothesis that incidents can be detected using operations data by exploiting the difference between the observed traffic state and the traffic state predicted by applying a discrete state propagation model of traffic flow. A case study where the proposed methodology is implemented to an advanced traffic management system network is presented. A comparison of the operational performance of the methodology vis-à-vis the performance of previously developed methodologies is also presented. The dissertation concludes with a summary of the major findings and recommendations for future research.

CHAPTER I

OVERVIEW, MOTIVATION AND ORGANIZATION

1.1 Incident Management Overview

Incidents are defined as random and nonrecurring events such as vehicular crashes, disabled vehicles, spilled loads, temporary maintenance and construction activities, and other unusual events that disrupt the normal flow of traffic. Incident-related congestion is a common occurrence on busy roadways. The number of incidents per million-vehicle-miles has been reported to be between 20 and 200 and lane-blocking incidents lasting more than 45 minutes per 100 million-vehicle-miles have been reported to be 1.09. It has been estimated that 52 to 58 percent of the traffic congestion in urban areas is due to incidents, amounting to 2 billion vehicle-hours of delay and a cost of $40 billion in terms of hours of delay and excess fuel consumption in 2001, as reported in the 2003 Annual Urban Mobility Report (Schrank and Lomax, 2003). By 2005, the impacts of incidents in terms of hours of delay, wasted fuel consumption, and excess road user costs are expected to increase 5 fold over levels experienced 10 years ago (Carvell et al., 1997). Secondary impacts of incident-induced congestion include increased response time of emergency services, lost time and reduction in productivity, increased cost of goods and services, reduced air quality, increased vehicle maintenance costs and reduced quality of life.

Incident management programs have been implemented as a component of freeway management systems to mitigate such effects. In the Traffic Incident Management Handbook (FHWA, 2000), traffic incident management has been defined as the *"systematic, planned and coordinated use of human, institutional, mechanical, and technical resources to reduce the duration and impact of incidents, and improved the safety of motorists, crash victims, and incident responders"*. Incident management involves detection and verification of incidents, assessing their magnitude and identifying the resources and actions necessary to restore the facility to normal operations and provide appropriate response in the form of control, information and aid. The control action plans may include dispatching of emergency services to the incident scene, diverting traffic from the affected freeway, and the like.

1.2 Incident Detection Algorithms

Implicit to the response to an incident is its detection. Under medium to heavy traffic conditions, the effect of a lane-blocking incident on traffic is an inverse function of the time taken to clear it up. Again, the promptness of the response is a direct function of the time taken to detect the incident. Accurate and early detection of incidents is vital for subsequent management action plans that aim to reduce the congestion caused by incidents. This research effort is focused on developing an incident detection algorithm that will detect incidents on the roadways in a quick and effective manner. Use of this incident detection algorithm will reduce the overall average time taken to detect incidents and thereby help in reducing congestion.

The issues that need to be considered for incident detection and verification technologies have been identified in module 8 of the Freeway Management Handbook (Carvell et al., 1997) as:

- Detection Speed
- Accuracy
- Costs
- Maintainability
- Personnel requirements
- Usefulness of data for other freeway management purposes
- Speed with which the technology can be implemented and benefits begin accruing

An incident detection algorithm is capable of providing fast and accurate detection with minimal investments on top of the current surveillance systems and has low maintenance and personnel requirements. In a study (Presley and Wyrosdick, 1998) conducted in Atlanta, Georgia it was observed that the Georgia Navigator system (Georgia's advanced traffic management system) has reduced the average incident duration time from 64 minutes to 41 minutes. This reduction of 23 minutes translated into a cost savings of 44.6 million dollars due to reduced delay time in 1997. Using a simple linear projection, it can be projected (approximately) that a decrease of 1 minute in overall incident duration would lead to 1.94 million dollars benefit. Use of an incident detection algorithm, involving a trivial deployment overhead of a few thousand dollars, has the potential to reduce the response time by faster detection of incidents. This alone provides enough motivation to invest in research of incident detection algorithms.

1.3 Motivation

Objective: The objective of this research is to develop an algorithm that will facilitate efficient real time detection of incidents using Intelligent Transportation Systems (ITS) traffic operations data.

Past research in this area has concentrated on generically extracting the characteristics of the traffic operations data to identify the occurrence of incidents. The traffic flow prediction based approaches that have been used are usually spatially limited and dependent on single dimensional temporal extrapolation. The traffic modeling approaches have employed complex formulations that have elevated the calibration demands of the algorithms and seriously impaired their ease of deployment. However, the modeling approach possesses considerable potential, especially in reducing false alarms caused by recurrent congestion. The need for a traffic flow model based incident detection algorithm that would ensure robustness in terms of low rate of detection errors, and concurrently allow easy calibration and fast deployment, motivated the development of the methodology presented in this research.

1.4 Organization of the Study

This work proposes a new approach to operations data based incident detection. This approach builds on the knowledge derived from previous research. Chapter II presents the findings of previous studies on incident detection algorithms. These studies provide a valuable insight to the developments in operations data based incident detection to date. Identification of the problems faced by previous researchers in this area in the development and implementation of the algorithms expose the areas of possible improvement. In addition, chapter II includes a review of the methodologies for traffic flow prediction and operations data processing, which are vital components of the algorithm presented here.

The review of the literature indicated a gap between the development of incident detection algorithms and their implementation. A survey was undertaken to identify the implementation issues of these algorithms and the user needs and expectations for these algorithms. Chapter III presents the objectives, design principles and methodology of the survey. It goes on to present the results of the survey and draw conclusions based on the results which are then tied to the design considerations of the algorithm.

Chapter IV lays down the theoretical foundations of the development of the methodology in explicit detail. The hypothesis and objectives are identified. Then, an overview of the methodology is described. Identification of the assumptions of the methodology follows. Then the individual components of the models are discussed. The chapter closes with the identification and discussion of the limitations of the methodology.

Chapter V presents a case study that validates the plausibility of the developed methodology. It describes the developed experimental design, site selection and data description, data processing and analysis. The implementation presented in this chapter follows the methodology presented in Chapter IV. It provides a step by step evaluation of the components of the methodology, followed by a comprehensive evaluation of the complete methodology. In addition, it provides the details of a comparative evaluation of the methodology with other methodologies developed in the past in similar studies. Finally the last chapter (Chapter V) summarizes the results of this research and provides recommendations for future research in this area.

CHAPTER II

BACKGROUND

2.1 Overview

This research proposes a new approach to real time detection of incidents using operations data. The first step in the realization of this objective is an assessment of the current and past methodologies applied towards this purpose.

2.2 Chapter Structure

The concept of incident detection and the previous methodologies applied towards this purpose are presented in this Chapter. Section 2.3 gives a summary overview of the different technologies applied to incident detection in real time. Section 2.4 provides methodological highlights of several different algorithms developed in the past for detection of incidents from operations data. Section 2.5 presents models that have been used in the past for prediction of traffic parameters such as flow, average speed or lane occupancy, or have the potential for such a use. Section 2.6 presents some of the studies that provided comparative evaluation of several algorithms. Section 2.7 presents several traffic prediction models. Section 2.8 presents a review of the several approaches that have been used in the past for filtering traffic operations data.

Chapter IV provides the methodology that ties up the concepts introduced in Section 2.3 to 2.7. Section 5.4 in Chapter V uses the concepts introduced in Section 2.8 and extends them for implementation specific to the case study.

2.3 Approaches in Incident Detection

The usefulness of incident management as a tool for congestion mitigation has been firmly established. As a corollary it has been realized that faster detection of incidents leads to savings of incident-response time and a subsequent reduction in vehicle-hours of delay. Consequently incident detection technology has received significant attention. With the advancements of the traffic management systems and widespread deployment of Intelligent Transportation Systems (ITS) technologies, several approaches involving a wide range of technologies have been investigated and implemented for fast and reliable detection of roadway incidents. Listed below are the some of the most popular among these technologies:

- **Mobile phone calls:** Motorists can call a toll free number (like *DOT) to report roadway incidents. There are operators in the TMCs (TMCs) who respond to these calls, obtain the relevant information from the callers and take incident-response measures as necessary. With the large market penetration of the mobile phone technology, this methodology has become quite popular among the TMCs.

- **Freeway service patrol:** Some TMCs co-ordinate with police patrols on freeways for information about incidents on roadways.

- **Peak period motorcycle patrols:** Some law enforcement authorities deploy extra personnel on the highways during peak period traffic. The TMCs co-ordinate with these authorities to obtain information regarding roadway incidents.

- **Fleet operators:** Often TMCs have their own floating vehicles in the traffic stream patroling the highways and watching out for incidents. While the primary task of these patrol units is to respond to incidents and ensure a safe and efficient clearance of the roadway, they also play an important role in detecting incidents.

- **Closed Circuit TV:** Closed Circuit TV (CCTV) has recently become quite popular for monitoring highways for detection and verification of incidents as well as real time monitoring of the clearance activities. There are operators constantly watching the monitors at the TMC for incidents. With time, the operators develop a sense for the hot-spots as to where to expect the incidents and this expertise becomes very useful in fast detection.

- **Motorist call boxes:** Several states have call boxes beside the roadway spaced out every few miles or even closer in some regions. Motorists can call the TMC to report incidents or ask for roadside assistance.

- **Aircraft patrols:** Some TMCs like the Minnesota Department of Transportation (DOT) and the Indiana DOT use helicopters and other aerial means for detection of incidents.

- **Fixed observers/ volunteers:** Some traffic management centres have deployed fixed observers along the roadway and recruited volunteers to report incidents.

- **Citizen Band Radio monitoring:** Some TMCs have deployed personnel to monitor the citizen band (CB) radio conversations between truck operators and other users of such devices to find information about occurence of incidents if any.

It is quite evident that all these technologies have scalability issues. Patrols, Call boxes and CCTV technology are resources and/or manpower intensive. There is no direct control over mobile phone calls from motorists implying that when an incident occurs, there is no guarantee when or if someone will call in to report it. Others technologies like the CB Radio monitoring have problems of reliability of the information.

Hence, the concept of incident detection algorithms gained popularity. These algorithms provided an automated technique for detection of incidents. Also, they solved the scalability issue because increase in coverage area implied increased capital investment but did not significantly increase the recurring costs of personnel. The next section (Section 2.4) outlines the evolution of incident detection algorithms through time in the last three decades.

2.4 Classification of Incident Detection Algorithms

The concept of incident detection algorithms is not new. Algorithms have been developed as early as the 1970s and new algorithms are being developed even now. Depending on how an algorithm analyzes the operations data in order to detect incidents, an algorithm is usually classified into one of five major categories: comparative algorithms, statistical algorithms, time-series and filtering based algorithms, traffic theory based algorithms, and advanced algorithms.

2.4.1 <u>Comparative Algorithms</u>

Comparative algorithms compare the tracking variables against certain thresholds or against one another to identify anomalies. The tracking variable is usually one of the traffic parameters or a variable derived from the traffic parameters. Occupancy is the most common tracking variable. The comparative algorithms are also sometimes referred to as the pattern recognition algorithms as the process is analogous to identification of patterns of behavior of the variables under incident conditions. The California algorithm (refer to Section 2.5.5) is a classic example of this category.

2.4.2 <u>Statistical Algorithms</u>

Statistical algorithms use standard statistical techniques to identify sudden changes and other unusual behavior in the variable. Incidents usually result in unusual behavior of the traffic variables. These algorithms are based on the premise that the reverse is also true under most circumstances and that such behavior indicates incidents. The regular traffic variables – flow average speed and lane occupancy – as well as variables derived from these primary variables have been used as tracking variables. Examples of the statistical approach include the Standard Normal Deviate (refer Section 2.5.5) and the Bayesian Algorithm (refer Section 2.5.5).

2.4.3 <u>Time Series and Filtering Algorithms</u>

Time series and filtering algorithms treat the tracking variable as a time-series variable. Deviation of the variable from the modeled time-series behavior is used for indication of incidents. The challenge here is to differentiate random variations from variations due to incidents. These models include the Auto-Regressive Integrated Moving Average (ARIMA) based (refer Section 2.5.5), the exponential smoothing based (refer Section 2.5.5) and the Kalman filtering based (refer Section 2.5.5) algorithms.

2.4.4 Traffic Theory based Algorithms

The traffic theory based algorithms depend on the relationship between the traffic variables for their analysis. For example, the McMaster algorithm which is based on the catastrophe theory determines the state of traffic based on its position in the flow-density plot and detects incidents based on the transition of the point from one state to another. The GLR algorithm (refer Section 2.5.5) and the McMaster algorithm (refer Section 2.5.5) are examples of traffic theory based algorithms.

2.4.5 Advanced Algorithms

The latest trend has been the development of algorithms with advanced mathematical formulation based techniques and algorithms that incorporate inexact reasoning and uncertainty into the detection logic. These algorithms are based on Artificial Intelligence techniques like Fuzzy Adaptive Resonance Theory and Probabilistic Neural Networks. For example in the Neural Network algorithm (refer Section 2.5.5), the traffic data is input into the black box of learning layers and a binary decision is generated.

2.5 Evolution of Incident Detection Algorithms

Subsections 2.5.1 through 2.5.23 discuss some of the present algorithms in more details. The algorithms are presented in the temporal chronology of their associated publications. The emphasis is on providing the outline of those algorithms that are methodologically significantly different rather than describing all the available algorithms in meticulous detail. In addition, algorithms developed for urban streets such as the Correlation Analysis based algorithm (Takaba and Matsuno, 1985) are considered to be outside the purview of this study.

2.5.1 <u>Standard Normal Deviate Algorithm</u>

The Standard Normal Deviate (SND) based incident detection algorithm (Dudek et al., 1974) was developed at the Texas Transportation Institute (TTI). The SND of a variable is computed as the difference of the given variable from its mean, divided by the standard deviation of the data set. A high value of the SND of a control variable would indicate a major change in the operational conditions in the system. Lane occupancy and energy (kinetic energy) were evaluated as control variables in the belief that tracking the SND of these variables would allow identification of passage of shockwaves through the detection station and in turn identification of incidents. Tests were performed with 3 and 5 minute time bases for computation of the mean and standard deviation used in calculating the SND. The TTI researchers tested two strategies – one requiring only one SND value to be critical, and another requiring two successive values to be critical. The performance of the occupancy variable was observed to be superior in the first method. Effect of the time base on performance was not significant. The second method gave a higher detection ratio with occupancy but a lower detection ratio with the energy variable as compared to the first method. The occupancy variable was not sensitive to the time base in the second method either, but the energy variable showed an increase in detection ratio with a larger time base. Dudek et al. reported a 92 % detection ratio with 1.3 % false alarm rate during peak periods was reported. The time to detect was 1.1 minutes on average. Comparison with the other algorithms developed by Courage and Levin (1968) showed the SND algorithm to be as good as the composite model which was supposedly the best existing model.

2.5.2 Double Exponential Smoothing

The double exponential smoothing algorithm (Cook and Cleveland, 1974) was developed using data from the John C. Lodge Freeway in Detroit. This method used double exponential smoothing for generating a forecast variable. A tracking signal was generated as the algebraic sum of all the previous estimate errors to the present minute, divided by the current estimate of the standard deviation. When the tracking signal deviated from zero beyond a pre-specified threshold, detection was indicated. The threshold could be computed based either on the variability of the data or likelihood of false alarms.

A set of 13 traffic variables which were derived from the basic traffic variables of volume, occupancy, and speed, were tested with this algorithm for performance. The variables were:

1. Station volume
2. Station occupancy
3. Station speed (volume/occupancy)

4. Station volume-occupancy (root of squared sum of errors for both was used for the error values)
5. Station speed-occupancy (analogous to volume-occupancy)
6. Station kinetic energy
7. Station discontinuity
8. Subsystem volume
9. Subsystem occupancy
10. Subsystem speed
11. Subsystem kinetic energy
12. Subsystem volume-occupancy discontinuity
13. Subsystem speed-occupancy discontinuity

Station discontinuity is computed in the same manner as Courage and Levin (1968). Kinetic energy computations use the surrogate for speed.

Station occupancy, volume and discontinuity were found to give better performance in terms of detection levels at different levels of false-alarms.

2.5.3 Low Volume

An algorithm (Dudek et al., 1975) was specifically developed at the TTI for detecting vehicles under low volume conditions. This algorithm uses tracking of individual vehicle input-output. The time of exit of a vehicle from the control section, the edges of which are defined by detectors, is projected as the summation of the time of entry with the ratio of distance between detectors to speed of vehicle at the time of entry. The TTI researchers made a preliminary assumption of constant speed of the vehicle over the section. Two different approaches are defined here – a time-scan operation system and an event-scan operation system.

In the time scan operation, fixed sized accounting intervals are considered and the number of vehicles entering and exiting during these intervals are balanced. Projected times of exit are computed for each vehicle entering the control section within an accounting interval, and if the projected time falls within that interval the vehicle is expected to exit within that interval. If the vehicle fails to do so an alarm is raised. If nothing had happened to the vehicle and it was just a lowering of speed that delayed the exit, then the alarm would be a false one. Waiting for one more accounting period does not alleviate the problem because a similar situation may arise in the next interval and the accounting will still show one less vehicle exiting than expected.

This problem is addressed in the event scan approach. This uses a variable time interval for vehicle accounting. For each vehicle, a set of three computations are executed: the shortest possible time the vehicle can take to arrive based on an upper speed limit of 100 miles per hour (mph), the expected arrival time of the vehicle based on the constant speed assumption, and a late expected exit time based on a speed with a 10% factor of safety. If a second vehicle does not arrive at the beginning of the section before the late expected exit time, the accounting interval is closed. If a vehicle did arrive, the process is repeated till such a situation arises when no vehicle arrives at the upstream detector before the late expected exit time at the downstream detector. If a vehicle is not accounted for at the close of the accounting period, an alarm is raised.

Some results pertaining to detector spacing requirements for event scan operations were obtained from simulation runs. Actual data was used to validate the claim that pattern recognition of headway, occupancy and speed has to supplement volume counts, for the algorithm to work satisfactorily. An average of one false alarm per 10 minutes at 200 vehicles per hour (vph) on a 3 lane directional freeway was observed during use of this algorithm.

2.5.4 Dynamic Model (MM and GLR)

Chow et al. (Chow et al., 1977a; Chow et al., 1977b; Greene et al., 1977; Kurkijian et al., 1977) proposed an incident detection approach based on a dynamic model that would "make full use of all information about the dynamic and stochastic evolution of traffic variables in time and space." Two algorithms resulted from this approach – the Multiple Model (MM) algorithm and the Generalized Likelihood Ratio (GLR) algorithm. The dynamic model uses the Payne equations (Isaksen and Payne, 1973).

The MM algorithm models different scenarios with one of them being the occurrence of an incident. Constant gain Kalman filters are used on the output of the model for the different scenarios and compared with the observations. The residuals from these filters are fed into a probability calculator that is subsequently used in a set of detection rules to isolate incidents.

In the GLR algorithm only one extended Kalman filter is used corresponding to the normal operations scenario. Using some Incident Innovations Signatures (IIS) that are pre-determined from simulations, a correlation is drawn between the residuals of the filter to the corresponding IIS to obtain the likelihoods of different events. These likelihoods are used for the final isolation of incidents.

Unlike the other algorithms that perform well in heavy traffic, these algorithms were found to perform well under light and moderate traffic as well.

2.5.5 California Algorithm

The California Algorithms (Payne and Tignor, 1978) are a set of 10 algorithms that are based on the same principle. They use a decision tree based on traffic states for incident detection. In this set, Algorithm # 8 and Algorithm # 7 are the most popular ones. The California algorithms, developed using data from the Los Angeles system, are one of the first full-scale incident detection algorithms developed. They are usually used as benchmarks for evaluating the performance of other algorithms. At present several modified forms of the original California algorithms exist and are implemented in several TMCs.

The algorithms use 20 and 30 second occupancies and volumes averaged over all lanes at a station. Several variables are derived based on the occupancy values at the concerned station, the station downstream, and occupancy values at these two stations at different time points. Some of the prominent ones are: Downstream Occupancy (DOCC), Spatial Difference in Occupancies (OCCD), Relative spatial difference in occupancies (OCCRD), and Relative temporal difference in downstream occupancy (DOCCTD). Each of these derived variables are evaluated at each time-step at each station in the concerned section of roadway, and compared to thresholds at different points in a decision tree to determine whether an incident has occurred in the system. The thresholds are determined during calibration of the algorithm by minimizing the false alarm rate for a given level of detection rate. The algorithms in this set that used derived variables based on volume and volume-to-occupancy ratio were found to be inferior to algorithms based purely on occupancy based measures. Algorithm #7 uses a persistence requirement and replaces the variable DOCCTD in the last stage of the decision tree with the variable DOCC. This is done in order to account for two observations: 1 – non-incident-related compression waves traveling upstream cause false alarms; and 2 – drops in downstream occupancies are much greater in magnitude in cases of incidents than in normal compression waves generated by recurrent congestion. Algorithm #8, in addition to this, turns off incident detection for 5 minutes after the detection of a compression wave at the downstream detector. This is supposed to give better suppression of False Alarms.

2.5.6 <u>Bayesian</u>

An incident detection algorithm based on Bayesian probability theory was developed by the Illinois DOT (Levin and Krause, 1978). This approach can be used on top of any algorithm to decrease the false alarm rate of the algorithm. The basic idea is the use of values of probability of occurrence of an incident for a given tracking signal. The signal can be any traffic variable or a variable derived from a traffic variable such as those used by the California algorithms. The requirement of the variable is its stability during the occurrence of the incident. The frequency distribution functions of the variable during incident and non-incident conditions are derived based on historical data during the algorithm calibration. These frequency distributions are used to derive values of Bayesian probability of occurrence of incident for strings of signal from the variable. The strings consist of a series of "ones" and "zeros" depending on the presence and absence of the signal respectively. A signal is generated when the value of the variable crosses a calibrated threshold. There can be several thresholds for operation under different traffic conditions, and different geometric conditions. The requirement for length of the string (string of consecutive "ones") is determined from the probability values associated with the string of signals. It was found that a string length of 4 was sufficient for the section over which the algorithm was tested. In other words, a string of four consecutive "ones" indicated the occurrence of an incident.

Determination of proper thresholds for the signal and the frequency distribution of the variables are critical to the proper functioning of the algorithm. The main drawback of this algorithm is its increased detection time. The logic ensures a lowering of false alarms and if the base signal variable is stable enough, the detection ratio would not depreciate with the use of this logic. But depending on the length of the string required to obtain a high value of probability of occurrence of an incident, the time required to detect the incident would increase. The tests conducted during the validation of the algorithm observed an increase of 2 – 2.5 minutes of increase in detection time.

Many of the other algorithm developers have mentioned the use of persistence tests. This algorithm provides a statistical way of creating a persistence test. The persistence test can reduce the false alarm occurrence, but the detection ratio and the time to detect values depend primarily on the base signal or the base algorithm that feeds this logic.

2.5.7 Committee Decision Logic Units based Algorithm

Tsai and Case (Tsai and Case, 1979) proposed two techniques designed to operate on top of the basic incident detection algorithm to improve detection performance.

The first technique, Incident Detection Persistence test, proposed in this study is a logic for reduction of False Alarms by distinguishing false alarms from true alarms. The logic is developed on top of a modified California Algorithm. It uses Bayes optimal decision rule to determine a duration threshold that maximizes the likelihood that an alarm with duration less than the threshold duration is a false alarm. Alarm duration data for both false alarms and true alarms are used to determine this threshold. The reduction of false alarms using this technique was observed to have an adverse effect on detection ratio, which decreased (adversely) with a reduction in false alarms by introduction of the persistence interval logic.

The second technique uses a committee-machine approach to determine the lane of the multilane freeway on which the incident has occurred. The output of several detection algorithms in the form of the incident lane number is used in the first layer – in which the individual decision units are designated as committee decision logic units (CLDU)s. The second layer of the committee machine structure consists of a vote-taking logic unit (VTLU) that uses the decision outputs from the first layer and determines the lane where the incident has occurred according to the majority decision principle.

2.5.8 HIOCC and PATREG

The High Occupancy (HIOCC) and Pattern Recognition (PATREG) algorithms (Collins et al., 1979; Collins, 1983) were developed at the Transport and Road Research Laboratory in Berkshire, U.K.

The HIOCC algorithm is primarily a congestion detection algorithm. Slow moving or stopped vehicles are detected by using the resulting high occupancy values over detectors under such conditions. Instantaneous occupancy values at one tenth of a second sampling rate are smoothed using an exponential filter before use in the algorithm. The threshold is so chosen that an alarm will be indicated when the passenger-car speed will be less than 6 mph or the long-vehicle speed will be less than 14 mph. To avoid multiple alarms resulting from fluctuations of the observations, the occupancy values are artificially raised to a 90% level at the beginning of the congestion so that the high is maintained till the occupancy comes back to the level before the congestion. Also to account for stop and go traffic, an 8 second threshold of zero instantaneous occupancy is used to eliminate the case of stopped traffic from triggering an end of congestion indication.

The PATREG algorithm identifies incidents using patterns of significant speed changes. If the speed lies outside the pre-determined lower and upper thresholds specific to a lane, for the duration of the pre-set persistence interval, an alarm is indicated. The PATREG algorithm works efficiently under low to medium volume conditions whereas the HIOCC algorithm deals with the high volume conditions.

2.5.9 ARIMA

The prediction of freeway traffic variables with an ARIMA(0,1,3) model has been successfully used in the development of an incident detection algorithm (Ahmed and Cook, 1982). The 95% confidence intervals for the predictions of occupancy are computed and used to classify traffic state as incident condition or non-incident condition based on the occurrence of the observed value outside or inside the confidence intervals respectively. Time-to-detect incidents were reported under one minute. 100% detection rates were obtained at false alarm rates ranging between 1.4 and 2.6 percent.

2.5.10 McMaster Algorithm

The McMaster Algorithm was developed using data from Queen Elizabeth Way, Mississauga, Ontario. The basic McMaster Algorithm (Persaud and Hall, 1989; Persaud et al., 1990) (Persaud et al., 1990; Hall et al., 1993) is a congestion detection algorithm. It uses a catastrophe theory model for description of the flow-occupancy-speed relationship. Three regions of operation are defined on the flow-occupancy diagram as depicted in Figure 2.1 (the three areas are separated by the dashed lines) – Area 1: Free flow, Area 2: Congested flow with lane occupancy less than critical occupancy and Area 3: Congested flow with lane occupancy greater than critical occupancy. Calibration of the algorithm involves distinguishing between the congested and uncongested regions. The template for each station is calibrated separately. The minimum uncongested speed is estimated for the station. This is used to create the boundary between Area 1 and 3. A quadratic equation is estimated to obtain flow as a function of occupancy at the station, and a constant flow value is estimated, which is to be subtracted from the function to create the boundary between Area 1 and 2. Updating of the template – to account for various changes in conditions (e.g. weather conditions) – is achieved by using an updating factor. The updating factor is calculated as the smoothed average of recent ratios of observed uncongested flows to predicted flows.

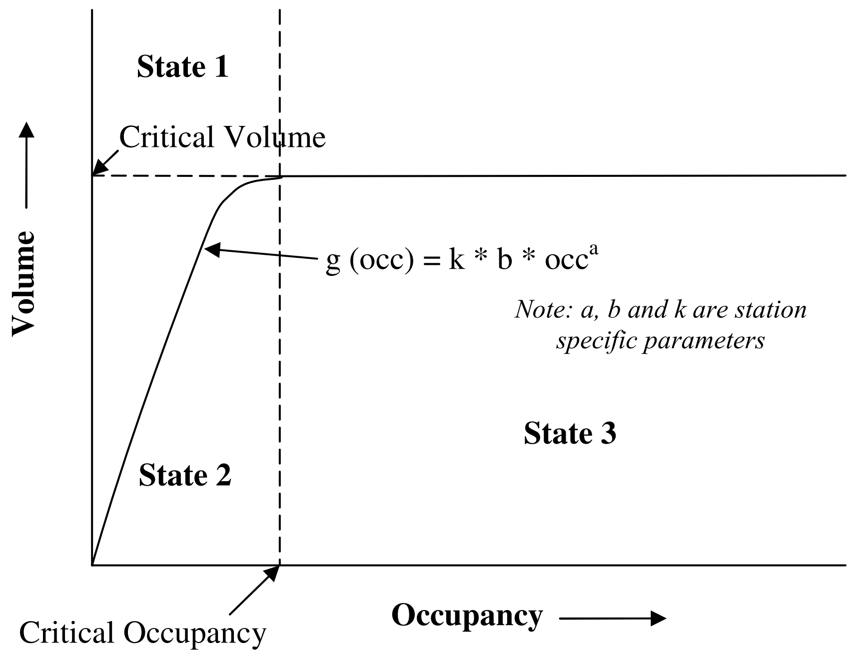

Figure 2.1: McMaster Template for Congestion Identification

Incident Detection is achieved by using a segregation logic (Gall and Hall, 1989) (Hall et al., 1993) that separates incident congestion from recurrent congestion. This logic is primarily designed to be applicable as a wrapper on algorithms which successfully identify congestion in the first step. This logic makes use of a flow-occupancy template in a manner quite similar to the basic McMaster Algorithm. The difference is that, this logic defines 4 regions (Figure 2.2) as compared to the 3 regions in the McMaster Algorithm. Area 3 of the McMaster algorithm template is further divided into two – Area 3 and Area 4 – by the critical flow. During calibration of the algorithm critical flow is obtained by estimating the minimum discharge volume[1]. A decision tree is used to identify incident congestion. If a station is in state 2 or 3 (flow-occupancy data pair is in Area 2 or Area 3 of the template), the state of the downstream detector is checked. If the downstream detector state is either 1 or 2, then incident congestion is identified at the current detector. If the downstream detector state is 3, then the state of the detector further downstream is checked. If the state of the downstream detector is 4 then it is easily categorized as recurrent congestion.

[1] Discharge volumes are volumes corresponding to traffic flows downstream of bottlenecks like those induced by entrance ramps, lane drops etc.

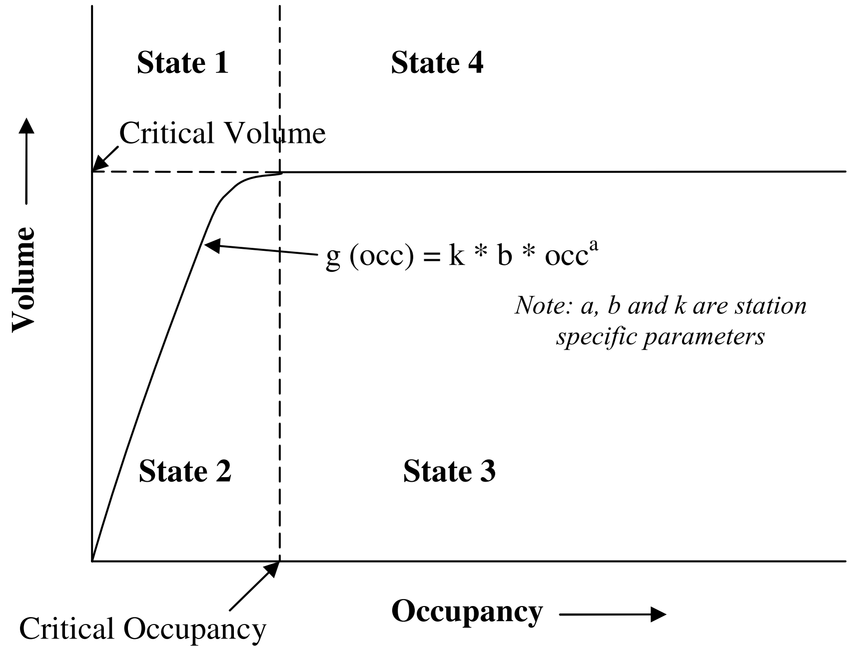

Figure 2.2: McMaster Template for Incident Detection

This is primarily a single detector logic algorithm. Therefore it overcomes the usual disadvantages of comparative algorithms which usually run into problems where there are changes in occupancy between successive detection stations due to natural changes in geometry and grade.

This algorithm has the capability of identifying congestion even when traffic flow occurs below the critical occupancy value. Most of the other approaches depend on the critical occupancy as a threshold value for activation of the detection logic.

Since this is a single station algorithm, it does not suppress detection of incidents at stations close to an incident.

2.5.11 Multi-Layer Feed-forward

Several algorithms (Cheu et al., 1991; Ritchie and Cheu, 1993; Cheu and Ritchie, 1995; Stephanedes and Liu, 1995; Dia and Rose, 1997) have used a Multi-Layer Feed-forward (MLF) neural network structure for incident detection. An artificial neural network consists of a network of many very simple processors ("units" or "neurons"), each possibly having a small amount of local memory. The units are connected by unidirectional communication channels ("connections"), which carry numeric (as opposed to symbolic) data. The units operate only on their local data and on the inputs they receive via the connections. Mostly these structures have three layers – the input layer, the hidden layer and the output layer – with unidirectional connections between neurons in adjacent layers. In the MLF neural network structure the training is performed using a back-propagation method. The neurons in the input layer receive detector data in the form of input vectors. At each hidden neuron, the weighted sum between the input vector and the weight vector associated to the hidden neuron is computed. A bias term related to the hidden neuron is added to the weighted sum and the output computed from a sigmoid transfer function. A similar operation is performed between the hidden and output layers. The transfer functions for both the nodes in the hidden and output layers are sigmoid functions. The output from the output layer neuron is a binary value indicating an incident or incident-free condition.

2.5.12 <u>DELOS</u>

The Detection Logic with Smoothing (DELOS) algorithm (Chassiakos and Stephanedes, 1993) was developed at the University of Minnesota. In this scheme, values for spatial occupancy differences across two consecutive stations are compared at two time windows. The values from each of the time windows can be obtained by using any one of the three smoothing schemes – moving average, median, exponential smoothing. Algorithm performance is tested for different smoothing schemes: moving average in both past and current periods, median in both periods, exponential smoothing in both periods and moving average for current period with exponential smoothing for past period. Window sizes from 5 to 20 terms for past and 3 to 10 for current period in the moving average method and exponential smoothing factors of 0.03 to 0.10 were considered. The size of the windows for smoothing is limited by excessive delays in algorithm response associated with longer windows. The moving average and exponential smoothing schemes provided better performance than the statistical median. Comparison with the performance of the Double Exponential algorithm and the California algorithms showed better performance results from the DELOS algorithms.

2.5.13 <u>Image Processing</u>

Apart from the algorithms that rely on operations data for incident detections, there is another class of algorithms that use an analysis of the image data from the cameras used for surveillance (and collection of operations data in many cases). These algorithms (Michalopoulos et al., 1993a; Michalopoulos et al., 1993b; Kimachi et al., 1994; Michalopoulos et al., 1994; Zifeng, 1997; Trivedi et al., 2000) rely on wide area detection for shockwaves and ancillary information such as detection of traffic on shoulders, stopped vehicles, lane changing and speed differential, traffic slow downs in the opposite direction etc. for detection of incidents. These algorithms are usually computationally demanding.

2.5.14 Fuzzy Logic

Several algorithms have been developed using the fuzzy logic in different forms. There are fuzzy set theory based algorithms (Chang, 1994; Chang and Wang, 1994), fuzzy expert system based algorithms (Lin and Chang, 1998), and algorithms using fuzzy logic in conjunction with neural networks (Hsiao et al., 1994; Ishak and Al-Deek, 1998a; Ishak and Al-Deek, 1998b; Srinivasan et al., 2001). The underlying development steps common to all these approaches usually are: traffic pattern evaluation, non-fuzzy traffic knowledge extraction, traffic knowledge fuzzification and fuzzy rule base construction. The traffic knowledge fuzzification step contains the sub-steps of crisp set identification, fuzzy set definition and fuzzification. In these steps the extracted numerical traffic knowledge, i.e. the range and duration of discrepancy patterns are associated with the fuzzy linguistic variables - “significance” and “persistence” and transform their values into fuzzy numbers through the selected membership functions. Next, the non-fuzzy traffic knowledge is transformed into fuzzy knowledge by defining a set of hierarchical fuzzy rules constructed from the training set data. A Genetic Algorithm (GA) approach has been successfully used by Srinivasan et al. (2001) for training the Multiplexer layers which are similar to the neural network layers. Comparison with MLF neural network algorithm has shown comparable performance whereas comparison with the California and McMaster algorithm has produced significantly better results.

2.5.15 Principal Component Analysis

An incident detection algorithm based on the statistical technique of Novelty detection using Principal Component Analysis was developed at the University of Leeds (Chen, 1997). The flow, speed and occupancy at two adjacent detectors form the 6-dimensional input vector which is subsequently normalized to prevent variables with large magnitudes from dominating. The principal components computed from this input data normally have a much lesser dimension than the input data and mask out unwanted noise effects and at the same time preserves the generality of the data. A calibrated threshold value is used to distinguish the novel input vectors from normal data. The novel input vectors so identified are indicative of incidents. Encouraging results were obtained by using this detection scheme on a simulated data-set.

2.5.16 Cumulative Sum of Occupancy

This detection algorithm (Lin and Daganzo, 1997), developed at the University of California, Berkeley, is based on a comparison of cumulative occupancy data for the two detectors on both sides of a hypothetical incident. Thereby this is a two-detector algorithm, unlike most of the others that are single detector algorithms. However this scheme still relies on the road being more crowded upstream than downstream for an extended period of time – a situation which is also the case in recurrent congestion at bottlenecks. Consequently this algorithm, like most other algorithms, is prone to generating false alarms under recurrent congestion. Incidents are detected by tracking the fluctuation of the difference of the cumulative sum of occupancies at the two detectors. If the fluctuation is more than a time-variant threshold, which increases linearly with passage of time, then an incident is indicated. Effects of variations in occupancy induced by individual driving patterns and faulty detector reporting can be absorbed by carefully choosing an appropriate threshold value.

2.5.17 Probabilistic Neural Network

In the Probabilistic Neural Network (PNN) algorithm (Abdulhai and Ritchie, 1999a; Abdulhai and Ritchie, 1999b; Jin et al., 2002) the transfer functions of the hidden layer is a radial-basis function, and that for the output layer is a competitive-transfer function. The PNN consists of four layers – the input layer, the pattern layer, the summation layer and the output layer. The input layer distributes the input vector to the pattern layer. The neurons in the pattern layer are divided into two groups representing incident and incident free conditions. The summation layer consists of two neurons, one for each class (incident and non-incident). Each of the summation neurons computes an average output signal of the associated pattern units and scales it. The output neuron selects the higher value between the two and determines the class (incident or non-incident) based on that. Compared to MLF, PNN has been shown to have lower Detection Rates (95-100%) and higher False Alarm rates (less than 0.33%). However PNN has a better adaptation potential.

Postprocessor feature extractors and postprocessor probabilistic output interpreters have been used successfully (Abdulhai and Ritchie, 1999b) to improve performance. Use of DWTs (Roy and Abdulhai, 2003) has also been explored for training of the PNN with encouraging results.

2.5.18 Fuzzy Wavelet Radial Basis Function Neural Network Algorithm

Adeli and Karim (Adeli and Karim, 2000; Karim and Adeli, 2002a) proposed an algorithm using a Discrete Wavelet Transform (DWT) for noise reduction and feature extraction, followed by a fuzzy c-mean clustering to reduce the dimensionality of the input vector and finally using a Radial Basis Function Neural Network (RBFNN) to classify the input pattern as incident pattern or non-incident pattern. Sixteen consecutive data-points for occupancy and speed from the immediate past are used to form the input signal. This signal is normalized and the DWT is computed using Daubechies wavelet system of length 8. The wavelet coefficients are filtered using a soft-thresholding nonlinearity, followed by an inverse DWT to obtain the de-noised normalizes sequence. A fuzzy c-mean clustering is used to reduce the dimensionality of the pattern. The extracted 8 elements (4 for occupancy and 4 for speed) are fed into a trained RBFNN. The output is compared against a preset threshold to indicate an incident condition or otherwise.

This algorithm was compared with the California Algorithm #8 and was found to produce very low false alarms (on the order of 0.07%) as compared to the California algorithm (on the order of 3.82%) under the same detection rate scenarios when tested with simulated data. Limited tests with real data gave 0% false alarms at 95% detection ratio for this algorithm when the California algorithm produced 0.63% false alarms at a 90% detection ratio.

2.5.19 Adaptive Conjugate Gradient Neural Network-Wavelet Algorithm

Another algorithm that was developed based on DWT (Adeli and Samant, 2000; Samant and Adeli, 2000; Samant and Adeli, 2001) used an Adaptive Conjugate Gradient Neural Network (ACGNN) and a Linear Discriminant Analysis (LDA). The DWT and LDA operations were used to filter and preprocess the data and the ACGNN was used as the state classifier (incident or non-incident). High incident detection rates of 97.8% and low false alarm rates of around 1% were obtained based on simulated data.

2.5.20 Wavelet Energy with Radial Basis Function Neural Network Algorithm

An algorithm using Wavelet Energy representation of traffic patterns was proposed (2002b; 2003) as an enhancement (in terms of the detection time) over the Fuzzy-Wavelet RBFNN Incident Detection model proposed earlier by the same authors (2000; 2002a). The algorithm is based on an advanced energy representation of the time series pattern developed using wavelet theory. The desirable features of the traffic pattern are enhanced and at the same time a denoising of the traffic pattern is achieved by performing a DWT operation to break the input signal into several time-frequency components that enables the extraction of features desirable for signal identification and recognition. A RBFNN is then used to classify the pattern as incident-induced or non-incident-induced traffic pattern. A sixteen data-point series of the occupancy data and another with the flow data is used to provide the input signal. Each signal is normalized to remove the effects of magnitude, followed by padding at both ends to extend the series size to 32 data-points. A two stage low pass filter (Daubechies filter) is applied. Next the sequence is enhanced with the squared scaling coefficients – a measure of energy in the wavelet domain which are subsequently extracted. The extracted 4 element sequences of the occupancy and flow data are then concatenated to form the input vector of the RBFNN with 8 input vectors, 12 hidden nodes with Gaussian transfer functions and 1 output node with a linear transfer function. If the output is greater than a pre-selected threshold (such as 0.2) then an incident is indicated.

The algorithm was tested extensively with simulated data and to some limited extent with real data. The simulated data gave a 0% false alarm rate and the real data performed well with false alarms rates going to a maximum of 1.04 % in one of the cases and remaining under 0.13% in others.

2.5.21 <u>Discrete Wavelet Transform</u>

Another incident detection technique (Teng and Qi, 2003b) using the DWT technique proposed a different approach to the problem using the same tool. Unlike the previous algorithms (Adeli and Karim, 2000; Adeli and Samant, 2000; Samant and Adeli, 2000; Samant and Adeli, 2001; Karim and Adeli, 2002a; Karim and Adeli, 2002b; Ghosh-Dastidar and Adeli, 2003; Karim and Adeli, 2003) that used DWT mostly as a tool for denoising the dataset, this approach proposed the direct use of the extracted features in the detection of changes in traffic flow. The difference of occupancies between two stations is used as the input signal. A search for large absolute values in the finest scale level (third stage) of the DWT of the signal comprises the first check. A subsequent check of the direction of change using the scale coefficients of the DWT is used to confirm the incident. This algorithm was compared with the MLF Neural Network algorithm, PNN algorithm, Fuzzy-wavelet RBFNN algorithm, Low pass filtering algorithm, and the California algorithm. The DWT based algorithm was found to perform superiorly to all these algorithms in terms of the detection rate versus false alarm rate curve.

2.5.22 <u>CUSUM</u>

A detection delay based optimization problem formulation approach to incident detection (Teng and Qi, 2003a) was proposed along with a simplified procedure for its implementation. The algorithms developed are based on the Cumulative Sum of deviations of subgroups statistic (the CUSUM statistic). Three algorithms DCUSUM[2], CUSUM1 and CUSUM2, involving different assumptions and different treatments of the problem, were developed in the process. The DCUSUM uses Difference of occupancies. CUSUM1 assumes that the correlation between individual observations (of occupancy) is zero, while CUSUM2 does not make this assumption. A substantial change in the difference between the cumulative sum of the log-likelihood ratio for the existing time period and the minimum cumulative sum up to the existing time period is used to indicate a change in state of the process and thereby indicate incident conditions. The DCUSUM algorithm was found to provide the best performance. A

[2] The authors (Teng and Qi) did not provide an expansion of the acronyms

comparison with the low pass filtering algorithm, the MLF algorithm and California algorithm #7 showed that the DCUSUM algorithm outperformed the other algorithms.

2.5.23 Support Vector Machine

An algorithm using the Support Vector Machine (SVM) pattern classifier was proposed by Yuan and Cheu (2003). The SVM pattern classifier classifies an input vector into one of two classes with a decision boundary developed based on the concept of structural risk minimization of classification error using the statistical learning theory. Three different SVM models were implemented with different embedded kernel functions. A linear function, a polynomial function and a radial basis function were the three kernel functions used for this purpose. Comparative results of these three implementations along with comparisons with the MLF algorithm and the PNN algorithm are presented as applied to arterial data and freeway data. SVMs were shown to produce lower Misclassification Rates, higher Detection Ratios, lower False Alarm Rates and in some cases smaller Time to Detect compared to the other algorithms.

2.6 Evaluation of Incident Detection Algorithms

2.6.1 Overview

As can be seen from the discussion in the previous section (Section 2.5), there are several widely varying approaches to algorithms for incident detection using operations data. Every new algorithm is usually accompanied by a comparison with other algorithms. The choice of the comparison algorithms is at the discretion of the authors. The California algorithms are used in most cases and over time they have received the status of a benchmark algorithm. But even in the California algorithm there are several variants (basic, #7and #8 are the most popular ones) and different researchers choose different variants. Moreover the sizes, temporal and spatial coverage of the datasets being used also affect the results of such comparisons to a large extent.

2.6.2 <u>Literature based Comparison</u>

Even in the face of such odds, a few studies have been directed towards a cross-cutting comparison of several detection algorithms based on the reported results in the literature. One such study (Balke, 1993) was performed at TTI in co-operation with the Texas DOT and the Federal Highway Administration (FHWA). The study included site visits to several of the freeway management systems that were actively using an incident detection algorithm or had used one in the past. The algorithms that were compared were:

- California
  - Basic
  - Algorithm #7
  - Algorithm #8
  - APID
- PATREG
- HIOCC
- Standard Normal Deviate
- Bayesian
- Time Series ARIMA

- Exponential Smoothing
- Low-Pass Filter
- Dynamic Model
- McMaster

The TTI researchers produced comparative charts for the traffic parameters used in each algorithm, the intervals and update cycles of the traffic parameters and the perceived degree of complexity and ease of integration of the algorithms into a given freeway surveillance system. They also produced a table that listed the reported (in the literature) best performances of the different algorithms with detection rate, false alarm rate and average detection time as the performance measure parameters.

A similar study (Mahmassani et al., 1999) was performed at the Center for Transportation Research, again in co-operation with the Texas DOT and FHWA. This study too involved site visits of several freeway management systems. Some Neural Network algorithms and Fuzzy logic based techniques, which had been developed since the previous referenced study, were added to the set of comparison algorithms. Unlike the previous study, this study produced a detection-ratio versus false-alarm-rate plot for all the candidate algorithms. As in the previous study, the report was based mostly on reported results in the literature.

2.6.3 <u>Implementation based Comparison</u>

Payne and Thompson (1997) reported an evaluation including the Bayesian, neural net and California-type algorithms using a single dataset. The algorithms were found to perform similarly based on a plot of detection-rate (fraction of incidents detected) versus the operational detection rate (fraction of alarms that prove to be incidents). This study, among other observations, recommended the development of macroscopic model based incident detection algorithms that would capture gross characteristics of the freeway segments and predict recurrent congestion and eliminate the problem of segregating recurrent congestion from incident congestion.

2.7 Traffic Prediction Models

2.7.1 Overview

One of the core components of the methodology developed in Chapter IV is a traffic prediction model. A review of the literature was considered essential to understanding the advantages and limitations of different traffic prediction approaches that have been developed in the past. As in the case of Section 2.5 the discussion here has been limited to the methodological highlights of the different models and generalization has been resorted to wherever possible, rather than a discourse on methodological details of numerous similar models. Moreover, in keeping with the essence of the topic, the discussion involves traffic flow forecasting techniques based on traffic operations data, which includes some macroscopic traffic flow models that lend themselves to easy implementation. Complex theoretical models of traffic flow that do not imply easy implementations and other models that rely on O-D matrixes for implementation have been precluded from this discussion.

2.7.2 Payne's model

A traffic model was introduced in the 1970s (Isaksen and Payne, 1973; Payne and Hurdle, 1979; Payne et al., 1987) that included a momentum equation along with the continuity equation characterizing the continuum model (LWR model). The momentum equation is derived from car following theory concepts. A discretization of the model by finite differences method yields the form:

$$\rho_j^{n+1} = \rho_j^n + \left(\frac{\Delta t}{l_j \Delta x_j}\right)\left(q_{j-1}^{n+1} + f_j^{ON,n+1} - q_j^{n+1} - f_j^{OFF,n+1}\right) \qquad 2\text{-}1$$

$$u_j^{n+1} = u_j^n - \Delta t\left[u_j^n\left(u_j^n - \frac{u_{j-1}^n}{\Delta x_j}\right) + \left(\frac{1}{K_T \Delta x_j}\right)\left(u_j^n - u_e \rho_j^n\right) + \left(\frac{K_v}{K_T}\right)\frac{\left(\rho_{j+1}^n - \rho_j^n\right)}{\Delta x_j}\right] \qquad 2\text{-}2$$

With boundary conditions

$$u_0^n = u_1^n \quad \text{and} \quad \rho_{N+1}^n = \rho_N^n \qquad 2\text{-}3$$

Where u, ρ, q, x, t and u_e are speed, density, flow, distance, time and equilibrium speed respectively. Superscripts denote time step, subscripts denote space step and f^{ON} and f^{OFF} indicate on and off ramp flows respectively. K_T is the relaxation coefficient and K_v is the anticipation coefficient. The second term on the right hand side of equation 2-2, involving K_T, represents the relaxation of equilibrium to incorporate the effect of drivers adjusting their speeds towards the equilibrium speed-density relationship. The third term on the right hand side of equation 2-2, involving K_v and K_T, represents the anticipation which incorporates the effect of drivers reacting to downstream traffic conditions. This represents a readily implementable form. The model, attempts to capture shorter term dynamic deviations from equilibrium values of traffic flow variables as well as the effects of downstream conditions. However this model has been reported to present several instability problems (Rathi et al., 1987).

2.7.3 Time Series Approaches

Ahmed (1986) investigated an autoregressive integrated moving average model of the form ARIMA(0,1,3) for lane occupancy prediction. Sets of observations at 1 minute intervals at a static detection station were treated as a time-series. It was observed that the fact that the first differences of traffic occupancies can be represented by a third order moving average model (characteristic of ARIMA(0,1,3) , was persistent across the time series data sets at all the detector stations. Ahmed found that the performance of the ARIMA(0,1,3) model was superior to the Moving Average model and the Exponential Smoothing model for prediction purposes on the basis of the Mean Absolute Error and the Mean Squared Error values.

The Box and Jenkins technique was used by Der (1977) to develop an ARIMA (1,0,1) model to forecast lane occupancies. Eldor (1977) used this technique to forecast 5 minute aggregate volumes. Ahmed and Cook (1979) used the Box-Jenkins approach to construct a predictor model for volume and lane occupancy. The application of the technique, on data from three different freeway systems with varying detector configurations and aggregation intervals, led to the development of a ARIMA (0,1,3) model for representing volume as well as lane occupancy data. The ARIMA(0,1,3) model proved to be superior to the Moving Average model and the Exponential Smoothing model with adaptive smoothing constants based on Mean Absolute Error and Mean Squared Error.

The Box and Jenkins time series technique was also used by Nihan and Holmesland (1980) for traffic forecasting. Spectral analysis of time series has been used by Nicholson and Swann (1974) for short term forecasts of traffic flow in tunnels. Another time series based forecasting method was explored by Moorthy and Ratcliffe (1988). Van Der Voort et al. (1996) proposed a methodology whereby Kohonen maps were used along with ARIMA models for traffic forecasting. The Kohonen maps allowed for an individual classification of the data and each class had an individually tuned ARIMA model associated with it to provide a higher accuracy than a model generically tuned for all cases.

2.7.4 Adaptive Prediction System Approaches

Lu (1990) investigated An adaptive prediction model for predicting traffic parameters. The objective function – minimizing the mean square error – was the same as the Kalman Filtering and time series approach. However, the adaptive prediction model used a simplified least mean square algorithm to obtain the optimal filter weights. The model was successfully used to predict traffic flow as 1 hour aggregates, with the simplicity of the optimization process lending efficiency and dynamicity to the process. However, the model had stability and convergence issues that needed to be considered during the implementation and use of the model.

A similar adaptive forecasting procedure was also proposed by Polak and Vythoulkas (1990) in the context of traffic forecasting for traveler information systems .

2.7.5 Network Model based Approach

Hobeika and Kim (1994) investigated an approach to prediction of traffic flow based on upstream traffic parameters. They developed three regression models based on the following combination of parameters: (a) Historical average at current station and traffic at upstream station; (b) Traffic at current station and traffic at upstream station; and (c) Historical average at current station, traffic at current station and traffic at upstream station. The model development was based on 15 minute aggregated data. The historical average component was computed using data at the station for the same time-of-day for several previous days. The upstream station was determined as the station from which the traffic took the given interval (15 minutes) to travel down to the current station. The upstream component used data from the stations immediately adjacent to the upstream station as well. Thereby the upstream component had 3 sub-components. In a similar fashion the "current traffic" component had 4 sub-components. Data at current time t and data from 3 previous time-steps ($t-1$), ($t-2$) and ($t-3$) formed the 4 sub-components. Hobeika and Kim proposed a heuristic adaptive weighing system for updating the coefficients of the models dynamically with change in traffic conditions. The third model usually proved to be the best model. However, they recommended the second model for use under conditions where the travel time along the network exceeded the monthly average travel times by 25 percent. The model provided results better than the historical average model – where the predictions were based simply on the historical average component used in this model.

2.7.6 Stochastic Modeling Approaches

Sheu (1999) proposed a stochastic modeling approach to prediction. This approach develops a methodology to model inter-lane traffic maneuvers such as lane changing behavior, using a discrete-time nonlinear stochastic model. The traffic state variables were assumed to follow homogeneous Gaussian-Markov processes and each state variable was assumed to be mutually independent of the other state variables. An estimation algorithm using an extended Kalman filter combined with truncation and normalization procedures, for traffic counts and a density updating procedure for lane densities was developed for estimating section-wide lane traffic characteristics. Comparison of estimated sequential lane-changing fraction to field data was used to demonstrate the potential of the proposed approach. Comparison of estimated time-varying lane density values to observed values demonstrated the accuracy of the predictions. Distributions of estimation errors in terms of estimated lane-changing fractions and lane density values were identified and prediction stability tests based on measures of the mean absolute error were performed. The estimation algorithm was demonstrated to be stable for dynamic prediction.

Another approach to prediction of traffic volumes using Kalman filtering theory was explored by Okutani and Stephanedes (1984). Shimizu et al. (1995) proposed three algorithms for forecasting hourly volumes based on three filters – a fixed interval filter, a basic Kalman filter and a M-Interval Polynomial Approximation (MIPA) Kalman filter. The fixed interval filter performed better than the basic Kalman filter. Estimates of the MIPA Kalman filter were found to be the most accurate and robust as compared with the estimates from the other filters. Davis et al (1990) proposed a technique based on statistical pattern recognition. This technique proved useful under heavy congestion when the linear time series analysis based algorithms failed to perform satisfactorily.

2.7.7 Finite Difference Method

A finite difference method based approach to macroscopic traffic modeling was proposed by Mughabghab et al. (1996). Traffic density and flow were predicted on the basis of the solution of a partial differential equation describing the conservation of the vehicles by applying initial and boundary conditions. The finite difference method was chosen for solving the partial differential equation. A Gaussian form of the speed-density relation was used along with the fundamental relation that proposes flow as a product of average speed and density. Four methods – the forward differencing method, the Lax method, the first upwind differencing method and the second upwind differencing method – were investigated for solving the conservation equation in its discrete form. The first upwind differencing method provided good predictions under low occupancy conditions whereas the Lax method proved to be more stable under high occupancy (congested) conditions.

2.7.8 Recursive Least Squares with Lattice Filtering

Kang et al. (1998) proposed a linear model for short term predictions of traffic volumes using a recursive least squares algorithm with a lattice filter. They assumed the traffic volume to be a function of the existing and past traffic volumes and hypothesized that this functional relationship was linear. The process used a lattice filtering technique that utilizes the characteristics of two independent prediction errors, such as a forward prediction error and a backward prediction error and builds an order-updated recursion of prediction errors. The model was compared with a Neural Network model and an ARMIA model (ARIMA(1,1,1) under non-incident conditions and ARIMA(4,1,0) and ARIMA(3,1,0) under incident conditions for upstream and downstream traffic volumes respectively). The recursive least squares with lattice filtering algorithm were found to produce percentage error values less than the ARIMA and Neural Network models in almost all the cases.

2.7.9 Multilayer Neural Network based Approaches

Cheu (1998) used a standard multilayer network with one hidden layer trained with the back-propagation algorithm to predict 30 second volume, lane occupancy and speed averaged across all lanes. Data at the two most recent intervals were used as input. Predictions were obtained for a single time-step as well as two steps into the future. The results obtained were evaluated on the basis of Root Mean Square Error and maximum error, and were found to be satisfactory. Similar neural network based models were proposed by Smith and Demetsky (1994a; 1994b), Huang and Xu (1996), Vythoulkas (1993) and Zhang et al. (1997).

2.7.10 Finite Impulse Response and Time-Delayed Recurrent Network

A performance evaluative comparison between MLF neural network, Finite Impulse Response (FIR) neural network and Time-Delayed Recurrent neural network was performed by Yun (1998) for several datasets involving state highways, national highways, and urban roads. The feedback mechanism of the error through time-learning technique in a time-delayed recurrent network naturally absorbs the dynamic change of any underlying nonlinear movement. The FIR and the MLF models are not as good in handling randomly fluctuating events. The time-delayed recurrent model was found to outperform the other models in forecasting very randomly moving data. The FIR model showed better forecasting accuracy than the time-delayed recurrent network for the relatively regular periodic data.

2.7.11 Genetically Optimized Time Delay Neural Network

A Time Delay Neural Network (TDNN) model optimized using DWTs (GA) was proposed for short term traffic flow prediction by Abdulhai et al. (1998; 2002). The model predicted flow and occupancy values based on their immediate past temporal profile (few minutes) at a given freeway site as well as the spatial contribution from neighboring stations (3 upstream and 3 downstream detection stations). Abdulhai et al. realized that both temporal and spatial effects were essential for proper prediction. They also studied and reported the effects on prediction accuracy of several factors such as the extent of look-back interval, the extent of prediction in the future, the effect of the spatial contribution, the resolution of the input data, etc. They found that the model performed better than the MLF model.

2.8 Operations Data Filtering

2.8.1 Overview

Traffic operations data is typically collected at 20 seconds to 1 minute intervals and aggregated to 5 minute to 1 hour bins for archiving. With a well designed and well maintained detection equipment deployment, the data at 15 minutes or 1 hour aggregations are predictable and follow the Greenshield's curve pretty closely. Unfortunately this is not the case at the finer levels of aggregation. This is quite apparent from Figure 2.3 and Figure 2.4, which represent the plots of flow versus density for a typical station over a day at 15 minute aggregation and 20 second aggregation respectively.

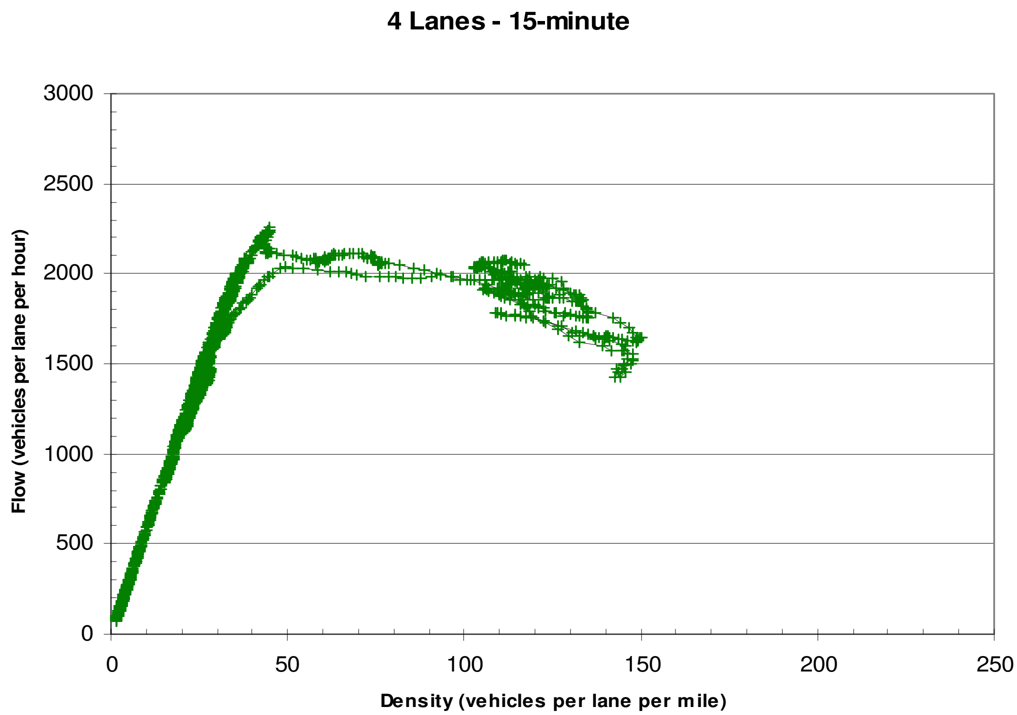

Figure 2.3: Flow Versus Density Plot for a Typical Station for 15 Minute Aggregates

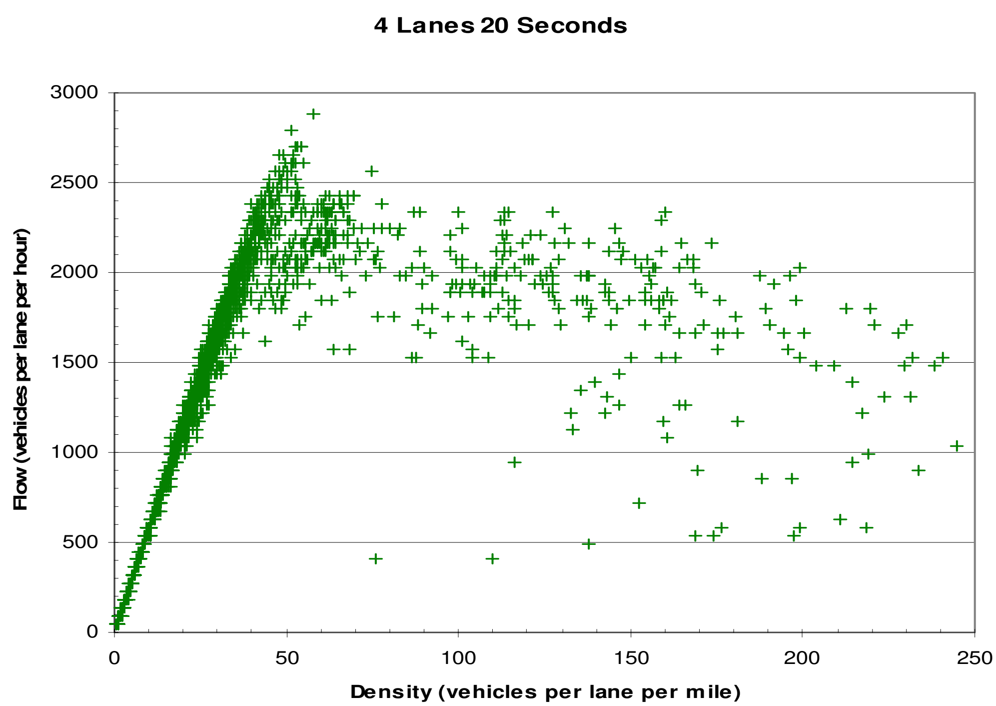

Figure 2.4: Flow versus Density Plot for a Typical Station for 20 Second Aggregates

The problem of using operations data for any real time traffic application is usually two-fold. On one hand there is the problem of detector errors. To complicate the situation even further there is some amount of white noise which does not lend itself to statistical modeling. On the other, there are issues of missing data. There can be several kinds of missing data in a traffic dataset. Mechanical faults in detectors can lead to two major types of inconsistencies. One possibility is that a detector could shut down completely. That would cause zeros, or nothing, or some default values (depending on the specifications in the system) in the dataset. Otherwise, sometimes detectors get "stuck." This would cause detectors to report the same value for a period of time even though the actual field conditions vary. Apart from these, observation errors sometimes originate from lack of proper calibration of the detectors. The first kind of error is pretty easy to detect. The second kind, namely, stuck detector related errors, is relatively difficult to detect. While the longer error strings get detected easily, the shorter strings usually evade detection. Of course, the net effect of the shorter strings is usually minimal and can be ignored in most cases. Detection of errors of the third kind requires data from alternative sources to check against. Checking and eliminating these errors are beyond the scope of this discussion. It is assumed that the detectors had been accurately calibrated during their deployment. The following subsections 2.8.2 and 2.8.3 discuss some of the approaches that have been explored earlier to alleviate these problems.

2.8.2 <u>Statistical Approaches</u>

The problem of missing data is quite common in traffic data. Several studies have proposed different procedures for filling in the gaps in the dataset caused by missing data.

Different strategies, ranging from linear interpolation to traffic model based imputation were evaluated and the nearest neighbor filter (Chen et al., 2003) was found to be best suited for addressing this issue in terms of providing a balance between the reliability of the imputation and the rigorousness of the computations and calibration involved. It provides a robust estimate because the computation uses input from several other detectors instead of just one and takes the median value so that the estimate is still reasonable when one of the neighboring detectors fail. Also this method can fill gaps that are longer in duration without significant deterioration in the accuracy of the estimate.

There has been a significant amount of work in investigating methods for cleaning up and processing of operations data. Coifman (2001) has presented techniques for improving the average length estimation and speed estimation from loop detectors. These techniques are based on the recognition of the fact that the estimated values of average length and speeds are more accurate under certain traffic flow conditions than others. Unlike most of the approaches that post process the collected data using a time domain filter (such as a simple moving average), this technique proposes improvement in real time data as the data is being collected. The procedure is very relevant to traffic management systems that use loop detectors for speed measurements. Gajewski et al. (2000) and Qiao et al. (2003) have presented some techniques for determining optimal aggregation intervals for ITS data. The techniques provide methods of aggregating data that would minimize the loss of useful information caused by the aggregation. Gajewski et al. has proposed two techniques: the cross-validated mean square error and the F-statistic algorithm. These statistical techniques proposed smaller widths (less than 1 minute) for peak time traffic and longer widths (1 hour) for off peak hours. It might be worthwhile to note that while the statistical approach is useful for archiving data for most statistical applications, some applications like traffic flow model validations might require data at more regular intervals than the optimized level. The wavelet decomposition technique presented by Qiao et al. not only optimizes the aggregation level, but also eliminates undesired components and noise in the data. The noise filtering can prove useful in data cleaning. Park et al. (2003) proposed a multivariate-screening method at the detector level incorporating ideas from the classical Hotelling's T^2 statistic and statistical trend removal and blocking. This method identifies outliers based on empirical thresholds generated from archival data using variants of the Mahalanobis distance. This study introduced the idea of using time-of-day blockings to cope with non-constant variability of data. A Locally Weighted Regression for Smoothing Scatterplots (LOESS) filter was suggested to fill in for the data identified as outliers. This study provides a quality control procedure to control the system-wide error rate. This can be quite useful in obtaining summary statistics for the performance of the surveillance systems.

There have also been efforts at identifying and filling in missing values in the data-set. Turner et al. (2000) proposed a rule-based screening procedure for identifying missing and suspect data. The rules are mostly based on basic principles of traffic flow theory. Some thresholds are used which can of course be fine tuned to the data-set being examined. An initiative was taken to compare the data obtained through the Advance Traffic Management System (ATMS) and the data obtained through the Automatic Traffic Recorders (ATR) with the ground truth. Based on their findings they recommended similar studies for any ITS data archiving system to evaluate the accuracy of the data. Turochy and Smith (2000) have proposed a test based on derivation of the average vehicle length from the observed traffic variables. This technique combines the threshold value tests with traffic flow based tests like those proposed by Turner et al. (2000). Chen et al. (2003) proposed a methodology for imputing missing values based on neighboring cell values in the time-space lattice. The method for detecting missing or suspect values is a definitive improvement over the previous methods that used single samples for decision purposes. Gold et al. (2001) proposed a methodology for diagnosing missing values based on location and time. They also compared several methods for imputing missing values based on the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) generated by the methods over the same dataset. Smith et al. (2003) have provided a survey of imputation techniques. They provided a closer look at metrics for evaluating the quality of data as well as the quality of imputations. Based on the positive results on the feasibility of imputation on ITS data, they have suggested a revision of the American Association of State Highway and Transportation Officials (AASHTO) recommendation discouraging imputation of data.

Williams and Hoel (2003) have shown that as a univariate data stream, traffic detector data can be considered and modeled as a seasonal ARIMA process. This finding has not yet been applied to data at the non-aggregated level. However, a simple Auto-Regressive Moving Average (ARMA) model (likely an ARIMA (1,1) based on the Williams and Hoel findings) could be applied to a series of the differences between real-time traffic observations and continuously updated exponentially smoothed averages for each time-of-day and day-of-the-week. This type of model would provide both an additional factor for rule-based data outlier detection and a basis for replacing missing or aberrant data. In relation to nearest neighbor techniques, the continuously updated exponentially smoothed averages replace the neighbor database. The series of differences between the observations and the corresponding averages will be stationary, thus allowing a single, simple ARMA model to provide the predictions and imputations without the need for specific time-of-day, day-of-the-week or peak/mid-day/off-peak models.

2.8.3 Signal Processing Approaches

There has been a recent trend in the use of digital signal processing concepts in the processing of traffic operations data. The wavelet transformation procedure has been used extensively in processing the data before using it in incident detection implementations (Adeli and Karim, 2000; Adeli and Samant, 2000; Samant and Adeli, 2000; Samant and Adeli, 2001; Karim and Adeli, 2002a; Karim and Adeli, 2002b; Ghosh-Dastidar and Adeli, 2003; Karim and Adeli, 2003).

The wavelet transformation technique involves performing a DWT on the data, removing the high frequency terms, and performing an Inverse Discrete Wavelet Transform (IDWT) on the remaining terms to obtain the filtered data. To start with, a subset of the data series consisting of a series of consecutive data points is selected. The number of the data points in the subset is required to be equal to some power of 2 (4, 6, 8, 16 etc.). Usually 16 is chosen for algorithm efficiency. The subset is normalized and then buffered at both ends with 8 data points at each end. A DWT is performed on the extended sequence to obtain 8 fine-resolution coefficients, 4 medium resolution coefficients and 4 coarse resolution coefficients. The 8 high resolution coefficients are discarded to eliminate the traffic fluctuations (white noise). The signal is regenerated using the medium and coarse resolution coefficients by performing an IDWT to obtain the de-noised data.

It is widely believed that observations at less-than-one-minute intervals are quite unstable and noisy. Traditionally the data has been aggregated to longer time intervals typically 5 or 15 minutes to stabilize the data. While this is necessary and sufficient for computing aggregate statistics, use of the data in other applications is seriously limited. For example the calibration and validation of traffic flow models becomes much coarser than can be actually performed with good less-than-one-minute interval data. Also applications such as incident detection algorithms cannot work productively with data aggregated to 15 minute intervals. Filters such as exponential smoothing and moving average filters suffer from some inherent limitations as pointed out by Coifman (1996). Figure 2.5 shows the frequency response of a medium-pass filter along with the other commonly used filters such as the moving average filter, cumulative sum filter, exponential smoothing filter, double exponential smoothing filter, and the low pass filter. The exponential smoothing filter allows only the lower frequencies of the signal to pass through. This means that the high and middle frequencies are chopped off. The moving average filter, which is very commonly used in several applications, has an irregular frequency response (which results in an irregular pattern in passing and blocking of middle frequencies of the signal). However, a well-designed medium-pass filter (Figure 2.3) can preserve the middle and lower frequencies with variable weights and cutoff points. This allows for a more realistic filtering of the data.

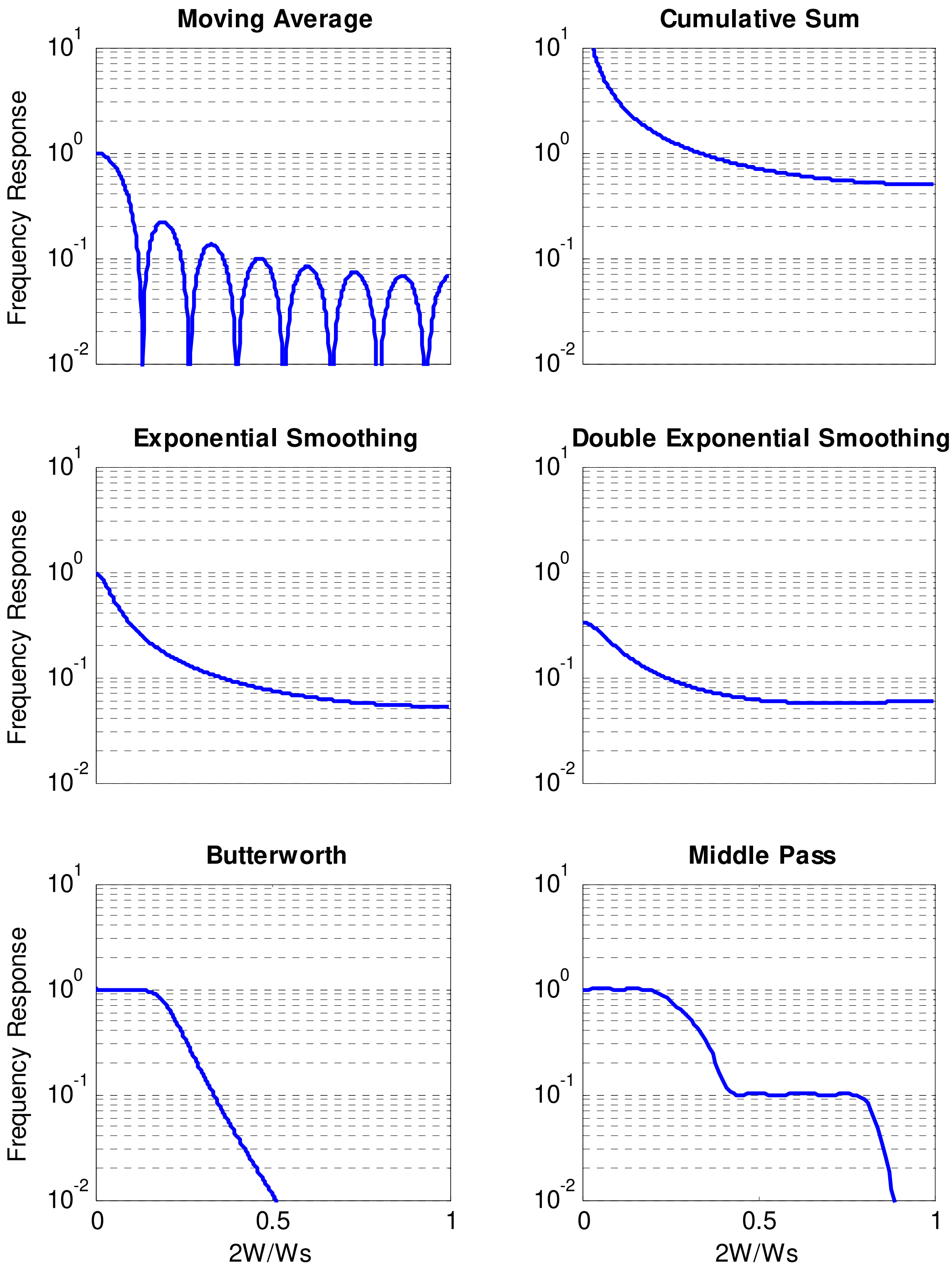

Figure 2.5: Frequency Response of Different Filters

2.9 Summary

This chapter provided an overview of the previous research that has been conducted in the area of incident detection from traffic operations data. The concept of incident detection algorithms is not new. Algorithms have been developed as early as the 1970s and new algorithms are being developed even now. Depending on how an algorithm analyzes the operations data in order to detect incidents, an algorithm is usually classified into one of five major categories: comparative algorithms, statistical algorithms, time-series and filtering based algorithms, traffic theory based algorithms, and advanced algorithms. The concentration of the discussion in this chapter was on Incident detection algorithms that were developed for freeway operations received. A review of the literature on evaluation of incident detection algorithms indicated the lack for a cross-cutting study that has decisively and conclusively ranked the different algorithms in their order of performance based on tests on a single data platform.

Since the developed application is quite data intensive and also data sensitive, an extensive literature review of the available data filtering techniques was in order. In addition to the literature on incident detection algorithms, the chapter also provided the background for the core modules of the methodology including traffic prediction models and operations data filtering methods. Review of the literature on existing traffic prediction models indicated their insufficiency in meeting the stringent demands of the methodology developed in this research; this lead to the development of a new one-step traffic prediction model. The model development process described in Chapter IV successfully assimilated and applied the knowledge derived from the literature on the previous traffic prediction models. Chapter IV and Chapter V revisits and expands upon the concepts introduced in this chapter regarding traffic prediction and data filtering.

Review of the literature indicated that there has been extensive research in this area during the last three decades, with many competing methods available for incident detection. However, it was observed that integration of incident detection algorithms in the incident detection framework in transportation management centers is pretty limited. An extensive nationwide survey was employed to accurately investigate the reasons for limited implementation and, the needs and expectations of the user community for incident detection algorithms. The methodology developed in Chapter IV and the implementation of the methodology in the case study described in Chapter V, took guidance from the results of this survey. The details of the methodology and the results of the survey are provided in Chapter III.

CHAPTER III

DEPLOYMENT STATUS EVALUATION SURVEY

This chapter outlines the context in which TMCs make decisions about whether or not to use automatic incident detection algorithms (AIDA) in their advanced freeway management system. The author performed a survey among the system managers, operators and end users, as well as the decision makers who set the operational policies and the priorities for future system enhancements. The survey responses point to a general consensus that the unacceptably high rates of false alarms generated by available incident detection algorithms is the major deterrent to the use of AIDAs in TMCs. This study not only provides an understanding of the causes of the limited implementation of incident detection algorithms, but also allows a direct comparison between the conventional incident detection technologies and automatic incident detection technology on the basis of their performance. Approximately 90 percent of the survey respondents feel that the current methods of incident detection are insufficient either at present (70 percent) or will be so in the future (20 percent). This finding alone motivates a need to redouble research efforts aimed at developing robust and accurate automatic detection methods. In this regard, the chapter presents promising directions to overcome the past AIDA deficiencies.

3.1 Problem Statement

AIDAs have been part of freeway management system software from the beginnings of ITS deployment. However, several studies revealed that in many cases the automatic incident alarms have been disabled or are simply ignored (Parkany and Bernstein, 1995). The general reason for disabling AIDAs is that the operational performance of AIDAs is very poor. However, the size and scope of the urban transportation networks under direct monitoring by transportation management centers are growing faster than are staffing levels and center resources. This trend is motivating renewed interest in the quest for reliable and accurate AIDA functionality. This chapter examines the reasons for limited implementation of AIDAs in detail and provides some recommendations regarding the possible research thrust in the future for AIDAs.

The first part of this chapter provides the premise of the study and lays out the objective. It then explains the design and development of the survey. Next, it presents, analyzes and interprets the survey results. It closes with a summary of the findings and some recommendations.

From time to time, comparative analyses of AIDAs have been performed in order to find out the relative advantages of one over the others (Stephanedes et al., 1992; Dia et al., 1996; Martin et al., 2001). Abdulhai and Ritchie (1999) discussed the problems arising during implementing an incident detection algorithm and proposed a set of characteristics for an operationally successful incident detection algorithm. But still the developments in incident detection algorithms seemed to be mostly at a scholastic level.

In spite of the rapid development of numerous algorithms the response of the industry seemed to be hesitant. The author envisioned a nationwide survey to understand the lukewarm response by the industry.

3.2 Objective

The objective of the survey was to evaluate the current status of existing implementation of algorithm based incident detection technology. The study compared the performance of this technology with other concurrent technologies like floating vehicle based and mobile phone based technologies. The study investigated the causes for limited implementation of Incident Detection Algorithms.

3.3 Survey Methodology

The author designed the survey (Appendix A) specifically to elicit responses from professionals, mostly state and federal employees, who are concerned about incident detection. The people who would be in a position to make a decision, or substantially influence a decision regarding the integration of algorithm based incident detection technology into the local advanced transportation management system were identified and chosen as the target population of the survey.

The author conducted the survey over the internet (http://www.gati.org/projects/AIDA-BW/survey/) because the internet survey methodology was deemed to produce the quickest responses, while it eliminated any interviewer bias. It also facilitated easy follow-up, such as sending reminders or clarifying responses if necessary. The requests were sent out by email to the target population. Candidate respondents were invited to visit the survey website and fill in a questionnaire. Each invitee was provided a unique id and the IP address of their machine was logged when the completed questionnaire was submitted. These steps facilitated the elimination of any duplicate responses. Also, the target population was provided with the option of asking for a paper copy of the questionnaire by fax or regular mail if they preferred to fill out a hard copy version. This helped mitigate biases related to internet usage that might otherwise have been introduced in the survey.

As is common in most email based internet surveys, the expected participation rate was quite low. To induce a higher rate of response one of the constraints imposed on the survey was its length. The survey questions were therefore limited to only sixteen questions, the bare minimum necessary to establish the key information.

The survey was also designed to be as objective as possible. Most of the questions were multiple choice or numeric open end type. While an opportunity to give subjective answers was provided at all stages, the questions were designed to be clear and direct and yield simple objective answers with little or no room for ambiguity. This facilitated statistical analysis of the responses without introducing any interpretative bias from the surveyor. The questionnaire was pre-tested using a small respondent group. Adjustments were made to the questionnaire based on the responses and feedback from this pilot-study.

The questions were separated into two groups. The first group consisted of questions regarding the operational statistics of the conventional incident detection technologies being used and the framework of data collection technology being used. While the basic infrastructure related information was available from sources such as the ITS deployment tracking website (USDOT, 2002), these questions were targeted to obtain more specific information. The second group consisted of algorithm based automatic incident detection related questions. While each of these question sets provided information that had significant informative value they, together, formed the superset that allowed for a case-by-case comparison and analysis.

3.4 Survey Response

The survey was sent out to key personnel in TMCs all over the United States and the Ontario Ministry of Transportation at Ontario, Canada. Out of the several TMCs, 39 were specifically chosen as targets for the survey based on their area of coverage and the load on the network that they serve. Out of these 39, 32 Centers responded, resulting in an 82 percent effective response (Figure 3.1). The survey results are based on responses from these 32 Centers from 20 States within the United States and Canada. Fifty two percent of the survey respondents were people in a position to make the decisions regarding incident detection policies in their respective TMCs. Another 40 percent were in a position to influence such decisions.

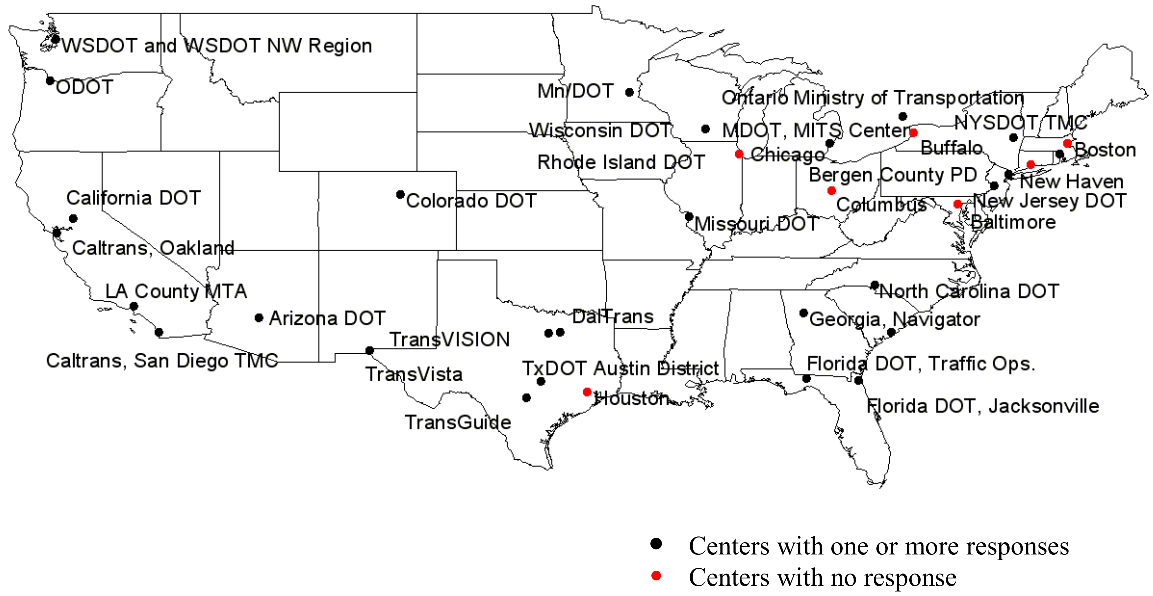

Figure 3.1: Organizations Targeted for Survey

3.5 <u>Survey Results</u>

3.5.1 <u>Incident Detection Technologies</u>

Review of the research and practice literature clearly reveals that previously developed automatic incident detection algorithms were designed and evaluated from a fully automated, stand-alone perspective. When the respondents were asked about their view on algorithm-based incident detection technology, an overwhelming majority (81 percent) agreed that if reliable and accurate automatic incident detection algorithms are developed, the algorithms will not completely replace other state-of-the-practice methods (such as mobile phone calls, operator visual detection, etc.) but rather will serve as a complement to these other detection methods in an overall incident detection system.

Several technologies exist for detection of incidents. Some TMCs use CCTV for monitoring the roadways. There are operators constantly watching the monitors at the TMC for incidents. With time, the operators develop a sense of the hot-spots as to where to expect the incidents and this expertise becomes very useful in fast detection. Some TMCs use floating vehicles in the traffic stream that watch out for incidents. While some TMCs like the Atlanta TMC have their own units (Highway Emergency Response Operators), a large number of TMCs work with the local law enforcement authorities' patrol cars in this regard. With the increase in the availability and widespread use of mobile phones, several TMCs have operators responding to calls from the travelers calling in with reports of incidents. Several states have call boxes beside the roadway spaced every few miles or even closer in some regions. Motorists can call in to the TMC to report an incident or ask for help. Some TMCs like the Minnesota DOT and the Indiana DOT also use helicopters and other aerial means for incident detection.

Visual detection of incidents by operators, detection by floating vehicles and detection by mobile phone operators were found to be the most widely used incident detection technologies. Whereas, visual detection of incidents by operators monitoring Closed-Circuit Television (CCTV) cameras was the most popular one, it was followed closely by detection by floating vehicles and detection by mobile-phone operators. (Figure 3.2) The other incident detection technologies that are used include Aerial detection (using helicopters or planes), detection by co-ordination with other agencies like emergency centers or the police, detection using call boxes, etc.

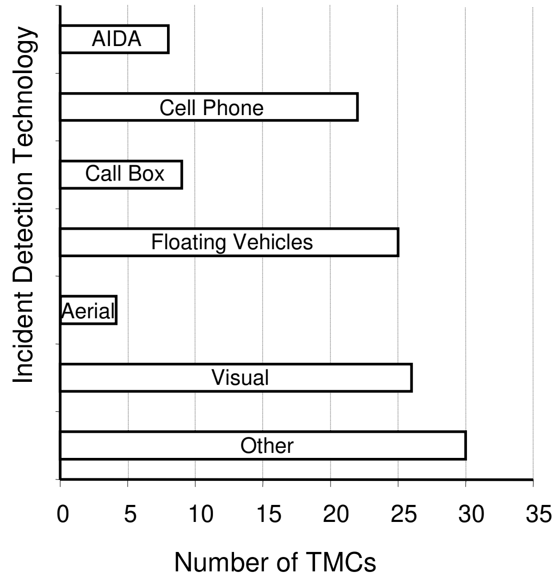

Figure 3.2: Use of Incident Detection Technology by Different Transportation Management Centers (TMCs)

The average time taken to detect an incident varies with the detection technology and also from center to center (Figure 3.3). This time depends on several factors like the size of the network being served, number of units/operators deployed, efficiency of the operators, design of the center/consoles, etc. But the most predominant factor is usually the detection technology. The overall average time taken to detect an incident using non-algorithmic techniques, averaged across all the TMCs, was found to be 8.5 minutes. Out of the several technologies, detection by mobile-phone operators has the lowest average time to detect, 4.5 minutes.

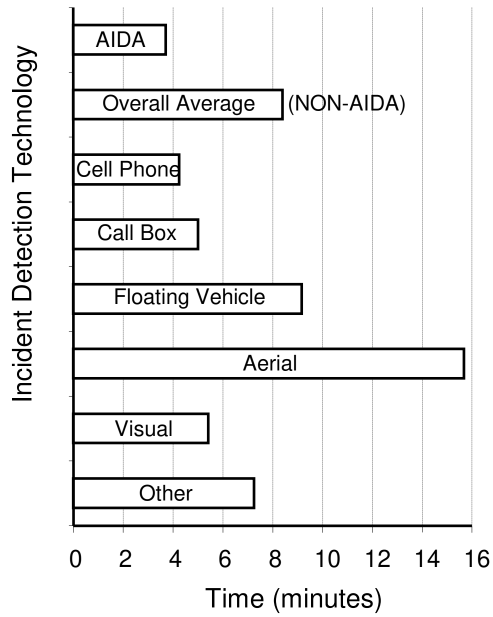

Figure 3.3: Average Time Taken by Different Incident Detection Technologies to Detect an Incident

The pilot study found that detection by mobile-phone users was one of the popular technologies. Nonetheless, only a small proportion (10 percent) of the respondents deemed that the current methods are sufficient for their organizations in the present as well as in the near future, while 20 percent of the respondents agreed that even if the current methods are sufficient at present they would fall short in the imminent future. The majority of the respondents (70 percent) considered the current methods of incident detection to be insufficient to meet the current demands. This strongly suggests that the need for alternative methods of detection has not been completely mitigated and the need for an automated detection technology like incident detection algorithms is more pertinent than ever.

3.5.2 Presence of Advanced Traffic Management System

Out of the 32 TMC surveyed only 5 do not have an ATMS whereas the rest have an ATMS with real time operations data collection capabilities. These 27 can easily integrate a well designed incident detection algorithm into their system with minimal cost and effort investments.

As shown in Figure 3.4 most of the ATMS systems collect data at 20 second or 30 second intervals while a few collect data at 1 minute or 5 minute intervals. With a detector spacing of about ⅓ to a ½ mile, and with observations at 20 or 30 seconds interval, the surveillance offered by the system is quite sufficient for using an incident detection system. (With a detector spacing of ⅓ mile or ½ mile and assuming a free flow speed of 60 mph., the cameras, theoretically, capture the state of the traffic in a piecewise continuous fashion.)

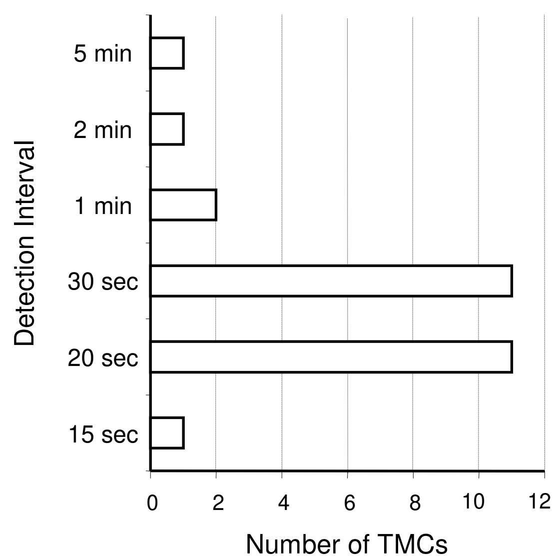

Figure 3.4: Detection Intervals used by Transportation Management Centers (TMCs)

Larger time intervals between observations or widely spaced observation stations would negatively impact the accuracy of the algorithms as well as the time to detect an incident. But with 20 or 30 second intervals, which are observed to be more prevalent, a well designed incident detection algorithm can provide accurate and fast detection.

3.5.3 <u>Vehicle Detection Technologies</u>

While Radio Detection and Ranging (RADAR) and video detection technologies for traffic monitoring are being implemented in several transportation management systems, magnetic induction loop technology is still predominant (see Figure 3.5). Generally the data that can be obtained directly from this technology consists of three parameters: vehicle count, average vehicle speed, and lane occupancy.

Lane occupancy can be used as a surrogate for traffic density. Lane occupancy can be measured by presence detectors as the percentage of time a detector is occupied by vehicles in a given time interval. Among other factors, occupancy is dependent on the length of the detector because of the nature of its measurement – a longer detector will require more time to cross and hence would indicate a higher occupancy. The length of detectors is pretty standard for magnetic induction loop detectors but they vary in radar and video based detectors. To estimate the density from the occupancy, the length of detector is important and should be obtained from the detector configuration instead of assuming any default value. This difference usually prevents defining definite thresholds such as those for detecting congestion using occupancy.

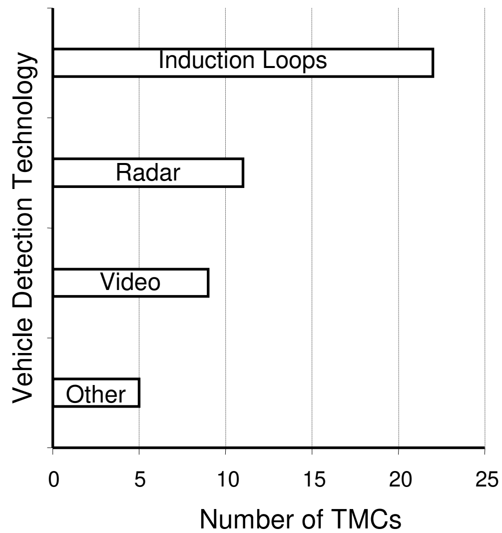

Figure 3.5: Vehicle Detection Technologies used by Transportation Management Centers (TMCs)

An application built on top of real-time operations data, such as an application for algorithm-based incident detection, should ideally be developed to work with these three parameters – vehicle count, average vehicle speed and lane occupancy – at a satisfactory level. Otherwise, implementation of the application will require an upgrade of the traffic monitoring technologies in many of the current systems. Such a requirement could significantly delay or preclude implementation of the real-time application.

It could be argued that the need for AIDAs is for larger, more heavily congested systems, and that such systems are more likely to have one of the advanced video or radar detection systems. However, it should be noted that some of the larger systems have different technologies at various locations within the systems.

Table 3.1 shows several examples of organizations that are using different vehicle detection technologies within the same system. Therefore, feasibility at the system-wide level requires that real-time applications be designed for the highest-common-factor of the data available from these different technologies, which usually boils down to the above mentioned three traffic parameters, vehicle count, average vehicle speed, and lane occupancy.

It should be noted, however, that an attempt to find a link between the detection technology being used and the satisfaction a TMC has with the incident detection technologies could be quite misleading. There are other factors like the area of coverage, the level of congestion etc. that affect the vehicle detection technology as well as the incident detection technology and an attempt to find a relation between these two factors should consider the existence of the other factors. There is a distinct difference between vehicle detection technology and incident detection technology and the two terms should not be confused. The vehicle detection technology data was collected in this study specifically to estimate the feasibility of using different incident detection technology including Incident Detection Algorithms.

Table 3.1: Use of Vehicle Detection Technology by Organizations with ATMS

Organization	*Induction Loops*	*Radar*	*Video*	*Acoustic*
Arizona DOT	x			x
California DOT, Sacramento, District 3	x	x		
California DOT, Oakland, District 4	x	x		
California DOT, San Diego, District 11	x			
County of Los Angeles	x		x	
Florida DOT	x		x	
Georgia DOT			x	
Michigan DOT	x	x		
Minnesota DOT	x			
Missouri DOT		x		
North Carolina DOT		x		
New Jersey DOT	x	x	x	
NY State DOT	x			
Ontario Ministry of Transportation	x	x		
Oregon DOT	x			
Rhode Island DOT			x	
Texas DOT, Dallas district, DalTrans	x	x	x	
Texas DOT, San Antonio, TransGuide	x		x	
Texas DOT, El Paso, TransVista	x			
Texas DOT, Austin district	x	x		x
Texas DOT, Fort Worth, TransVISION	x	x		
Toll Authority, NY State		x		
Washington State DOT	x	x		
Wisconsin DOT	x	x	x	

About 53 percent of the centers have an automatic incident detection algorithm integrated into their system (see Figure 3.6). However, the percentage of the centers which had the detection algorithm fully functional was only 12.5 percent as shown in Table 3.2. There are a few things worth noting here. Firstly, more than a 50 percent level of integration shows that there is sufficient interest in algorithm based detection. This in turn points towards the need of such methods to address the problem of incident detection. On the other hand, a large percentage of centers have not integrated the algorithm into their system. This shows reservation on the part of the centers, or a guarded approach. This observation is ratified by the low percentage of full functionality of the method. Also, the low percentage of full functionality purports that the experience of algorithm integration was not fully satisfactory to the centers that did implement this approach.

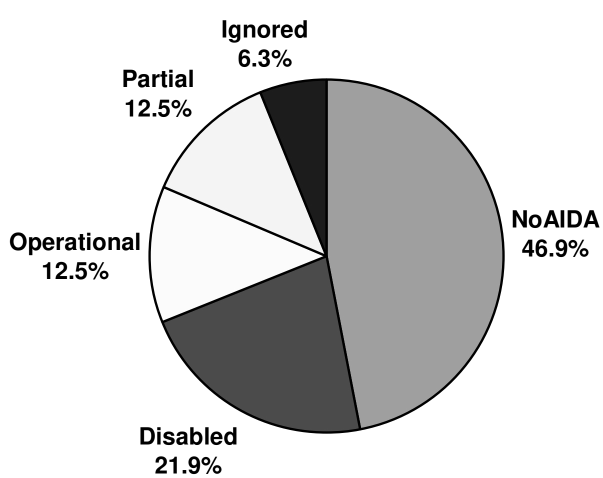

Figure 3.6: Use of Automatic Incident Detection Algorithms by Transportation Management Centers (TMCs)

3.5.4 Reasons for Limited Integration of Incident Detection Algorithms

When asked for the reasons for the limited integration of incident detection algorithms in the system, the users cited three principal reasons – occurrence of false alarms, difficulty of algorithm calibration and low detection rates.

3.5.4.1 False Alarms

The primary and most commonly cited reason was an unacceptably high rate of false alarms (Figure 3.7). The number of false alarms generated by the AIDA systems currently in use is high for operator comfort, and the distraction caused by the false alarms usually outweighs the benefits of faster detection.

Table 3.2: Use of Incident Detection Technologies by Traffic Management Centers

Organization	*AIDA*	*Mobile Phone*	*Call Box*	*Floating Vehicles*	*Aerial*	*Visual*	*Other*
Arizona DOT	x	x		x		x	(a) Other Highway Patrol (b) Other Maintenance team
California DOT, Oakland, District 4		x	x	x		x	
California DOT, Sacramento, District 3		x	x	x			(a) Maintenance vehicles (b) Traffic Management Team vehicles
California DOT, San Diego, District 11		x	x	x			
Colorado DOT		x	x	x		x	
County of Los Angeles		x	x	x		x	
Florida DOT		x	x	x		x	
Georgia DOT		x	x	x		x	(a) District office phone calls (b) Speed detector changes
Indiana DOT		x		x	x	x	
Michigan DOT		x		x		x	
Minnesota DOT		x		x	x	x	
Missouri DOT		x		x	x	x	(a) Police scanners (b) MoDOT field crews calls over radio and Nextel
New Jersey DOT				x		x	(a) Local and State Police (b) Maintenance Forces
North Carolina DOT	x			x		x	Communication w/ 911
NY State DOT				x			Other Wireless 911 calls
Ontario Ministry of Transportation						x	(a) Media calling in to confirm incidents reported to them by public. (b) Police, fire dept, and ambulance calling in to confirm incidents reported to them by public.
Oregon DOT		x		x		x	(a) Calls from police on our radios (b) Calls from police dispatcher over their radios
Rhode Island DOT		x		x		x	
Texas DOT, Austin district	x	x		x		x	(a) Land line phone call (b) Vehicle detector occupancy
Texas DOT, Dallas district, DalTrans	x			x		x	(a) Direct Police radio (b) Direct connection to traffic reporting services
Texas DOT, El Paso, TransVista	x	x		x		x	
Texas DOT, Fort Worth, TransVISION						x	(a) Aircraft from Traffic.com (b) Radio in by TxDOT Courtesy Patrol personnel
Texas DOT, San Antonio, TransGuide	x	x				x	
Toll Authority, NY State			x	x		x	
Washington State DOT		X	x	x		x	Monitoring State Patrol Communication Dispatch radio
Wisconsin DOT	x						Phone and data links to public safety computer aided dispatch and 911 call centers

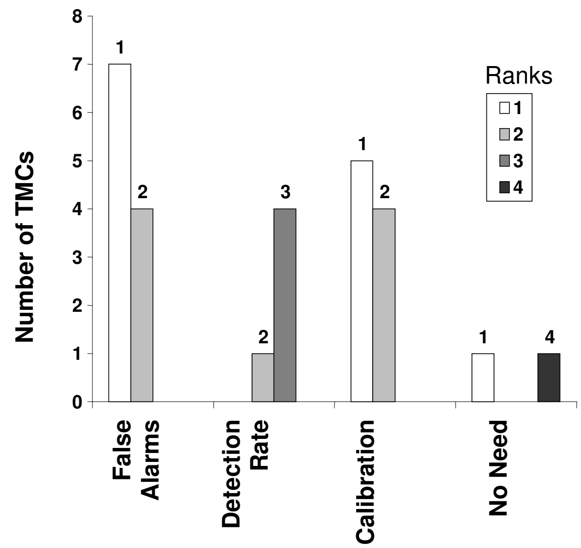

Figure 3.7: Ranks Awarded to Deterrents for use of Automatic Incident Detection Algorithms by the Transportation Management Centers (TMCs)

However this is not a new finding. Researchers as well as practitioners are well aware of this issue. The goal here was to verify this observation and at the same time identify a common ground where researchers and practitioners can agree about the acceptability of the performance of the algorithms. The survey requested input on the tolerance level for false alarms for two time intervals – hourly and daily. On an average, a maximum of three false alarms per hour are considered acceptable. On a daily basis, the average response was ten, i.e., it was purported that on an average, more than ten false alarms per day would cause too much distraction and render the automatic system unacceptable. Although in some cases the high occurrence of false alarms is interpreted as the failure of an algorithm, the literature supports that in almost all incident detection algorithms there is a tradeoff between false alarms and the detection rate. The algorithms can be tuned to reduce false alarms to a minimum. The consequence is a reduction in the detection rate as well.

3.5.4.2 Algorithm Calibration

The survey respondents indicated that the problem of initially calibrating the algorithm was second on the list of reasons for dissatisfaction generated by this technology. Unless the algorithm is properly calibrated it cannot be expected to function with an acceptable level of efficiency and accuracy. The calibration process in most of the algorithms is complicated and time-consuming and also requires an understanding of the details of the algorithm to a degree which is not realistically attainable for the local staff.

The pattern matching, statistical and mathematical modeling based algorithms that are currently available rely mostly on heuristic and inductive modeling based approaches for calibration. Such procedures of calibration require data pertinent to a diverse set of incidents that represent all possible scenarios. The accuracy of the available information determines the efficiency of the calibration. Although incidents in traffic streams are abundant, information pertaining to these incidents is often insufficient and scarce. In practice therefore, in some cases (artificial neural network based algorithms) it is necessary to use simulation generated artificial incident data for calibration. Not only does this limit the accuracy of the calibration, the simulation process involves substantial time and effort. Development of new simulation networks for the specific site of implementation is arduous. Some algorithms are capable of improving with time after implementation, with availability of more data. But incorporation of such capabilities requires manual feedback, which in turn delegates additional tasks for the local staffs.

There are two ways of addressing this problem. One way would be to find out ways to automate the calibration process as far as possible in the existing algorithms. If the algorithm implementation can be designed to adjust itself automatically to the existing and changing conditions of the environments and sites then it can be deployed with some initial configuration and minimal calibration. With the passage of time the accuracy of the algorithm would improve. There have been some efforts in this direction (Abdulhai and Ritchie, 1999).

However there is an alternative approach. If instead of the usual inductive modeling approach, a deductive modeling approach based on traffic flow theory is adopted, the algorithm would not suffer from the usual data constraints. The calibration would mostly involve operations data (flow, speed and occupancy). This data is definitely more accessible than incident information data. Some TMCs already archive this data and most of them can archive it, if necessary, at minimal costs. No elaborate simulations would be necessary for incident data generation.

3.5.4.3 Detection Rate

The survey respondents, in most cases, considered low detection rate (i.e. the percentage of incidents that was actually detected by the incident detection algorithm) a tertiary reason for rejecting incorporation of AIDAs in TMCs. Since a center usually employs several technologies which work in tandem to detect incidents, the chances of not detecting an incident that is seriously affecting traffic, are quite low. Therefore, although a high detection rate is very desirable, it is not considered a critically decisive factor in accepting or rejecting the use of an algorithm.

3.6 Conclusion

The survey shows that a sizeable number of the TMCs have the infrastructure to collect operations data over the traffic network at short (less than a minute) and regular intervals of time. These systems are ideal for using algorithms for automatic detection of incidents. It is quite apparent, therefore, that the infrastructure is available for implementing these algorithms. Also, the survey indicates that there is a demand for alternative detection procedures and the demand is increasing with the increase in the size of the coverage areas of the ATMS. These observations indicate a need for further research in this field. However, based on the general consensus among the survey respondents, it must be acknowledged that this new research thrust should recognize that AIDAs will not provide stand-alone incident detection, as was originally envisioned, but rather will be one component of an overall incident detection system that includes mobile phone call in, operator visual detection, freeway service patrol discovery, etc.

In addition, since the predominant cause for dissatisfaction of the users is the rate of false alarms, incident detection algorithms must be designed to operate with low false alarm rates. The efforts should be directed towards achieving stringent ceiling rates. Though detection ratios and time to detect incidents are still important parameters for estimating the efficiency of algorithms, a substantial effort should be devoted towards addressing the problem of false alarms which is ranked as the primary deterrent for deployment of AIDAs. The desired outcome of the AIDA research and development effort will be readily implementable algorithms that provide the maximum reduction in overall detection times without violating acceptable false alarm thresholds. Automatic incident detection built on traffic flow theory-based deductive modeling is a promising, yet essentially unexploited approach that should be fully explored in this new AIDA research thrust.

This chapter describes the nationwide survey undertaken to investigate the reasons for limited investigation and the needs and expectations of the user community for incident detection algorithms. The design methodology developed in the following chapters (Chapter IV) and the implementation thereof (Chapter V) was guided by results of this survey and the conclusions derived from it as outlined above.

CHAPTER IV

PROPOSED METHODOLOGY

The problem addressed in this dissertation is that of automatic detection of traffic incidents using operations data. Operations data usually consist of flow, occupancy and speed data collected continuously over short but regular intervals of time e.g. 20 seconds, 30 seconds, 1 minute, etc.

Given that the operations data is collected over such small intervals of time, analysis of the data holds the promise of rapidly and accurately revealing fluctuations in traffic conditions over time within a spatial boundary. The operations data, therefore, has a potential of supporting the detection of unexpected incidents within a very short time of the actual occurrence of the incident.

4.1 Statement of Problem

The problem of incident detection has usually been addressed in the past with either a pattern recognition approach or a data mining approach. The former approach tries to associate the occurrence of incidents with the occurrence of certain patterns in the traffic flow variables. The latter approach tries to find occurrences of anomalies in the data that can be attributed to incidents. The proposed Discrete State Propagation Model (DSPM) algorithm introduces a new approach to this problem. A discrete form of the popular hydrodynamic model of traffic flow (Lighthill-Whitham-Richards model (Lighthill and

Whitham, 1955a; Lighthill and Whitham, 1955b; Richards, 1956) or the LWR model) provides the foundation for tackling the problem of incident detection.

4.2 Hypothesis to Be Tested

The purpose of this work was to create a methodology to detect traffic incidents on freeways using operations data that can be used to accomplish the first step in traffic incident management – namely detection of an incident. The research hypothesis can be encapsulated by the following:

Research Hypothesis: *Incidents can be detected using operations data by using the difference between the observed traffic state and the traffic state predicted using a discrete state propagation model of traffic flow.*

This hypothesis will be tested by developing and implementing a methodology that integrates real time information at successive stations to provide accurate short term predictions that differ substantially from observations during incident influenced traffic conditions. If the developed methodology can successfully distinguish incident conditions from free flowing and recurrent congestion conditions, then the hypothesis will be demonstrated to be true. The following section (Section 4.3) provides the design objectives of the methodology.

4.3 Design Objectives

The constraints in the development of the methodology and the guiding principles used in the implementation can be encapsulated in three primary objectives:

<u>Objective 1</u>: Incorporate knowledge derived from previous models and technologies into the development of this methodology.

A comprehensive literature review of the existing incident detection algorithms was the first step towards this objective. A survey directed towards the user community of detection algorithms provided valuable information in laying out the goals for design of the methodology. The following sections (Sections 4.5 through 4.6) elucidate how this objective is accomplished.

<u>Objective 2</u>: Create a methodology that accurately tracks the shift of traffic regime into incident influenced regime.

This objective summarily defines the principal purpose of the study. It involves the development of a methodology for detecting incidents using operations data that can be successfully implemented in real time. The steps involved in attaining this objective are laid out in the following sections (Sections 4.4 through 4.7).

<u>Objective 3</u>: Demonstrate the applicability of the methodology through its implementation in a case study.

This objective provides a comprehensive implementation of the developed methodology and tests the transferability (repeatability) of the methodology and its robustness in the presence of adverse real world data. Chapter V describes the steps involved in the implementation of the methodology and achievement of this objective.

4.4 Proposed Methodology Overview

The components of the proposed algorithm are illustrated in Figure 4.1. The flow of information follows the direction of the arrows.

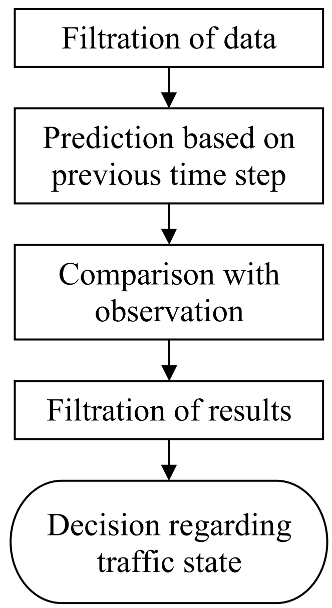

Figure 4.1: Components of Detection Algorithm

The development of the proposed algorithm follows the following steps:

- Choice of appropriate prediction model
- Calibration of error thresholds
- Development of filters for elimination of erroneous detection
- Calibration of filter thresholds

Section 4.5 states the assumptions that are made during different stages of development of the methodology. Sections 4.6 through 4.8 expand on the aforementioned steps. Section 4.9 enumerates the limitations of the methodology. Section 4.10 ties up the component steps and provides a synopsis of the same.

4.5 Assumptions

There are several assumptions that pertain to the development of the methodology. The assumptions are usually specific to a given development step. Following is a list of the assumptions, classified by the concerned step:

Prediction:

- Traffic flow follows the tenets of the LWR model.
- Characteristics of traffic flow can be simplified to the form proposed by Newell (1993b)
- Traffic characteristics at a given location can be forecasted based on the characteristics at adjacent locations at earlier points in time.

Error Threshold Calibration

- The difference between the predicted and observed value is significantly larger during incident conditions than the differences under non-incident conditions.

Filter Threshold Calibration

1. The maximum density per lane value at a given point is equal to the maximum number of passenger cars that can be fit into a one mile segment of a lane with no headway.

2. The maximum plausible flow and density change between successive points in time can be bounded by a threshold.

3. The maximum plausible difference between the prediction and observation can be bounded by a threshold.

Incident Detection

4. Incidents may or may not have a significant effect on the flow of the traffic.

5. Incidents that do not have a significant effect on the traffic are of lesser concern to incident management teams (although they may be graded differently by other emergency management authorities).

6. Incidents that do not have a significant effect on the traffic can not be detected by any incident detection algorithm that relies exclusively on traffic operations data.

7. The effect of an incident on traffic under stop-and-go conditions is not discernable.

4.6 Choice of Prediction Model

The desirable features of the prediction model would be:

- Accurate predictions
- Short term predictions (one step predictions at the base system time interval) possible
- Predictions should assimilate ambient conditions
- Computationally efficient and implementable predictions in real time

The time-series based models (Williams, 2001) are good for prediction at 5 minute levels. The smoothing and filter based models (Kalman filter (Jiang, 2003), Double exponential smoothing (Cook and Cleveland, 1974) etc.) eliminate the high frequency components of the signal. They too are more suited for prediction at larger intervals and are capable of predicting accurately further into the future. The neural network based models (Smith and Demetsky, 1994; Amin et al., 1998; Cheu, 1998; Abdulhai et al., 2002; Ishak and Alecsandru, 2003; Xiao et al., 2003) are computationally quite intensive. Also they require a significant amount of calibration. A comprehensive literature review of traffic prediction models revealed that the lagged cell transmission model (Daganzo, 1993; Daganzo, 1994a; Daganzo, 1994b; Daganzo, 1995; Daganzo, 1999) satisfies most of these requirements. It can make accurate predictions over short time steps. Also it takes into account the fact that the traffic state at a point not only depends on the history of the traffic states at that point but also on the traffic states at the adjacent points. This drawback of the other single station based prediction models was effectively overcome by the lagged cell transmission model.

In the lagged cell transmission model it is assumed that the roadway can be divided into small homogeneous segments (d_j) (Figure 4.2). Time is divided into small intervals (ε). The traffic states within these cells are assumed to be homogeneous, and the state measured at the center of the cell represents the state over the entire cell. The cell dimensions are chosen such that the time step is less than or equal to the time required by the backward moving traffic characteristics to traverse a cell. The discontinuity is at the edges of the cells. The difference in the inflow and outflow across the cell boundaries is used to adjust the successive traffic states.

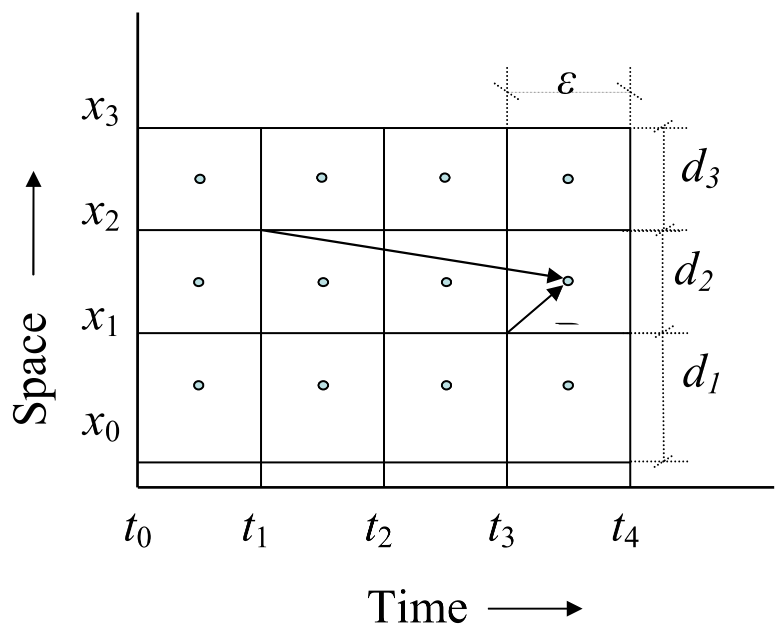

Figure 4.2: Time-Space Lattice

The model can be expressed as:

$$K(t+\varepsilon, X_i) = K(t, x_i) - (\varepsilon/d)\left[Q(t+\varepsilon/2, x_i + d_i/2) - Q(t+\varepsilon/2, x_i - d_i/2)\right] \quad (4\text{-}1)$$

Where K(t_i , x_i) denotes the average density for the i^{th} cell at time t_i , and Q($t_i + \varepsilon/2$, $x_i + d_i/2$) denoting the average flow advancing from cell i to cell i + 1 in the time interval [t_i , $t_i + 1$]. Q is expressed in terms of the upstream sending function S and downstream receiving function R as

$$Q(t+\varepsilon/2, x_i + d_i/2) = \min\{S^k(K(t-f_i, x_i)), R^k(K(t-l_{i+1}, x_{i+1}))\} \quad (4\text{-}2)$$

and

$$Q(t+\varepsilon/2, x_i + d_i/2) = \min\{S^k(K(t-f_i, x_{i-1})), R^k(K(t-l_{i+1}, x_i))\} \quad (4\text{-}3)$$

Where f_i is the forward lag for the i^{th} cell, constrained as:

$$\varepsilon \le d_i / [|S^k|_{\max} (2f_i + 1)] \quad (4\text{-}4)$$

And l_i is the lag for the i^{th} cell, defined as:

$$\varepsilon \le d_i / [|R^k|_{\max} (2l_i + 1)] \quad (4\text{-}5)$$

Figure 4.3 shows a diagrammatic representation of Newell's simplification (Newell, 1993a; Newell, 1993b; Newell, 1993c; Newell, 1993d) of LWR theory. The dotted line represents the LWR model for the relation between flow and density. Newell's simplification implies a simplification of this function with a piecewise linear function as shown in the figure (bold lines).

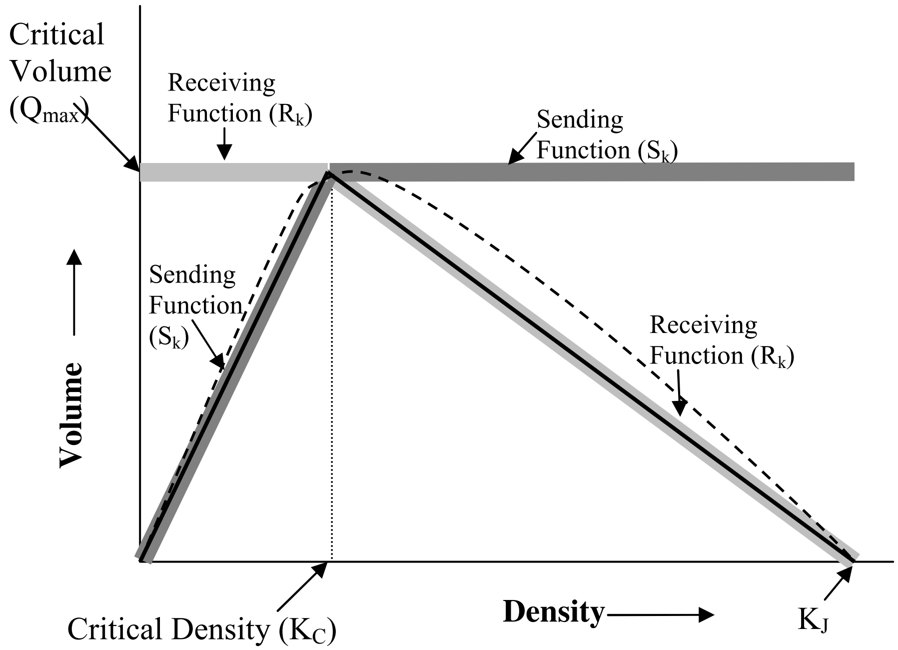

Figure 4.3: Newell's Simplified form

The implication of using the piecewise linear function is an assumption that for a homogeneous section of highway there are only two possible values of kinematic wave velocities (and wave paces, the inverse of wave velocities) – one positive and the other negative. The wave paces are independent of the flow values. The positive wave pace is equal to the vehicle pace under uncongested conditions and can be denoted by $1/S_k$ where S_k is the positive wave speed. The negative wave pace is equal in magnitude to the inverse of the speed of the backward moving kinematic waves and can be denoted as $1/R_k$ where R_k is the backward wave speed.

During uncongested conditions, if the speed is assumed to be constant and equal to the free flow speed, the flow is directly proportional to the density. So the flow that can exit the cell is proportional to the density. However, when the conditions becomes congested, the flow exiting the cell is limited by a value Q_{max} , equal to the capacity of the section. In a similar fashion, a cell can receive traffic flow upto the capacity as long as the conditions are uncongested. When the conditions become congested, as the traffic becomes denser, lesser vehicles can pass the section. Therefore the receiving capacity reduces with the increase in density. Accordingly, the sending function uses a linear relationship between density and flow in the uncongested region ($K < K_C$) and a constant value in the congested region ($K \geq K_C$). The receiving function uses a constant value in the uncongested region ($K < K_C$) and a linear relationship between density and flow in the congested region ($K \geq K_C$). Therefore, the sending and receiving functions (as shown by the thick gray lines and light gray lines respectively in Figure 4.3) can be defined as:

$$S^k(K(t,x_i)) = \begin{cases} K(t, x_i) \times Q_{\max} & \text{if } K < K_C \\ Q_{\max} & \text{if } K \geq K_C \end{cases} \tag{4-6}$$

$$R^k(K(t,x_i)) = \begin{cases} Q_{\max} & \text{if } K < K_C \\ (K_J - K(t, x_i)) \times Q_{\max} / (K_J - K_C) & \text{if } K \geq K_C \end{cases} \tag{4-7}$$

Where K_J is the jam density, K_C is the critical density and Q_{max} is the critical flow where traffic breaks down. The forward (S_k) and backward (R_k) wave speeds are expressed as:

$$S_k = \frac{Q_{\max}}{K_C} \quad \text{and} \quad R_k = \frac{Q_{\max}}{K_J - K_C} \tag{4-8}$$

Using this simplified formulation, the model, as originally represented in Equations 4-1 through 4-3, can be expressed as a set of two equations based on the regime of traffic.

In the uncongested regime ($K < K_C$):

$$K(t+\varepsilon, x_i) = \left(1 - \frac{S_k \varepsilon}{d_i}\right) K(t, x_i) + \frac{S_k \varepsilon}{d_i} K(t, x_{i-1}) \tag{4-9}$$

In the congested regime ($K \geq K_C$):

$$K(t+\varepsilon, x_i) = K(t, x_i) + \frac{R_k \varepsilon}{d_i} K(t-\varepsilon, x_i) - \frac{R_k \varepsilon}{d_i} K(t-\varepsilon, x_{i+1}) \tag{4-10}$$

As is evident from the above equations, for the prediction at the next time-step, this simplified form, in effect, involves a smoothing of the upstream or downstream traffic states with the previously observed traffic state at the point of interest. This smoothing with a previous state gets increasingly more inaccurate as the number of time steps it takes for the kinematic waves to travel between the adjacent station and the station under analysis increases.

Also with reference to Figure 4.2 it is apparent that this model effectively quantifies the traffic state at the center of the cell based on measurements at the boundaries. However in a typical ATMS's data collection setup, the measurements at the edge of the cells are available but there is no data at the center of the cell. Because of the temporal and spatial disparity, prediction at the center of the cell lags the observation at the boundary. This of course, is not a deficiency of the model. It just indicates the lack of suitability of the application of the model to this problem. Consequently, it was necessary to develop a prediction model that could address this issue more effectively.

4.7 Development of Prediction Model

The developed prediction model, hereafter referred to as the DSPM model, is founded on the following assumptions:

- Under un-congested traffic conditions, kinematic waves (Newell, 1993a; Newell, 1993b; Newell, 1993c; Newell, 1993d) travel in the direction of traffic at a characteristic speed (equal to the free flow speed of traffic under Newell's simplified theory).
- Under congested conditions, kinematic waves travel in the direction opposite to the direction of movement of traffic.
- The traffic transitions from the un-congested regime to the congested regime at a given level of density (critical density). The transition is instantaneous as per Newell's simplified theory. Mathematically, this implies a point of discontinuity and does not present any complexity in representation. However, in the real world, such an instantaneous change is not possible. The change does involve some time. Nevertheless, the change is usually so fast that this assumption facilitates a reasonable approximation for all practical purposes.
- The traffic characteristics are unable to cross a standing wave which exists at an active bottleneck.

- The traffic characteristics are unable to cross the shock waves that exist at the back of congestion queues.

The following implementation specific assumption is also necessary:

1. The bottlenecks on the roadway can be identified and the traffic parameters (flow, speed, density / occupancy) can be measured successfully at these points.

In the DSPM model, short term predictions of the traffic states are computed as an approximation to the measured states. The value of a given traffic parameter is computed as the weighted average of the adjacent measured traffic states. A series of possible situations are used to illustrate the concept of this model.

4.7.1 Uncongested Regime

Figure 4.4[1] shows the conditions in an uncongested regime. It shows a section of roadway with two consecutive cells (1 and 2) with detectors at the edges of the cells. Assuming the forward speed of the traffic characteristics to be S_k and the size of the time interval to be ε, the traffic state at a point travels a distance of S_k times ε in one time step. So the traffic state that was measured and reported at station $i-1$ at time t is between station $i-1$ and point A. The traffic state that was reported at station $i-1$ at $t-\varepsilon$ is between A and B. And the traffic state that was reported at station i is between station i and point D. The dashed rectangle marks the traffic states that would be reported at

[1] Figures 4.4 through 4.8 are not to scale and the figures of the cars are used only to illustrate the level of congestion at a point

station i at time $t + \varepsilon$. Therefore the traffic state at station i at time $t + \varepsilon$ is estimated as the weighted average of the traffic states from station $i - 1$ that overlap with the dashed rectangle.

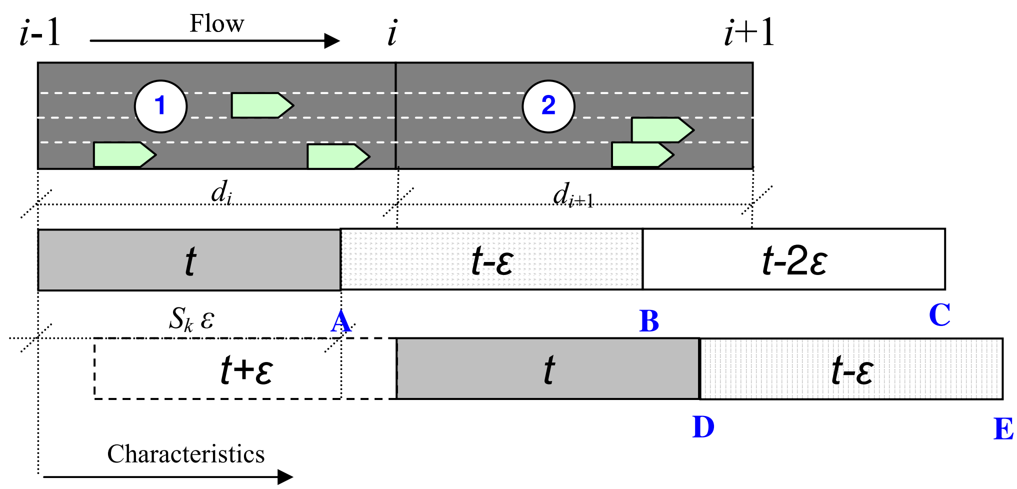

Figure 4.4: DSPM Model under Uncongested Regime with Distance between Detectors Greater than Distance Covered by Kinematic Wave in one Time-step.

If length of the segment is greater than the distance the kinematic waves travel in n time-steps but less than the distance traveled in n+1 time-steps, i.e.,

$$nS_k\varepsilon < d_i < (n+1)S_k\varepsilon \tag{4-11}$$

where n is a positive integer,

the equations become:

$$K(t+\varepsilon,x_i)=\frac{\left((n+1)S_k\varepsilon-d_i\right)}{S_k\varepsilon}K(t-(n-1)\varepsilon,x_{i-1})+\frac{\left(d_i-nS_k\varepsilon\right)}{S_k\varepsilon}K(t-n\varepsilon,x_{i-1}) \quad (4\text{-}12)$$

$$Q(t+\varepsilon,x_i)=\frac{\left((n+1)S_k\varepsilon-d_i\right)}{S_k\varepsilon}Q(t-(n-1)\varepsilon,x_{i-1})+\frac{\left(d_i-nS_k\varepsilon\right)}{S_k\varepsilon}Q(t-n\varepsilon,x_{i-1}) \quad (4\text{-}13)$$

If n is 1, i.e. if the length of the segment is greater than the distance the kinematic waves travel in one time-step but less than the distance traveled in two time-steps, i.e. $2S_k\,\varepsilon > d_i > S_k\,\varepsilon$:

Model I-A

$$K(t+\varepsilon,x_i)=\frac{\left(2S_k\varepsilon-d_i\right)}{S_k\varepsilon}K(t,x_{i-1})+\frac{\left(d_i-S_k\varepsilon\right)}{S_k\varepsilon}K(t-\varepsilon,x_{i-1}) \quad (4\text{-}14)$$

$$Q(t+\varepsilon,x_i)=\frac{\left(2S_k\varepsilon-d_i\right)}{S_k\varepsilon}Q(t,x_{i-1})+\frac{\left(d_i-S_k\varepsilon\right)}{S_k\varepsilon}Q(t-\varepsilon,x_{i-1}) \quad (4\text{-}15)$$

where K: Density

Q: Flow

d_i: Distance of station i from upstream detection station

However, if $n = 0$, implying that the length of the segment is less than the distance the kinematic waves travel in one time-step (Figure 4.5), i.e. $d_i < S_k\,\varepsilon$, then the state at station i at time $t + \varepsilon$ is estimated as the weighted average of the traffic states that overlap with the dashed rectangle. This can be either the states measured at station $i - 2$ at t and t - ε or the states at station $i - 2$ and station $i - 1$ at t (with reference to Figure 4.5).

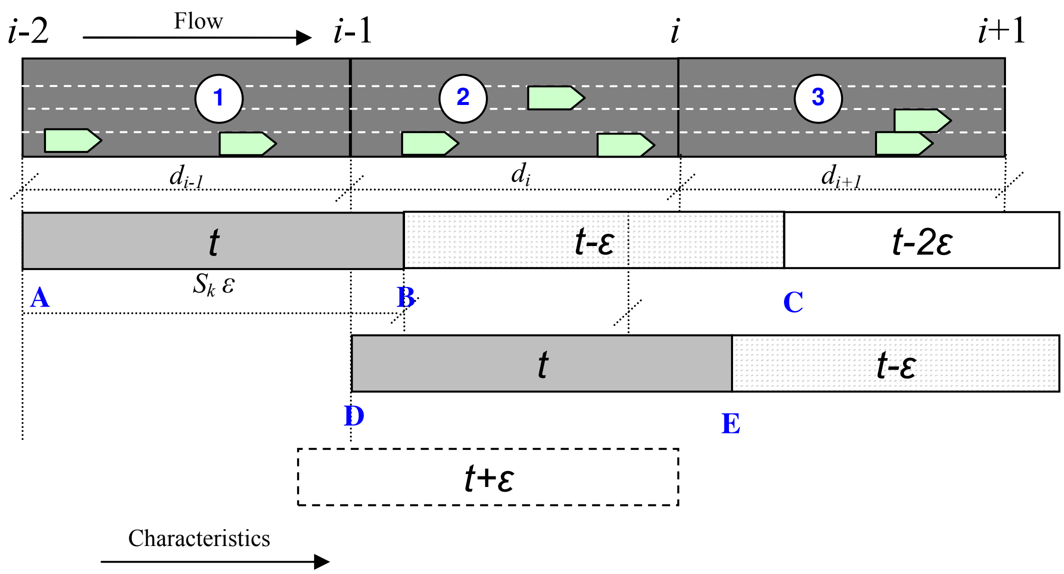

Figure 4.5: DSPM Model under Uncongested Regime with Distance between Detectors Lesser than Distance Covered by Kinematic Wave in one Time-step.

If the states from station $i-2$ are used, the equations become:

Model I-B

$$K(t+\varepsilon,x_i)=\frac{\left(2S_k\varepsilon-(d_{i-1}+d_i)\right)}{S_k\varepsilon}K(t,x_{i-2})+\frac{\left((d_{i-1}+d_i)-S_k\varepsilon\right)}{S_k\varepsilon}K(t-\varepsilon,x_{i-2}) \quad (4\text{-}16)$$

$$Q(t+\varepsilon,x_i)=\frac{\left(2S_k\varepsilon-(d_{i-1}+d_i)\right)}{S_k\varepsilon}Q(t,x_{i-2})+\frac{\left((d_{i-1}+d_i)-S_k\varepsilon\right)}{S_k\varepsilon}Q(t-\varepsilon,x_{i-2}) \quad (4\text{-}17)$$

If the states at station $i-2$ and station $i-1$ at t are used:

Model I C

$$K(t+\varepsilon,x_i)=\frac{\left(S_k\varepsilon-d_i\right)}{S_k\varepsilon}K(t,x_{i-2})+\frac{d_i}{S_k\varepsilon}K(t,x_{i-1}) \quad (4\text{-}18)$$

$$Q(t+\varepsilon,x_i)=\frac{\left(S_k\varepsilon-d_i\right)}{S_k\varepsilon}Q(t,x_{i-2})+\frac{d_i}{S_k\varepsilon}Q(t,x_{i-1}) \quad (4\text{-}19)$$

If the states at station $i - 1$ at t and $t + \varepsilon$ is used (use of data from the future timestamp is an option specific to the implementation in the incident detection algorithm[2]) :

Model I -D

$$K(t+\varepsilon,x_i) = \frac{d_i}{S_k\varepsilon}K(t+\varepsilon,x_{i-1}) + \frac{(S_k\varepsilon - d_i)}{S_k\varepsilon}K(t,x_{i-1}) \tag{4-20}$$

$$Q(t+\varepsilon,x_i) = \frac{d_i}{S_k\varepsilon}Q(t+\varepsilon,x_{i-1}) + \frac{(S_k\varepsilon - d_i)}{S_k\varepsilon}Q(t,x_{i-1}) \tag{4-21}$$

In the case of ramps or at the beginning of a section, where there are no data at x_{i-2} available, a dummy node is assumed at x_{i-2} and the data at x_{i-1} is used for that node.

4.7.2 Congestion Downstream

Figure 4.6 shows the conditions in a congested regime. In this regime the characteristics are moving backward. Assuming the backward speed of the traffic characteristics to be R_k and the size of the time interval to be ε, the traffic state at a point now travels a distance of R_k times ε in one time step. Given the slower speeds of backward waves as compared to forward waves, the traffic state measured at station $i + 1$ at time t is between station $i + 1$ and point B. Therefore the traffic state at station i at time $t + \varepsilon$ is estimated as the weighted average of the traffic states overlapping the dashed rectangle as shown in Figure 4.6.

[2] While this is not a strictly predictive model in that we are using the upstream state from the same time-step, we are only concerned with our best estimate to compare to the observation. We will still be able to calculate the error as soon as the next observation is available.

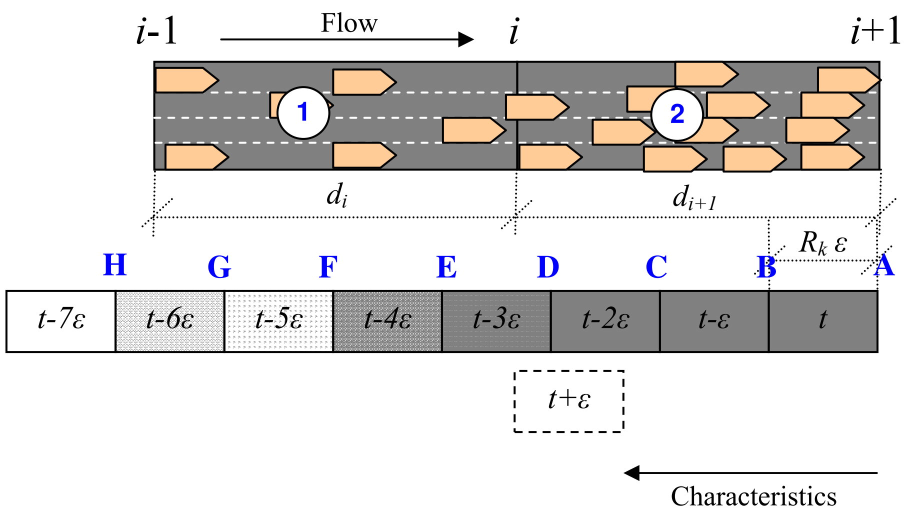

Figure 4.6: DSPM Model under Congested Regime

Model II

If,

$$3R_k\varepsilon < d_i < 4R_k\varepsilon \tag{4-22}$$

Model II (for the congested regime) can be expressed as:

$$K(t+\varepsilon, x_i) = \left(\frac{4R_k\varepsilon - d_i}{R_k\varepsilon}\right)K(t-2\varepsilon, x_{i+1}) + \left(\frac{d_i - 3R_k\varepsilon}{R_k\varepsilon}\right)K(t-3\varepsilon, x_{i+1}) \tag{4-23}$$

$$Q(t+\varepsilon, x_i) = \left(\frac{4R_k\varepsilon - d_i}{R_k\varepsilon}\right)Q(t-2\varepsilon, x_{i+1}) + \left(\frac{d_i - 3R_k\varepsilon}{R_k\varepsilon}\right)Q(t-3\varepsilon, x_{i+1}) \tag{4-24}$$

In the generic case,

$$(n-1)R_k\varepsilon < d_i < nR_k\varepsilon \qquad (4\text{-}25)$$

where n is a positive integer, the equations become:

$$K(t+\varepsilon, x_i) = \left(\frac{nR_k\varepsilon - d_i}{R_k\varepsilon}\right)K(t-(n-2)\varepsilon, x_{i+1}) + \left(\frac{d_i-(n-1)R_k\varepsilon}{R_k\varepsilon}\right)K(t-(n-1)\varepsilon, x_{i+1}) \qquad (4\text{-}26)$$

$$Q(t+\varepsilon, x_i) = \left(\frac{nR_k\varepsilon - d_i}{R_k\varepsilon}\right)Q(t-(n-2)\varepsilon, x_{i+1}) + \left(\frac{d_i-(n-1)R_k\varepsilon}{R_k\varepsilon}\right)Q(t-(n-1)\varepsilon, x_{i+1}) \qquad (4\text{-}27)$$

4.7.3 Congestion Upstream

Figure 4.7 illustrates the case when there is congestion at the upstream detector. The shockwaves (backward moving kinematic waves) emanating from station i – 1 are moving backward. However, there is queue discharge flow downstream of station i – 1. So there are forward moving characteristics flowing down from this station as well. The shockwaves travel a distance of R_k times ε in one time step while the forward waves travel a distance of S_k times ε in one time step. The traffic state that was measured at station i – 1 at time t is between points C and D. Again, the state that was just downstream of the bottleneck at station i – 1 has traveled in the forward direction. Strictly speaking the states at station i cannot be estimated from states at station i – 1 because of the point of discontinuity. However since traffic volumes are conserved, the volume crossing station i – 1 will affect the volume at station i. Therefore the volumes at station i at time $t + \varepsilon$ is estimated as the weighted average of the traffic states overlapping the dashed rectangle in Figure 4.7. However, the speed values and the density values cannot be estimated in a similar fashion. Speeds values will be the free flow speed for station i and density values have to be estimated as flow divided by free flow speed.

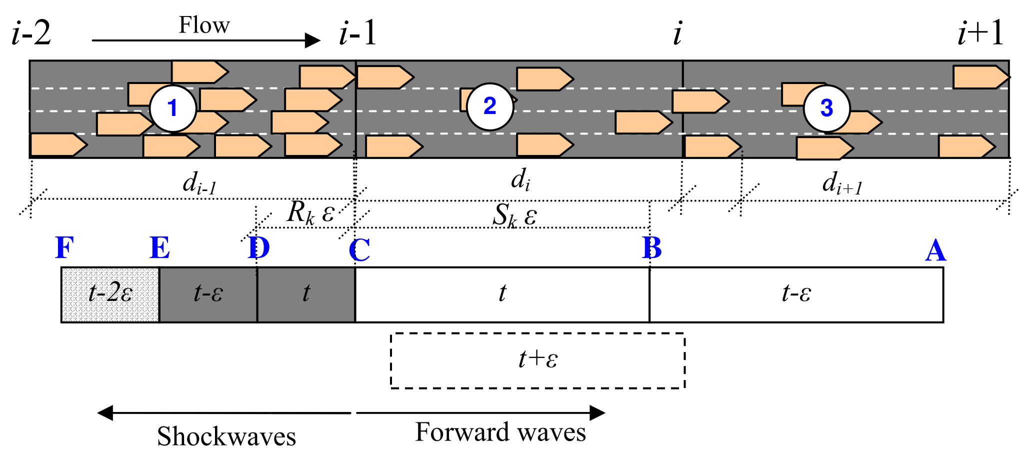

Figure 4.7: DSPM Model under Upstream Congestion

If length of the segment is greater than the distance the kinematic waves travel in one time-step i.e. $d_i > S_k\,\varepsilon$:

Model III-A

$$Q(t+\varepsilon, x_i) = \frac{(2S_k\varepsilon - d_i)}{S_k\varepsilon} Q(t, x_{i-1}) + \frac{(d_i - S_k\varepsilon)}{S_k\varepsilon} Q(t-\varepsilon, x_{i-1}) \qquad (4\text{-}28)$$

Else, if length of the segment is less than the distance the kinematic waves travel in one time-step i.e. $d_i < S_k \varepsilon$:

Model III-D

$$Q(t+\varepsilon, x_i) = \frac{d_i}{S_k \varepsilon} Q(t+\varepsilon, x_{i-1}) + \frac{(S_k \varepsilon - d_i)}{S_k \varepsilon} Q(t, x_{i-1}) \tag{4-29}$$

Models III-B and III-C corresponding to models I-B and I-C (refer discussion in Section 4.7.1) cannot be formulated because they use the states from station $i-2$, but the characteristics from station $i-2$ are unable to cross the standing wave at station i - 1. Density is not predicted separately as in the other cases but obtained from the predicted flow as:

$$K(t+\varepsilon, x_i) = \frac{Q(t+\varepsilon, x_i)}{S_k} \tag{4-30}$$

In the case of ramps or at the beginning of a section, where there are no data at x_{i-2} available, a dummy node is assumed at x_{i-2} and the data at x_{i-1} is used for that node.

4.7.4 Bottleneck at Detection Station

Figure 4.8 illustrates the case when congestion starts from the current station. A typical case will be where there is a station exactly at (or just upstream of) a bottleneck. The shockwaves (backward moving kinematic waves) emanating from station i are moving backward. There is a queue discharge flow downstream of station i and there are forward moving characteristics flowing down from this station. Since all the characteristics from this station are outgoing, and there are no incoming characteristics, the state at this station cannot be obtained as an approximation of the nearby states. The flow at the station will be equal to the queue discharge flow of the bottleneck. The density and speed will be a factor of each other and cannot be computed reliably. The last observed values for flow, density and speed are chosen as the best estimates for the next step under such conditions.

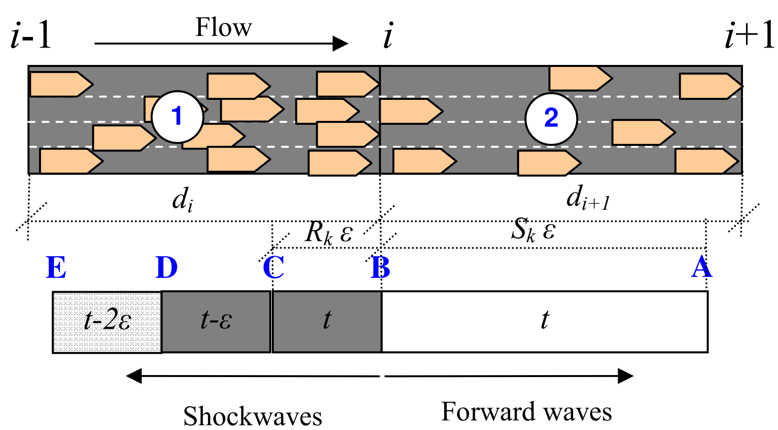

Figure 4.8: DSPM Model under Bottleneck Congestion at Detection Station

Model IV can therefore be expressed as:

Model IV

$$
\begin{aligned}
K(t+\varepsilon, x_i) &= K(t, x_i) \\
Q(t+\varepsilon, x_i) &= Q(t, x_i) \\
S(t+\varepsilon, x_i) &= S(t, x_i)
\end{aligned}
\tag{4-31}
$$

4.8 Development of Incident Detection Model

This algorithm is founded on the assumption that under non-incident conditions, traffic states can be predicted accurately based on previous states, the adjacent states and the surrounding conditions, whereas under incident conditions the predictions fail to match the observations closely. The DSPM model, described in Section 4.7, is capable of modeling uncongested traffic as well as recurrent congestion quite satisfactorily, and is thereby used in this algorithm to predict the traffic states. These predictions are compared with the corresponding observations. A substantial difference between the observations and the predictions is used to identify incident congestion.

4.8.1 Development of Filters

Keeping in view the nature of fluctuation of traffic conditions reported at one minute or less aggregation levels, it can be anticipated that there will be several conditions leading up to erroneous detection. To eliminate these situations, the following filters are envisioned that ensure:

- Detection accuracy
- Minimal traffic stability
- Rational traffic behavior
- Rational surveillance behavior

4.8.1.1 Assumptions

The filters are based on the following assumptions:

1. **Detection accuracy**: Maximum variability of a traffic parameter between two consecutive states is bounded by a threshold. If the difference between the traffic parameter values at two consecutive time-steps exceeds a threshold value, it is assumed that the data at either of the time-steps is erroneous. Each threshold is understandably dependent on the specific parameter; for example, speed is liable to more rapid changes than flow.

2. **Minimal traffic stability**: If the traffic speed goes below a certain level, the traffic enters a highly unstable regime often referred to as "stop-and-go" conditions. Due to the abundance of small transient shockwaves under these conditions, which are a consequence of the heavily increased level of interaction between the individual units in the traffic, it is virtually impossible to obtain coherent predictions from a macroscopic traffic flow model such as

the one used here. Incident detection efforts are abandoned under such conditions.

3. **Rational traffic behavior**: If there is incident-induced congestion at a point, the observation station downstream of the incident is expected to show a drop in flow and density whereas the observation station upstream would show an increase in density if and when the shockwave emanating from this point reaches the station.

4. **Rational surveillance behavior**: It is assumed that if there is an incident detected near a station, it would be followed by surveillance for at least a short interval (e.g. 5 minutes). In that case, operation of the detection algorithm at that station is redundant. Therefore, detection is disabled at the station for a brief period of time following a detection. This allows for elimination of multiple alarms that could be generated by a single incident.

4.8.1.2 Assumption Implications

These assumptions have a significant impact on the performance of the algorithm. Discretion must be used while choosing the thresholds in each case. If the thresholds for the detection accuracy filter are set too tightly, some good data-points will potentially be thrown away and reduce the possibility of successful detection of incidents occurring in the vicinity of the discarded data-point. Similarly the threshold for traffic stability should be used for the purpose it is developed. It should be set to filter out only stop-and-go traffic and not all congested traffic. Setting a higher threshold will reduce the false alarms at the cost of severely reducing the sensitivity of the algorithm in congested traffic. The rational traffic behavior filter helps in eliminating false alarms that could be generated by random traffic fluctuations. The rational surveillance behavior filter affects the capability of the incident to detect secondary incidents within the time-span of the threshold. However, it should be remembered that the occurrence of an incident will be followed by verification and surveillance of the location; it is not necessary to detect a secondary incident with an incident detection algorithm because there will be other more reliable (albeit resource intensive) technologies of detection will be active at that location.

4.9 Limitations

The proposed methodology is not without limitations. Firstly, it suffers from the limitations that are inherent to any incident detection algorithm based on operations data. Unless the traffic is sufficiently affected by an incident the algorithm cannot detect the incident. Most "shoulder stall" and "debris on highway" types of incidents do not affect traffic during off peak hours. These kinds of incidents are very difficult to detect.

This algorithm is dependent on the detection of shockwaves emanating from the incident, for accurate detection of incidents. Due to the nature of traffic behavior under very heavy congestion, this algorithm is incapable of working efficiently under such conditions.

Also this algorithm is highly dependent on the accuracy of the detector data. If the incoming data is of low quality the detection accuracy suffers. To ensure the quality of the detection indications, suspicious detector data is filtered out. This could possibly lead to non-detection of real incidents.

The algorithm's performance depends on the accuracy of the predictions. The prediction model assumes that a true picture of the roadway section has been encoded. Failure to code in the presence of a bottleneck at a given location will lead to faulty predictions near the bottleneck and false indications of incident occurrences at the location.

Moreover this algorithm is a multiple detector algorithm – which means it requires data from multiple detection stations for detection. While this increases the accuracy of the detection process, it reduces the robustness of the algorithm because failure of multiple ($n \geq 2$) consecutive detectors would lead to missed detection at several ($n+2$) detectors. Usually the failure of a single detector can be absorbed by the model unless that detector is at a bottleneck, but the failure of more than one detector severely undermines the accuracy of the predictions and thereby the accuracy of the incident indications. In this respect the single station algorithms like the time-series based algorithms prove to be more robust.

4.10 Summary

This chapter presented the proposed DSPM based Incident Detection methodology. The chapter started with an overview of the process. It then identified the objectives and assumptions of the methodology. Next it provided a detailed description and explanation of the major components of the methodology.

The first discussed component was the DSPM model. This model addressed the problem of obtaining accurate short term predictions for traffic parameters. The predictions assimilated the information from the ambient conditions. The computational overhead of the procedure is low enough to allow real time predictions and is scalable for larger systems. Section 4.7 provided the details of the model and discussed the development of the model. The DSPM model implemented the use of several sub-models depending on the traffic conditions and also on the temporal and spatial separation between the stations. Section 4.7 enumerated several assumptions regarding the kinematic waves in the traffic and their implications for the model development process.

The chapter also presented the other major component of the methodology: the detection logic. The detection logic addresses the problem of identifying traffic conditions under the influence of incidents, in an efficient manner. Section 4.8 identified the assumptions for the development of the filters over the detection logic. The assumptions involve the detection accuracy, minimal traffic stability, rational traffic behavior and rational surveillance behavior. Section 4.8 also discussed their implications of the assumptions in improving and limiting the performance and accuracy of the detection logic.

Section 4.9 enumerated the limitations of the proposed methodology in terms of algorithm performance. The major limitations involve the effect of different factors on the percentage of incidents accurately detected. The following chapter (chapter V) will provide a case study which involves a practical implementation of the proposed methodology. Chapter V will also present quantitative and statistical methods for calibrating and validating the different components of the methodology as well as the methodology itself.

CHAPTER V

CASE STUDY

Evaluation and testing of the methodology presented in Chapter IV involved a full scale offline testing of the algorithm in a section of the network of the Georgia Navigator – the ATMS of the state of Georgia.

This chapter introduces the developed experimental design, site selection and data description, data processing and analysis. It then goes on to present the prediction model evaluation followed by the standalone evaluation and the comparative evaluation of the algorithm. The implementation presented in this chapter follows the methodology presented in Chapter IV. Section 5.1 restates the hypothesis to be tested that was presented in section 4.2. Section 5.5 corresponds to section 4.7 of the methodology. Section 5.6 corresponds to section 4.8. Section 5.7 presents the implementation of several other algorithms that are used as a benchmark for comparing the performance of the DSPMID algorithm. The corresponding results are summarized in sub-sections 5.6.2 and 5.7.3 respectively. Finally, section 0 summarizes the results of the test of the hypothesis presented in section 5.1.

5.1 Hypothesis to Be Tested

The purpose of this work was to create a methodology to detect traffic incidents on freeways from operations data that can be used to accomplish the first step in traffic incident management – namely detection of an incident. The methodology developed in chapter IV in sections 4.7 and 4.8 is implemented in this chapter by integrating real time information at successive stations to provide accurate short term predictions that differ substantially from observations during incident influenced traffic conditions. The research hypothesis tested in this chapter can be restated (originally presented in Section 4.2) as:

Research Hypothesis: *Incidents can be detected from operations data by using the difference between the observed traffic state and the traffic state predicted using a discrete state propagation model of traffic flow.*

5.2 Experimental Design

The experimental design comprised of three distinctive steps – prediction model evaluation, incident detection algorithm calibration and evaluation, and comparative evaluation of the incident detection algorithm.

5.2.1 Model Evaluation

The first step was the evaluation of the one-step prediction algorithm based on the DSPM model as developed in section 4.3. Since the algorithm has to work efficiently at the 20 second level of aggregation, data at several detection stations were used for the predictions. The observed data at the next time-point were used as the base data against which the veracity of the predictions was evaluated.

5.2.2 Algorithm Calibration and Evaluation

Before the algorithm could be expected to produce satisfactory results, calibration was necessary to incorporate the features of the subject dataset. The robustness of the calibration effort depended on the sensitivity of the results to the thresholds. After the calibration, the detection algorithm was rigorously tested on 6 months of data including weekdays as well as weekends and round-the-clock data. Unlike previous algorithm testing efforts that used dataset fragments consisting of approximately 15 minutes of data before the incident and 15 minutes of data after the occurrence of the incident, this testing used data at multiple stations around the station primarily affected by the incident and at all times of the day to exhaustively cover all scenarios and give a true picture of the expected rate of false alarms produced by the algorithm.

5.2.3 Comparative Evaluation of Algorithms

To evaluate the performance of the algorithm as compared to the previously developed algorithms, the author selected a representative sample of the available algorithms. This representative sample included two of the most widely accepted and implemented algorithms to be used as comparison benchmark algorithms. These algorithms have typically been chosen by other researchers for comparison of their algorithms, so comparisons with these two algorithms also open the possibilities of performing a virtual comparison with a wide variety of other algorithms. Since one of the goals of this study, as established in Chapter III, is to ensure a low rate of false alarm generation in the algorithm, one of the state-of-the-art algorithms was chosen that was reported to produce nearly zero percent false alarm rate.

5.3 Site Selection and Data Description

The implementation and testing of the methodology as envisioned in Section 5.2 required extensive operations data (count, average speed and lane occupancy) at very detailed levels over a reasonably long segment and with a supplementary incident database. None of the TMCs archived data at the level of detail required for the study. Most TMCs archive operations data as 5-minute aggregates. To overcome this hurdle, a connection between the Georgia DOT's TMC and a data-server at Georgia Tech was established. The TMC pushed operations data for selected portions of the Georgia Navigator network, in near real time (10 minute bundles) to Georgia Tech's data-server.

The data collection effort in this case consists of two different phases executed synchronously. One phase consists of collecting traffic count, occupancy and speed data. The other phase consists of collecting incident-related data. The data collected in both these phases are described in detail in the following sub-sections. The collected data had gaps arising from a myriad of different causes. Implementations of filtering techniques that are compatible with on-line applications are described in Section 5.4. The integration of the data from the two phases is explained in Sub-section 5.4.2.

5.3.1 Study Site Description

A section of state route Georgia 400 north of Atlanta metropolitan area was chosen for this study. This is one of the more heavily traveled and heavily congested sections of the Atlanta metro area freeway system. Commuter traffic predominates during the morning and afternoon peaks. This section regularly witnesses a number of incidents and is an ideal site for this study. Also this section is one of the new sections that have been brought into the ATMS infrastructure of the TMC of the Georgia DOT. Exploring automatic incident detection opportunities in this section of roadway has significant local value in addition to general applicability.

The section is 7 miles long and extends from I-285 (milepost 7.28) in the south to just north of Old Milton Parkway (milepost 19.78) in the north. Appendix A shows a detailed aerial photo of the immediate surroundings of the study site. Appendix B shows a schematic of the study section and gives detailed information of the lane configuration, on-ramp and off-ramp information along with the mileposts of the detection stations. A map of the Atlanta region is provided in Figure 5.1 to give an overall view of the location of the site. The gray shade denotes the area monitored by the Georgia Navigator system – the ITS system of Georgia. The study site used for this work is encircled by a bold oval in the figure.

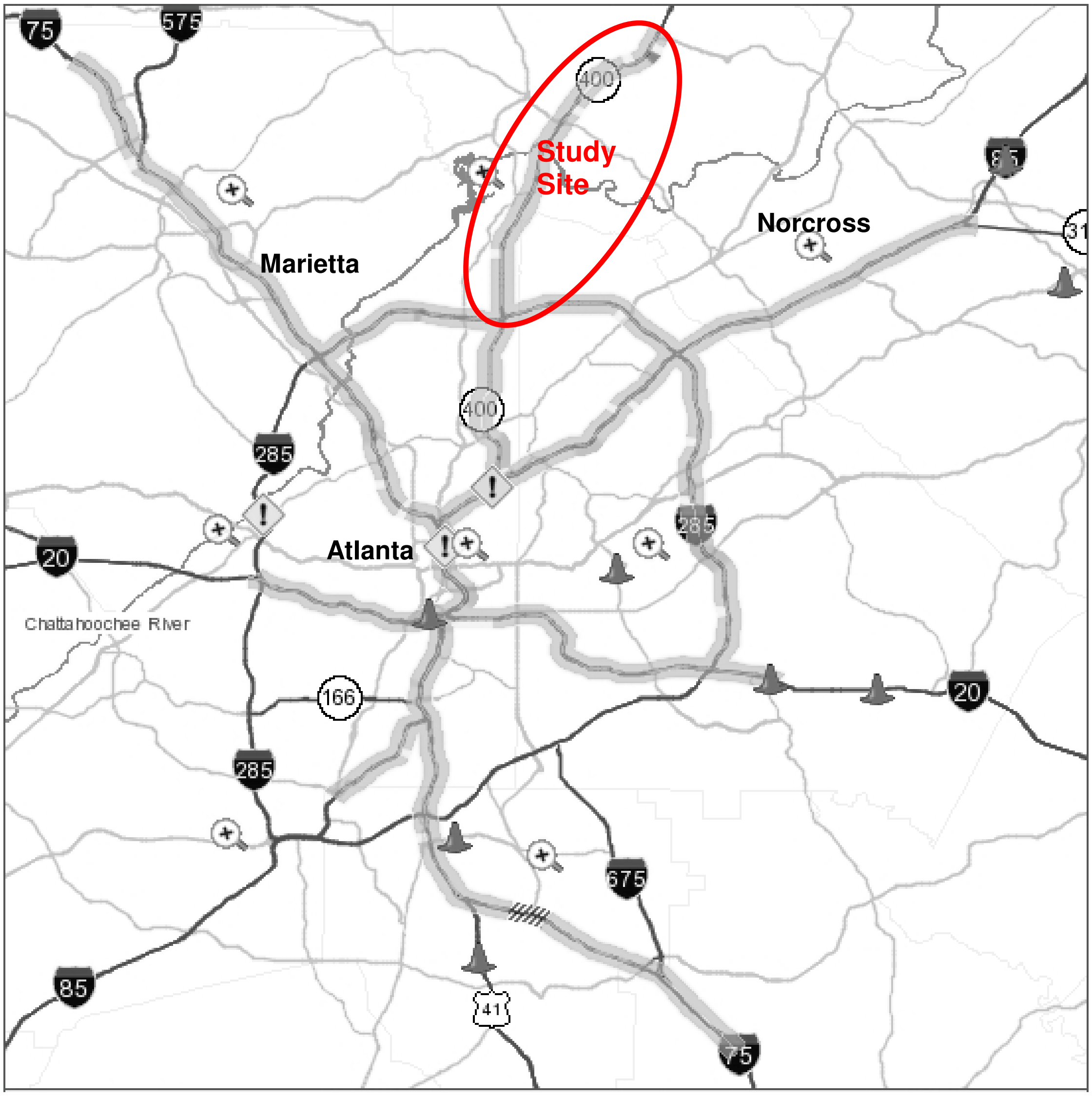

Figure 5.1: Study site map

5.3.2 Operations Data Description

Traffic conditions on the study site are monitored by video cameras which are deployed approximately every one-third mile of the road for each direction. One camera usually covers all the lanes in a single direction of the roadway. An image-processing software running in the background extracts traffic data from the videos using virtual loops placed over each lane to act as vehicle detectors. Traffic data is reported (mostly for bandwidth concerns) every 20 seconds. In most cases the names of the fields in the record-sets are self explanatory. However, detailed information regarding the computation of the fields in the dataset could be obtained from the equipment manufacturer in only a limited number of cases. Explanations based on the values in the fields are provided wherever possible. There were some fields that were not provided by the specific detection system although these fields are part of the overall architecture. This is duly noted where applicable in the explanations provided below. The fields in a typical sample are as follows:

- **Detector ID**: The ID associated with a detector at an observation station, e.g., 400178.
- **Sample Start Time**: Start time of the sample, e.g., 2003/10/01 13:02:00 EDT. The data is reported by the start time of sampling and not the end time of the sample. So for data between 13:00:00 and 13:00:20 the start time would be 13:00:00.
- **Status**: The activation status for a detector. The typical status codes are:
    - NO_ACT (No activation)
    - OK
    - SENSOR_FAILURE

- **Confidence**: The confidence of the current sample as reported by the processing software. The values range between 0 and 10, with 0 for minimum confidence and 10 for maximum confidence.
- **Volume Auto**: Count of passenger cars for the 20-second interval.
- **Volume Van**: Count of vans detected for the 20-second interval.
- **Volume Truck**: Count of trucks detected for the 20-second interval.
- **Volume Other**: Not provided by this system. This field is used for data from other systems where the vehicles are not categorized for the volume data.
- **Time Occupancy**: Percent of time, per 20 second interval, the detector has a vehicle present.
- **Space Occupancy**: Not provided by this system.
- **Time Mean Speed**: Time mean speed (TMS), in mi/h.
- **Space Mean Speed**: Not provided by this system.
- **Length**: Average length of the vehicles in the 20 second interval in metric units. The values of the variable in this field tend to repeat. For example, about 1000 samples in a day reported the length as exactly 8.2021. It leads the author to believe that this field is computed based on some preset thresholds.
- **Level of Service**: Not provided by this system.
- **Flow**: Not provided by this system.
- **Density**: A surrogate for traffic density computed as follows:

  Density in number of cars per km = (1000 * total number of cars in 20 seconds) / (total headway in meters + total length in decimeters / 10)

- **Gap**: Average gap between vehicles (in milliseconds).
- **Headway**: Not provided by this system.
- **Alarms**: Congestion alarms generated based on low speeds.

5.3.3 Data Statistics

Table 5.1 provides the data availability rates for the data. About 11 percent data is missing from the overall dataset. The missing rate is higher in the Northbound dataset than the Southbound dataset.

Table 5.1: Operations Data Statistics

Description	*Data Availability (percent)*	
	NB	***SB***
Mainline data per detector per day	85.36	90.35
Ramp data per detector per day	89.10	90.36
Missing days per month	1.4	

5.3.4 Incident Database Description

The incident database maintained by the Georgia DOT's TMC provides valuable information regarding time, location, response and severity of past incidents on the freeway network under surveillance. Following is a description of the fields from this database for which data were obtained for this study:

- **Incident ID:** A unique identifier assigned to each incident. Every update for the incident status is entered in the database as a new record, so there can be several records with the same Incident ID.
- **Incident Type Name:** Some pre-defined types of incidents. The available types are:
    - Accident
    - Construction
    - Congestion
    - Debris
    - Stall
    - Other Closure
    - Other
- **Detection Type Name:** Some pre-defined detection types. The available types are:
    - Call Report
    - Operator detected
    - Other
    - Unknown
- **Primary Route:** The primary roadway on which the incident occurred.
- **Secondary Route:** Name of the intersecting roadway closest to the incident for the purpose of locating the incident.
- **Location Type Name:** The type of the facility where the incident occurred, for example: Freeway, Exit Ramp, Intersection, Arterial etc.

- **Location Text:** Gives the same information as contained separately in the fields Direction, Primary Route and Secondary Route.
- **Direction:** Direction of travel of the primary route in which the incident occurred.
- **Affected Lane Type ID:** An ID for the lanes affected by the incident. The mapping of the Affected Lane Type ID to the Affected Lane Type Name is as follows:
    - 0 : None
    - 1 : Left lanes
    - 2 : Rights lanes
    - 3 : Center lanes
    - 4 : All lanes
    - 5 : Off road (left)
    - 6 : Off road (right)
    - 7 : Left shoulder
    - 8 : Right shoulder
    - 9 : Gore area (left)
    - 10 : Gore area (right)
- **Affected Lane Type Name:** Explanation of the Affected Lane Type ID.
- **Num Lanes Affected:** Number of lanes affected. This field can be used to assess the severity of an incident to some extent.
- **Segment ID:** An ID for the road-segment nearest to the incident. A node is placed wherever there is a change in road features like lane add/drop, barrier

add/drop, ramps, etc. The connector between the nodes forms a link. This link node system was used for this study. However, for an incident-response operation, the location of an incident is important only with its reference to the available entry points into the access controlled freeway – namely the on and off ramps. Therefore a segment is defined as a combination of all the links between two successive on-ramps. The link ID is inconsequential to the incident management system – the segment ID is the important location parameter. However, for the current research effort, the segment IDs were too coarse for use because of the length of the segments and lane IDs if available would have been of more use in verifying the node numbers between which the incident had occurred.

- **Estimated End:** An estimate by the operator regarding the time when the incident is expected to be cleared.
- **Impact Type Name:** The observed impact of the incident on the traffic. The categories are High, Medium, Low and No Impact. The information in this field is highly subjective, depending largely on operator training and experience, and is not useable in drawing definitive conclusions regarding the effect of the incident on the traffic in this research.
- **Number Calls:** Total number of calls that are answered for each incident. However, since responding to the incident deserves and receives higher priority than filling in the logs, this field is rarely populated consistently. For this reason, even this field was not usable in drawing definitive conclusions regarding the effect of the incident on the traffic in this research.

- **Reported Via Name:** This field is applicable only for scheduled closures due to construction or otherwise and provides information regarding the method of information acquisition. The only valid entries observed are “Highband” and “Phone”.
- **Scheduled Start:** This field is applicable only for scheduled closures due to construction or otherwise and provides the time when the closure is scheduled to start.
- **Scheduled End:** Similar to the previous field, this field is applicable only for scheduled closures due to construction or otherwise. It provides the time when the closure is scheduled to end.
- **Actual Start:** Similar to the “Scheduled Start” field, this field is applicable only for scheduled closures due to construction or otherwise. It provides the time when the closure actually goes into effect.
- **Actual End:** Similar to the previous field, this field is applicable only for scheduled closures due to construction or otherwise. It provides the time when the closure actually ends.
- **Confirm Flag:** When the incident is confirmed by an operator visually (using the closed circuit TV cameras) or otherwise, this field is set to 1. The default value of this binary is 0.
- **Confirm Time:** This field gives the time when the incident was confirmed by the operator.
- **Last Update Time:** This field is automatically entered by the system when an update is made to the status of an incident. The last entry for the update time

for a given incident ID can be used as a reasonably accurate log of the time of termination of the incident.

- **Action Pending:** This field gives an ID for the actions that need to be performed – such as “a HERO is needed”, “alarm time has expired” etc.
- **Plan Flag:** This is an indication that the automated response plan generation package has something to suggest for the given conditions.
- **Alarm Interval:** This field indicates how often the system will generate an alarm indicating an operator should review and update the status of an incident.
- **Incident Level:** This field gives an indication of the severity of the incident in a scale of 0-4. This is a GDOT classification scheme based on a number of factors defined in the operator training manual.
- **Comment:** This field gives textual description of the exact nature of the incident.

5.3.4.1 Data Limitations

The incident database is quite extensive and provides valuable information regarding the incidents; however, it has a few limitations.

As can be seen from the metadata description in Section 5.3.4 there is a field called Location-Text. This field is filled by the operators in real time and consists of a subjective description of the location. More often than not, the location description is quite ambiguous and can be interpreted in many ways.

The other major limitation is the time-stamp for the beginning of the incident. Every time an input is made, a new row is added to the table. The incident-id is repeated but the other information is updated. The database has a column called incident-start. This column is automatically filled when the data is entered and uses the concurrent time as the input value. There is no data-field that gives the exact time of occurrence of the incident.

The first issue can be dealt with by providing a GIS based input for the location or providing several fields that can be optionally filled, e.g. milepost, distance from nearby interchange, etc. The second issue can be dealt with by adding a field for "estimated start time" which is to be filled by the operator by using an estimated value at the beginning of the incident. While either of these recommendations cannot ensure perfectly precise information, they would reduce the uncertainty regarding location and time of incident to a large extent and would facilitate simulation or reconstruction of the incident scenarios more accurately.

5.3.4.2 Assumptions

Given the limitations of the incident database some assumptions were made in order to be able to work with the available data. The following assumptions addressed the spatial and temporal data inadequacies discussed in Section 5.3.4.1:

1. Each incident is associated with a detector station as can be estimated from the textual description of the location. If an incident is indicated by an algorithm at

the associated station or the immediate adjacent stations, the incident is assumed to be correctly detected by the algorithm.

2. Each incident is associated with the time-stamp of its first log. If an incident is detected by an algorithm within a reasonable time before or after the logged time-stamp (e.g. 15 minutes before the log and 5 minutes after the log), the incident is assumed to be correctly detected by the algorithm.

3. The average detection time as estimated by the Navigator system in the survey is 7 minutes. Based on this, it is assumed that all incidents occur 7 minutes before the logged time, and this assumption is used for computing the detection time of an incident for a given algorithm.

5.4 Data Processing

As outlined in Section 5.3, the data is in two parts, the operations data that is a time series data-set reported every 20 seconds and the incident database data that is an event based data-set which is updated only when new information about an incident is available. The following subsections outline the steps involved in processing and reduction of the dataset.

5.4.1 Operations Data

5.4.1.1 Preprocessing: Archiving

The first pre-processing step involved the archival of the incoming data. The data came into the data-server as compressed ASCII files containing individual data for each detector for each timestamp. Each file typically contained 10 minutes of data for all detectors at 20 second intervals for the given network. On a daily basis, the files for a day were uncompressed and separated by detectors. An ASCII file was created for each detector for all timestamps in a day. The data for the different lanes were combined (using a station to detector mapping configuration file) to produce the station data that reported the aggregate over all lanes. During the aggregation the vehicle count data was not inflated if one of the lanes reported missing data. However, the information about missing data was preserved in the "Status" field in the dataset. The average speed values were aggregated by performing a weighted average over lanes with the vehicle counts as the weights. The occupancy data was simply averaged over lanes. The text-based fields were concatenated with a pipe delimiter. A zipped archive file was created for all detectors for a given day. Similarly another zipped archive file was created for all stations for a given day for archival purposes.

5.4.1.2 Preprocessing: Extraction

The second step involved the extraction of the data and preparing the data-sets for input into the incident detection algorithm. The operations data was fed into the detection algorithm in batches. Each batch consisted of a full day of data for a given set of stations or detectors. Data processing scripts were created in Perl (Practical Extraction and Reporting Language) for extracting the data from the compressed archive files by using a filter file. The filter file allowed for specification of the date, time-period, station numbers or detector numbers and aggregation levels for extraction of the data.

Lane-by-lane data as well as aggregate-over-lanes data were used for development of the algorithm. However, the lack of a satisfactory model for accurately modeling lane changing behavior of vehicles at a macroscopic level, led to the use of aggregate-over-lanes model rather than the individual-lane model.

5.4.1.3 Filtering

The third step involved filtering the data. A custom low-cum-medium pass filter, based on the Yule-Walker filter, was used for the purpose. The choice for the filter was made based on a theoretical analysis of the frequency response of several filters as discussed by Coifman (1992), rather than an empirical analysis. This filter preserves the short term fluctuations of the data, unlike the double exponential smoothing filter, while blocking the high frequency fluctuations of the data (see Figure 5.2). Preserving the short term fluctuations is essential for this algorithm which depends on these fluctuations for incident detection. At the same time, elimination of the high frequency fluctuations was essential for reducing false alarms produced in the algorithm. Moreover this filter, unlike several other digital signal processing filters, allowed filtering of the data based completely on the past values without using any future values. This was essential since, the future values are unknown in a real time application such as this.

The filter was designed and developed using the Yule-Walker formulation. The coefficient matrixes for a filter of order 10 are provided in Table 5.2.

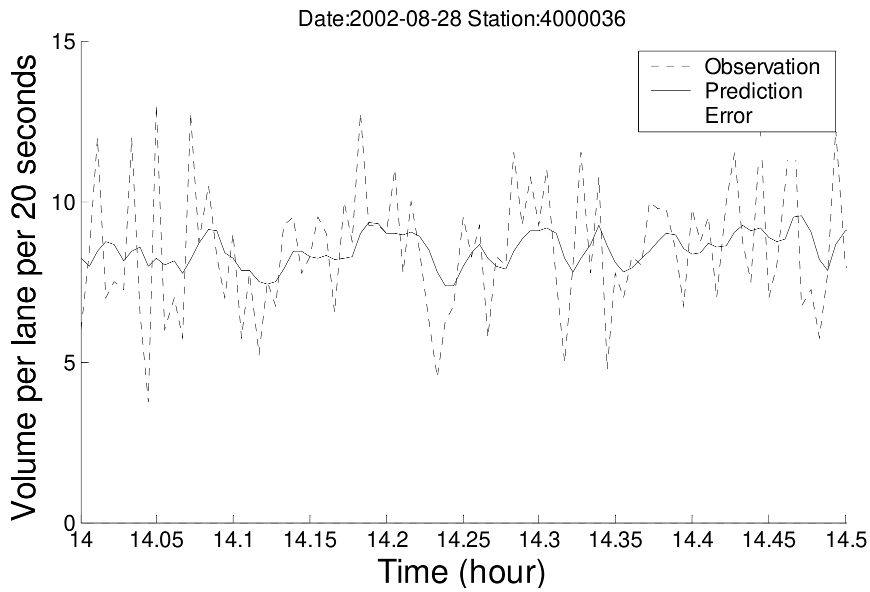

Figure 5.2: Comparison of Filtered Data with Raw Data

Table 5.2: Coefficient Matrix Values for Middle Pass Filter

A (Coefficient of *X(n)*)	**B (Coefficient of *Y(n-1)*)**
0.13919	1
0.13641	-1.1442
0.027146	0.56886
0.14102	0.36461
0.099818	-0.16553
-0.00499	-0.2869
0.076142	0.59387
0.057854	-0.26574
0.016263	0.01469
0.026533	0.052754
0.00645	-0.0105

The steps in the application of this filter are as follows:

1. A series of m consecutive data-points is taken to form a m x 1 matrix X_{mx1}. A higher value of m involves more computations, whereas a lower value of m gives a less accurate filter. A value of 10 gives a filter that is sufficiently accurate as shown in the frequency response diagram in Figure 5.3. The filtered-data matrix Y_{mx1} is initialized with a zero vector of size m x 1.

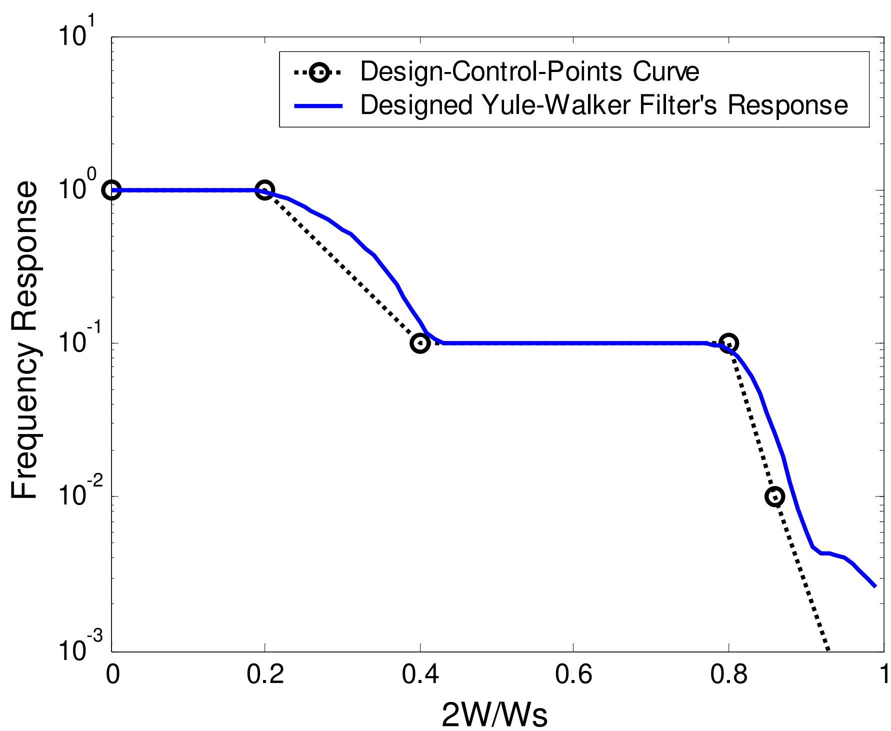

Figure 5.3: Frequency Response of Custom Middle-Pass Filter

2. The filtered data Y_{mx1} at a given step is obtained using the coefficient matrixes A_{1xm} and B_{1xm} and the matrixes X_{mx1} from the current step and Y_{mx1} from the previous step with the following matrix manipulation:

$$Y(n)_{mx1} = A_{1xm} \mathrm{x} X(n)_{1xm} - B_{mx1} \mathrm{x} Y(n-1)_{mx1} \quad 5\text{-}1$$

Figure 5.2 shows the time-series plot of the instantaneous flow values for a raw signal overlaid with a filtered signal. The smoothing effect of the signal is quite evident from the plot. It should be noted that the peaks and troughs in the raw signal are preserved to a large extent in the filtered signal because of the design of the filter that allows the medium frequency perturbations to pass. Preserving these features is vital to the functioning of the incident detection algorithm. However, a closer look at the plot and comparison of the peaks of the two signals will show that a lag of about 3 time-steps is introduced by using the filter. While this does not affect the accuracy of incident detection algorithm, it definitely causes an increase in the detection time. Figure 5.4 and Figure 5.5 show the time series plots of predictions and observations for the raw and filtered data respectively.

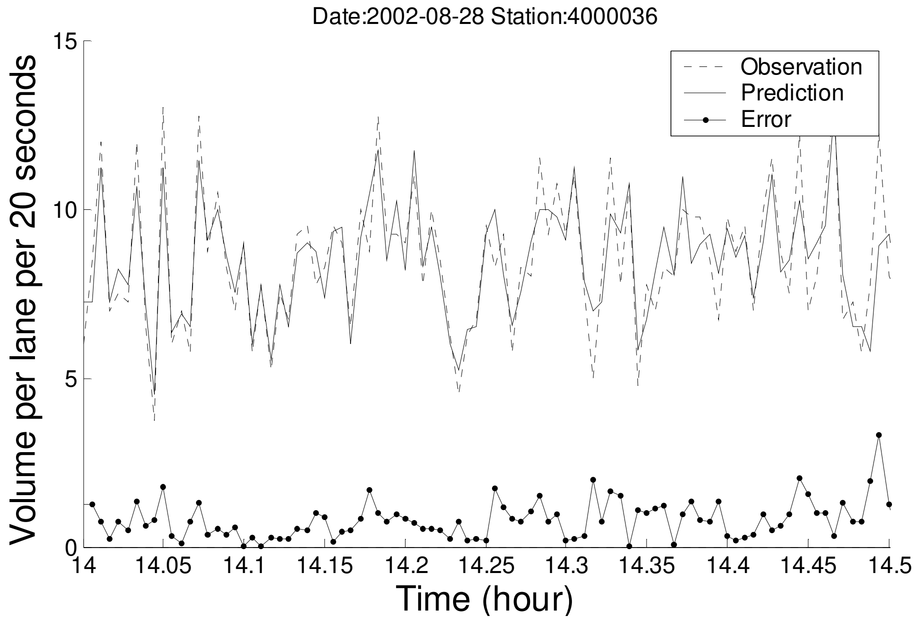

Figure 5.4: Predictions of Volume using Raw Data

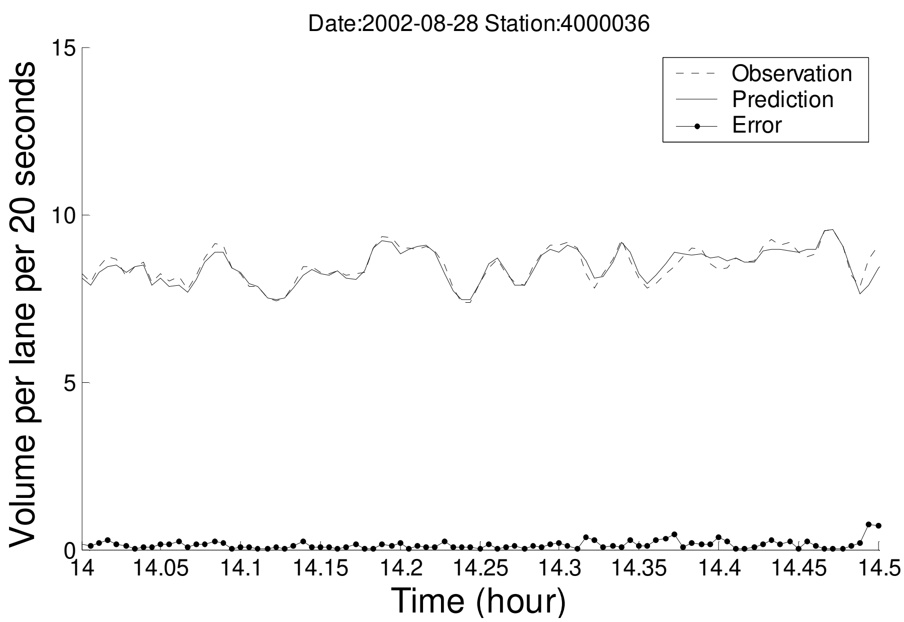

Figure 5.5: Predictions of Volume using Filtered Data

Table 5.3 shows the results from the paired-t test on the Mean Absolute Prediction Error (MAPE) for raw data and filtered data. The actual MAPE values for the two cases are available in Table C.1 in Appendix C. It can be concluded from Table 5.1 that the null hypothesis where the difference of the means of the two MAPEs is less than 4.1 can be rejected at 95% level of confidence. It can be safely concluded that the MAPE for predictions with the filtered data is significantly less than the MAPE for predictions with raw data.

Table 5.3: Paired-t Test for Mean Absolute Percentage Error of Predictions using Raw and Filtered Data with Model-C

Hypothesized Mean Difference = 0		
	Raw	Filtered
Mean	9.332955	4.50327
Variance	39.89519	22.83533
Observations	35	35
Pearson Correlation	0.942875	
Hypothesized Mean	0	
df	34	
t Stat	11.8512	
P(T<=t) one-tail	6.35E-14	
t Critical one-tail	1.690923	
P(T<=t) two-tail	1.27E-13	
t Critical two-tail	2.032243	

Hypothesized Mean Difference = 4.1
data:
x: Raw in ModelC , and
y: Filtered in ModelC
t = 1.7905, df = 34, p-value = 0.0411
alternative hypothesis: true mean of differences is greater than 4.1
95 percent confidence interval:
4.140587 NA
sample estimates:
mean of x - y: 4.829685

5.4.2 <u>Incident Database</u>

5.4.2.1 Location Information

As explained in section 5.3.4.1 the incident database lacks accurate location and time of occurrence information. The subjective "location text" information was converted to programmable objective information by linking the incidents to stations. A lookup table was created that provided the station number for a given cross-road name. In some cases this led to a one-to-many mapping. For example a station could be North, South or at road "x". Because of the non-uniformity of the style in which a location was referred to, these keywords could not be included in pinpointing the station. So a search using road "x" produced several station numbers. All these station numbers were assigned to the incident. The cases where multiple station numbers existed required a manual confirmation for the assignment. This increased the data processing time substantially. Inclusion of some more specific information regarding the location could have helped avoid this scenario. Of course if the subjective data input in the logs was replaced by an objective input, involving station numbers rather than road names, the confidence in the data could have improved significantly.

5.4.2.2 Severity of Effect on Traffic

The database has fields like Incident Type, Affected Lane Type, Affected Lane Number, Impact Type, and Incident Level. These fields give some idea about the severity of the incident and the possible effects on the traffic. However the actual effect was not accurately reflected by any combination of these fields. Sometimes a stall on the shoulder had more effect than an incident in the first lane. Therefore it was necessary to inspect the actual data for effects. Time series plots were produced for each station and inspected individually or in juxtaposition to identify possible effects. No severity classifications were made. Depending on whether there were any discernable effects, the incidents were associated with a binary value – 1 meaning "possibly had effect" and 0 meaning "had no effect at all". Fifty percent of the total incidents were screened out at this stage as having no effects on the traffic at all.

5.5 Model Evaluation

5.5.1 LCT Vs DSPM

Pertaining to the discussion in Chapter IV Section 4.6, the DSPM model is better suited to the current application based on a theoretical analysis. The hypothesis can therefore be stated as:

The DSPM model is better than the LCT model for one step predictions.

For hypothesis testing the null hypothesis can be stated as:

The mean absolute percentage error for the LCT model is equal to the mean absolute percentage error for the DSPM model.

For a one sided test, the alternative hypothesis would be:

The mean absolute percentage error for the LCT model is greater than the mean absolute percentage error for the DSPM model.

To verify this hypothesis, the two models were used to produce predictions and their MAPEs were computed based on a comparison with the actual observations. This was performed over all the non-incident days in the test dataset. The MAPE data for the individual stations over several days is presented in Table C.2 and Table C.3 in Appendix C. The author used a paired-t test to compare the MAPE values individually for each day. The results of a paired-t test are presented in Table 5.4. It was observed that the MAPE for the DSPM model was significantly smaller than the MAPE for the LCT model across all days. The empirical results, therefore, verified our hypothesis that the DSPM model performs better than the LCT model for one step predictions.

Table 5.4: Paired-t Test for MAPE of Predictions using DSPM Model C and the LCT Model

(a) Filtered Data

Hypothesized Mean Difference = 0		
	LCT	***ModelC***
Mean	5.22823	4.50327
Variance	22.84297	22.83533
Observations	35	35
Pearson Correlation	0.947548	
Hypothesized Mean	0	
df	34	
t Stat	2.770842	
P(T<=t) one-tail	0.004499	
t Critical one-tail	1.690923	
P(T<=t) two-tail	0.008998	
t Critical two-tail	2.032243	

Hypothesized Mean Difference = 0.28
data:
x: LCT in Filtered , and
y: ModelC in Filtered
t = 1.7007, df = 34, p-value = 0.0491
alternative hypothesis: true mean of differences is greater than 0.28
95 percent confidence interval:
0.2825486 NA
sample estimates:
mean of x - y: 0.7249602

(b) Raw Data

Hypothesized Mean Difference = 0		
	LCT Model	***Model C***
Mean	10.05778	9.332955
Variance	37.78388	39.89519
Observations	35	35
Pearson Correlation	0.964734	
Hypothesized Mean	0	
df	34	
t Stat	2.577823	
P(T<=t) one-tail	0.007225	
t Critical one-tail	1.690923	
P(T<=t) two-tail	0.014449	
t Critical two-tail	2.032243	

Hypothesized Mean Difference = 0.22
data:
x: LCT in Models , and
y: ModelC in Models
t = 1.7243, df = 34, p-value = 0.0469
alternative hypothesis: true mean of differences is greater than 0.24
95 percent confidence interval:
0.2493758 NA
sample estimates:
mean of x - y: 0.7248251

5.5.2 <u>Regime Separator</u>

Density and Speed were both good indicators of the traffic flow regime at a site. The MAPEs for predictions by using speed and density as regime separators had a significant difference between their means as can be seen from the results of the paired-t test (see Table 5.5; the data is in Table C.3 in Appendix C). Although Table 5.5 shows that the difference of mean is quite small (0.029) at 95% level of confidence, it implies that there exists a small but significant difference between the means of the percentage errors in the two cases (speed cutoff giving lesser percentage errors). Along with the empirical evidence to support, the flow versus density plots (Figure 5.6 and Figure 5.7) clearly show that speed has a sharper regime separation than density. The trend of movement from one regime was observed to be steadier for speed than for density. Hence speed was chosen as the regime separator for the DSPM model.

Table 5.5: Paired-t Test for Mean Absolute Percentage Error of Predictions using Different Regime Separators

Hypothesized Mean Difference = 0			***Hypothesized Mean Difference = 0.029***
	Density Cutoff	***Speed Cutoff***	
Mean	4.540403	4.474101	data:
Variance	22.94294	22.27866	x: DensityCutoff in SpdDen , and
Observations	35	35	y: SpeedCutoff in SpdDen
Pearson Correlation	0.999736		t = 1.7025, df = 34, p-value = 0.0489
Hypothesized Mean	0		alternative hypothesis: true mean of differences is greater than 0.029
df	34		
t Stat	3.026196		95 percent confidence interval:
P(T<=t) one-tail	0.002348		0.02925416 NA
t Critical one-tail	1.690923		sample estimates:
P(T<=t) two-tail	0.004695		mean of x - y: 0.06630171
t Critical two-tail	2.032243		

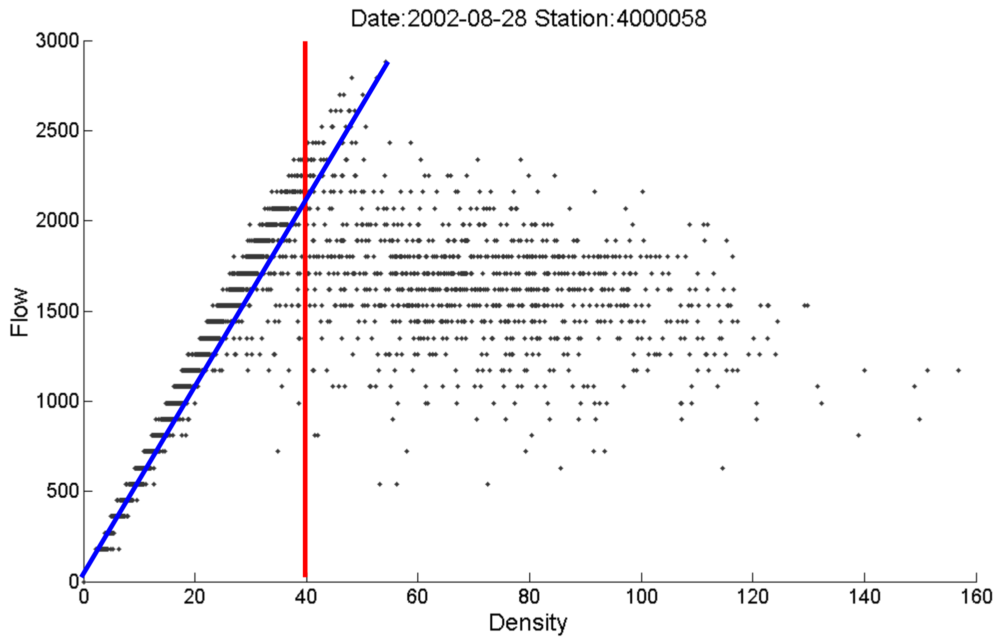

Figure 5.6: Flow versus Density Plot for a Station that Identifies the Regime Separation Density Threshold

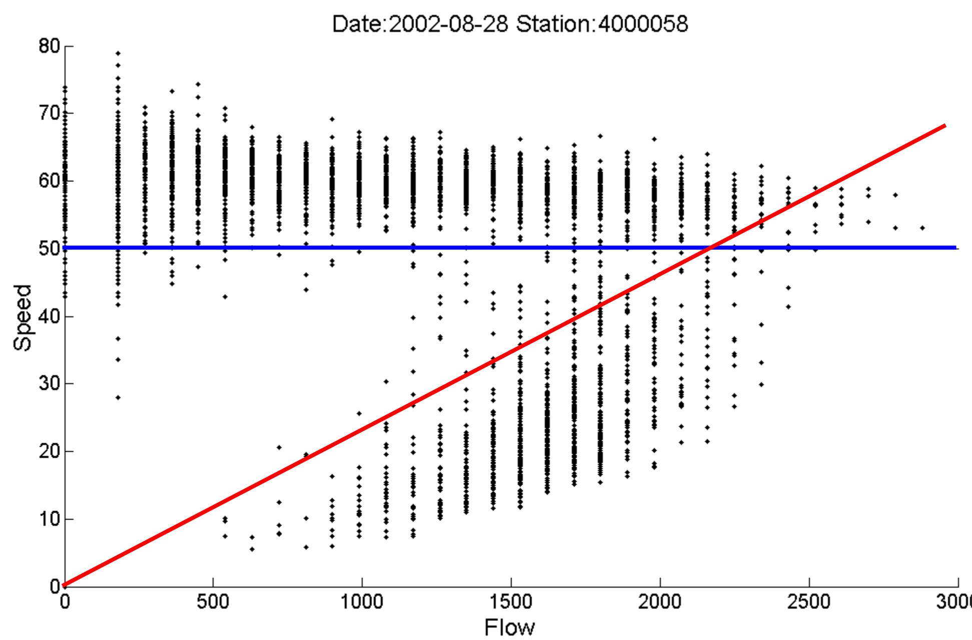

Figure 5.7: Speed versus Flow Plot for a Station that Identifies the Regime Separation Speed Threshold

5.5.3 Dynamic Pace Updating

The speed of the traffic varies spatially depending on the geometric conditions of the road. A static calibration can be performed at the beginning of deployment to incorporate these variations into the model. However, such a calibration procedure would require substantial manual work. A methodology involving a strategy of dynamic pace updates helped eliminate such manual calibration. The forward wave pace values used in the computations ($1/S_k.\varepsilon$) were updated in every time step for each station using the concurrent speed at that station. This of course added to the computational demands but the increase in accuracy and the considerable reduction in the manual calibration effort amply justified it. Moreover this methodology has the capability of adapting to long-term changes (such as the change induced by geometric changes to the section) as well as short term changes (such as night time and day time driving speeds) in traffic behavior. While the improvement in accuracy was marginal in cases where the generically assumed free-flow speed matched well with the actual free-flow speed at the station, the improvement was quite evident for the cases where the actual free-flow speed was different from the assumed free flow speed. Since, the pace updates made a difference only in cases where the traffic speed at the station differs from the assumed free-flow speed, it was meaningless to compare the overall errors for the two cases. A paired-t test was not deemed appropriate for this case. Rather a visual comparison is used here to illustrate the effect.

Figure 5.8 shows the time series plot of 20 second volume observations and predictions for the two cases. "Prediction(Static)" represents the predictions with assumed static forward wave-pace values. "Prediction(Dynamic)" represents the predictions with dynamically updated forward wave-pace values. It is quite apparent from the figure that Prediction(Dynamic) is consistently closer to the observations than Prediction(Static) is to the observations. Figure 5.9 shows the prediction errors from Prediction(Static) and Prediction(Dynamic). Again the Prediction(Dynamic) errors are consistently less than the Prediction(Static) errors, thereby clearly showing the superiority of the dynamic updating of forward-pace values methodology over the static calibration methodology.

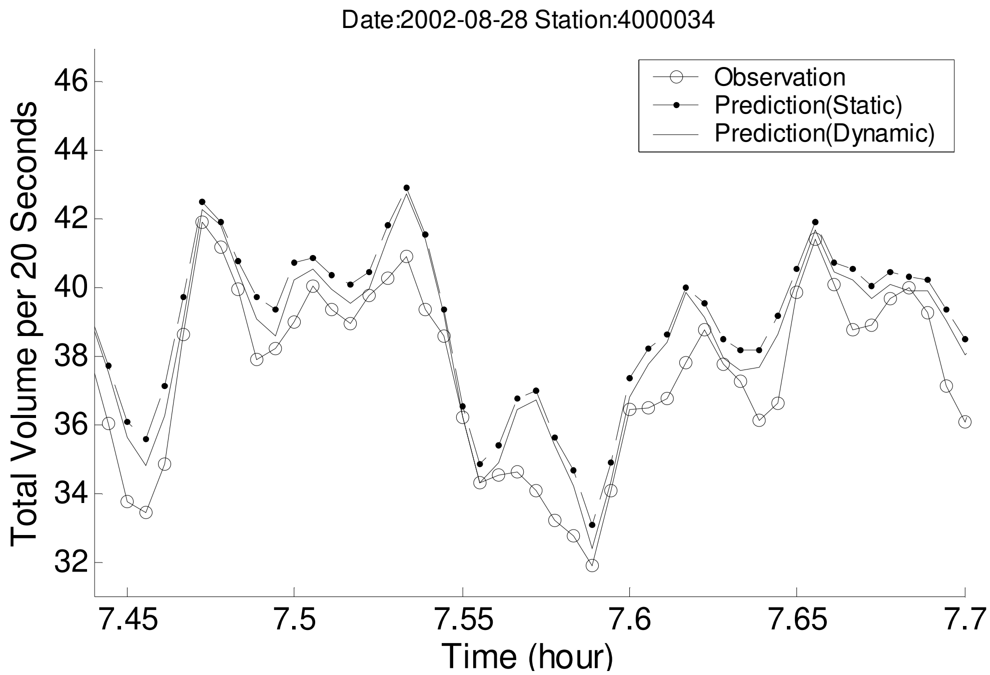

Figure 5.8: Effect of Dynamic Pace Updates on Predictions

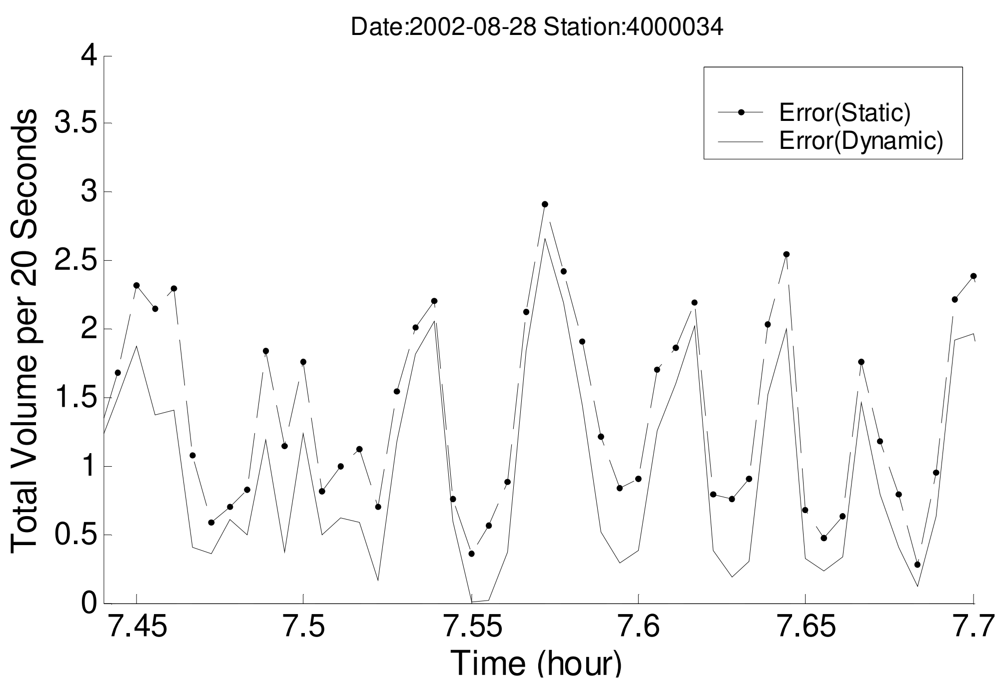

Figure 5.9: Effect of Dynamic Pace Updates on Prediction Errors

5.5.4 Alternative Models

The prediction methodology primarily had four models depending on the flow conditions at the given station and its adjacent stations. The conditions of applications are as follows:

Uncongested Regime:	Model I
Congestion Downstream:	Model II
Congestion Upstream:	Model III
Bottleneck at Detector Station:	Model IV

Model I has four alternative models embedded in them as represented by I-A, I-B, I-C, I-D respectively. As discussed in Chapter IV, Section 4.7, all the four alternative models are theoretically sound and perfectly viable options. To choose between the alternatives, an empirical approach is adopted.

A visual comparison of the output from model B, C and D is presented in Figure 5.10 and Figure 5.11.

The alternatives are compared based on their MAPEs. Table C.2 and C.4 in Appendix C shows MAPEs obtained from the different alternatives for the different stations using data from only the incident free days. Table 5.6 and Table 5.7 show the results of the paired t-test among the different alternatives. A significant difference between the mean of MAPEs of Model B and Model C is observed. The mean of MAPEs for Model B is significantly greater than the mean of MAPEs for Model C. On the other hand, no significant difference was observed between the mean of MAPEs of

Models D and C. However, referring to the discussion in Section 4.7.1, Model C eliminates the necessity of waiting for data from the next timestep for the prediction step. This provides a marginal temporal advantage for the overall incident detection process because with Model C, the prediction step can be completed before the observation for comparison comes in. Model C is therefore chosen wherever possible for rest of the algorithm development process.

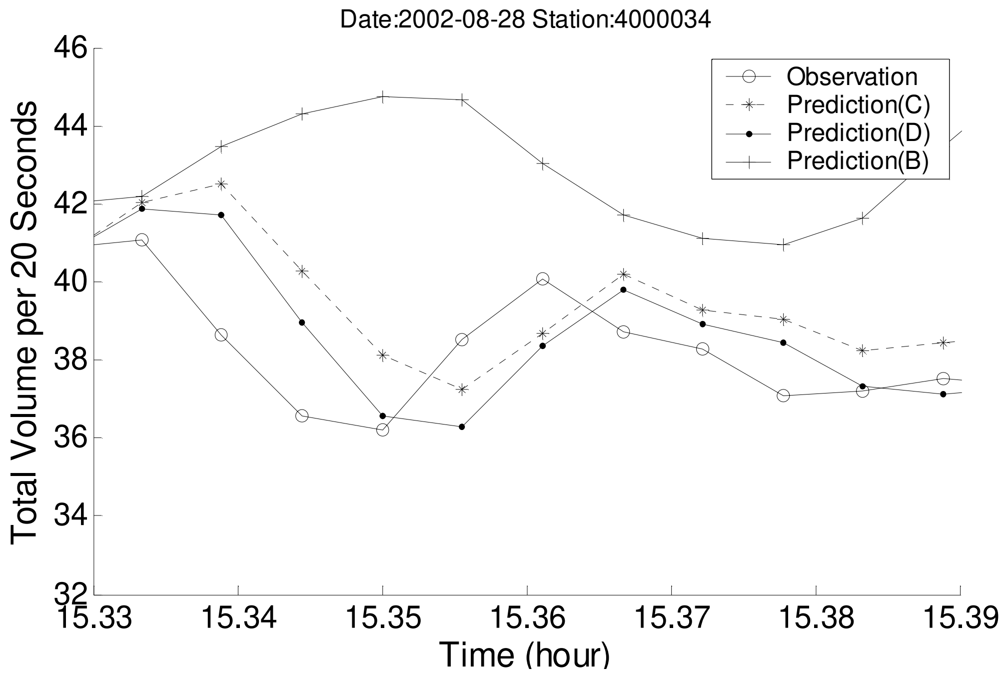

Figure 5.10: Effect of Alternative Models on Predictions

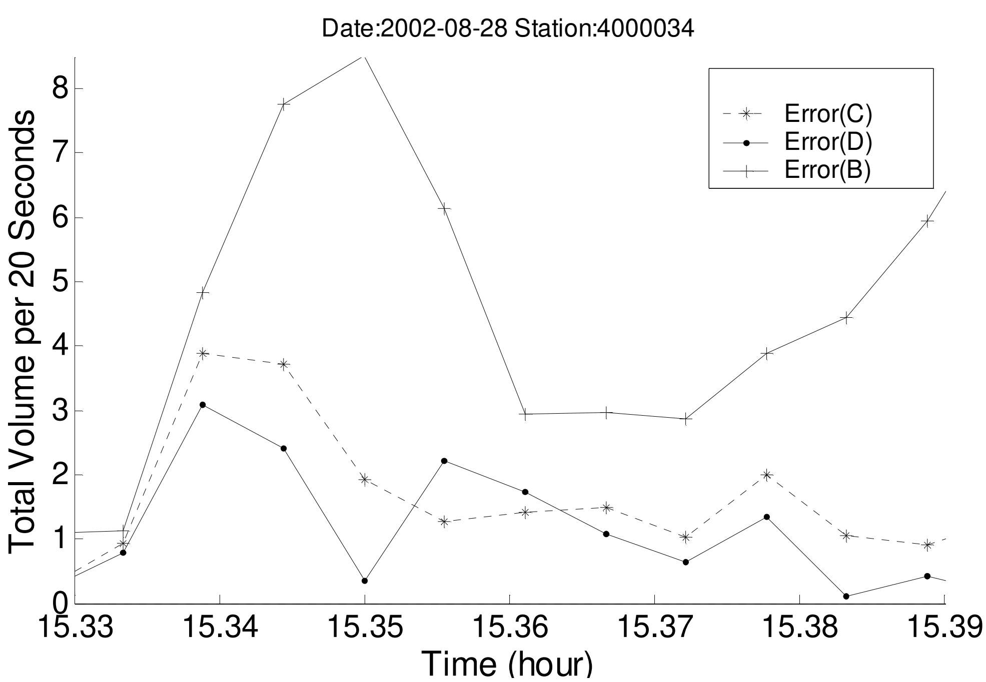

Figure 5.11: Effect of Alternative Models on Prediction Errors

Table 5.6: Paired-t Test for MAPE of Predictions using Model C and Model D

(a) Filtered Data

Hypothesized Mean Difference = 0		
	Model C	***Model D***
Mean	4.50327	4.470522
Variance	22.83533	22.33568
Observations	35	35
Pearson Correlation	0.997692	
Hypothesized Mean	0	
df	34	
t Stat	0.592222	
P(T<=t) one-tail	0.27881	
t Critical one-tail	1.690923	
P(T<=t) two-tail	0.55762	
t Critical two-tail	2.032243	

Hypothesized Mean Difference = 0
data:
x: ModelC in Filtered , and
y: ModelD in Filtered
t = 0.5922, df = 34, p-value = 0.5576
alternative hypothesis: true mean of differences is not equal to 0
95 percent confidence interval:
-0.07962918 0.14512560
sample estimates:
mean of x - y: 0.03274821

(b) Raw Data

Hypothesized Mean Difference = 0		
	Model C	***Model D***
Mean	9.332955	9.022858
Variance	39.89519	34.82645
Observations	35	35
Pearson Correlation	0.996518	
Hypothesized Mean	0	
df	34	
t Stat	2.792248	
P(T<=t) one-tail	0.004265	
t Critical one-tail	1.690923	
P(T<=t) two-tail	0.008529	
t Critical two-tail	2.032243	

Hypothesized Mean Difference = 0.12
data:
x: ModelC in Models , and
y: ModelD in Models
t = 1.7117, df = 34, p-value = 0.048
alternative hypothesis: true mean of differences is greater than 0.12
95 percent confidence interval:
0.1223093 NA
sample estimates:
mean of x - y: 0.3100977

Table 5.7: Paired-t Test for MAPE of Predictions using Model B and Model C

(b) Filtered Data

Hypothesized Mean Difference = 0		
	Model B	***Model C***
Mean	4.920566	4.50327
Variance	24.06704	22.83533
Observations	35	35
Pearson Correlation	0.979047	
Hypothesized Mean	0	
Df	34	
t Stat	2.470497	
P(T<=t) one-tail	0.009333	
t Critical one-tail	1.690923	
P(T<=t) two-tail	0.018666	
t Critical two-tail	2.032243	

Hypothesized Mean Difference = 0.13
data:
x: ModelB in Filtered , and
y: ModelC in Filtered
t = 1.7009, df = 34, p-value = 0.049
alternative hypothesis: true mean of differences is greater than 0.13
95 percent confidence interval:
0.131679 NA
sample estimates:
mean of x - y: 0.4172962

(b) Raw Data

Hypothesized Mean Difference = 0		
	Model B	***Model C***
Mean	9.869086	9.332955
Variance	36.07588	39.89519
Observations	35	35
Pearson Correlation	0.98353	
Hypothesized Mean	0	
df	34	
t Stat	2.734139	
P(T<=t) one-tail	0.004929	
t Critical one-tail	1.690923	
P(T<=t) two-tail	0.009859	
t Critical two-tail	2.032243	

Hypothesized Mean Difference = 0.2
data:
x: ModelB in Models , and
y: ModelC in Models
t = 1.7142, df = 34, p-value = 0.0478
alternative hypothesis: true mean of differences is greater than 0.2
95 percent confidence interval:
0.2045613 NA
sample estimates:
mean of x - y: 0.5361303

5.6 Algorithm Evaluation

The primary purpose of the evaluation of the algorithm was to verify the hypothesis stated in section 5.1. The test was performed using 6 full months of operations data, in one direction (Northbound). Since the algorithm development phase used mostly the Southbound data, the Northbound data was used in the testing to avoid effects of over-fitting the model to the data (in this case over-calibration of the algorithm).

5.6.1 Implementation of Algorithm

A brief description of the implementation specific details is provided in this section to facilitate the reproducibility of this research. The algorithm was implemented, using MATLAB – a powerful research oriented mathematical programming tool. The implementation was "off-line" meaning that the data fed into the algorithm did not come in real time from a detection system but from archived data-files. The implementation had a modular architecture to introduce flexibility in the development and testing process. The modules can be identified as follows:

1. Run Specifier
2. Parameter Loader
3. Data Loader
4. Predictor
5. Alarm Generator
6. Result Logger

Run Specifier: The algorithm processed data one day at a time. This helped the off-line implementation programmatically by limiting the memory requirements. From a statistical standpoint this allowed for a study of the variability of the results across days instead of producing a single mean data-point for the whole period of study. At the same time this fitted into the research goals by creating a piece-wise continuous evaluation over the whole period of study. Statistics were reported on the basis of full day's worth of data in order to eliminate the problem of artificial boosting of results that had been faced by other works in this area that used small chunks of dataset around the period of a given incident and ignored data at other periods. Such a procedure of restrictive data use resulted in a limited testing of the algorithms whereby the conditions conducive to false alarms that could arise at other times of the day at other detection stations, were effectively eliminated. Given a short string of data-points around the incident focuses the algorithm of one scenario and it becomes quite easy for the algorithm to detect the incident without generating numerous false alarms. Therefore, data across all time periods and the full segment with multiple stations were always evaluated and reported concurrently in this research to ensure an accurate estimate of the false alarm rate.

The run specifier module was used to perform multiple iterations (for threshold calibration) when necessary. The threshold values for use in the alarm generator module were declared here.

Parameter Loader: The implementation used a number of parameters that were used to control the data usage, data processing and the models used for the different tasks. To ensure congruity of implementation, the different models were coded into the same module and the flow of the data through different models were controlled by the parameters that were declared in two parameter definition files and loaded in the memory using the parameter loader module.

Data Loader: The data loader module imported the ASCII data into the MATLAB workspace into a 3 dimensional array (with station number, time and variable name as the three dimensions). In addition, it loaded the station connectivity matrix which provided the linking information of the stations and mile-points of the stations from which the lengths of the links were computed. This module also loaded the incident location and time information.

Predictor: The different alternative models for traffic prediction were implemented in this module. The definition of the flow control parameters from the parameter loader module determined which model was to be used for prediction purposes. The predictions were appended to the data array for input into the alarm generator module. The decisions regarding which model (I, II, III, IV) is to be applied were based on the traffic conditions at the three stations. The decision tree for the model choice is shown in Figure 5.12.

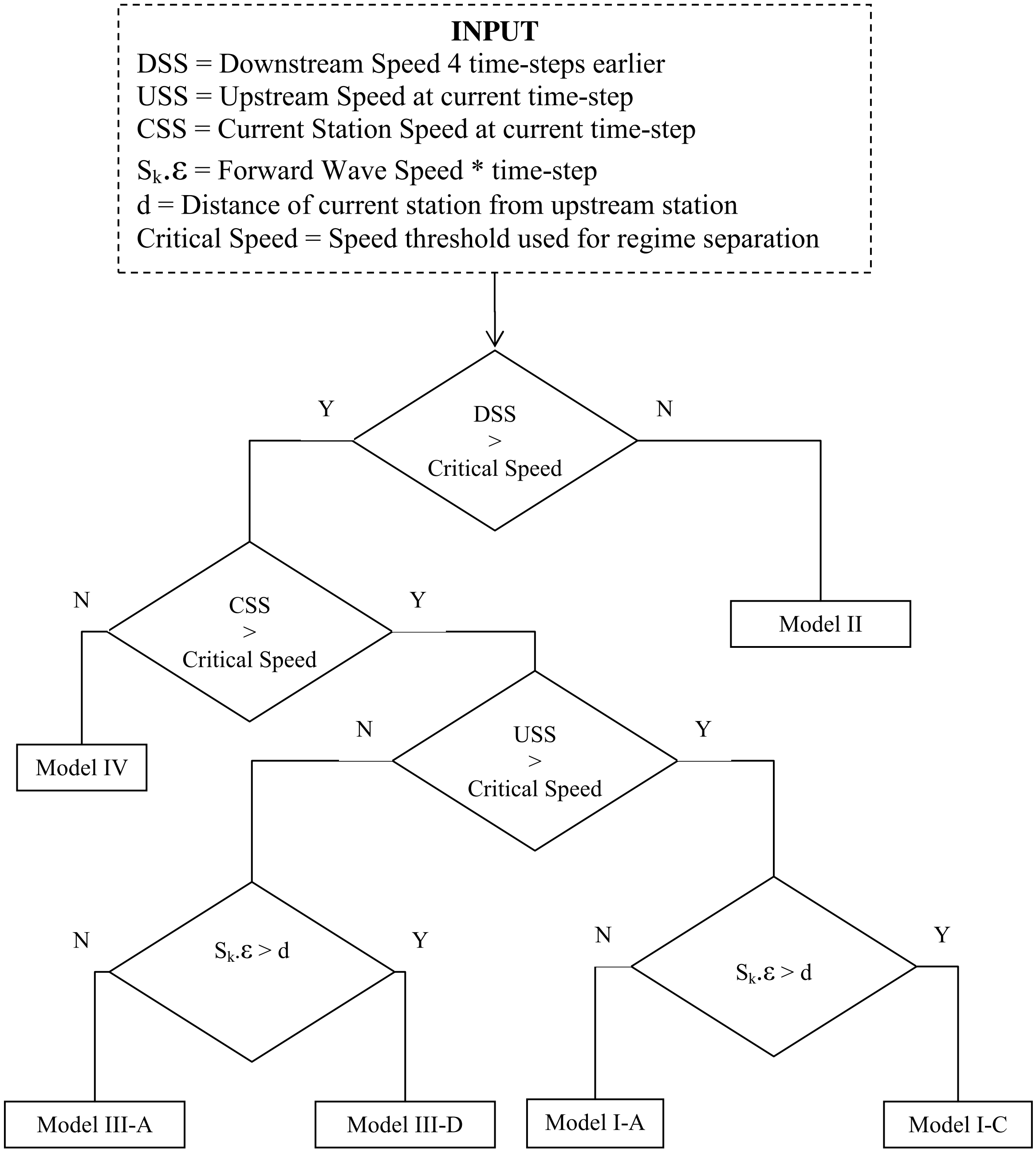

Figure 5.12: DSPM Algorithm Model Choice Decision Tree

<u>Alarm Generator:</u> The predictions in the predictor module were used along with the observations loaded in the data loader module to identify possible occurrences of incidents. The time and station number of each alarm was stored in an array and verified against the incident database information loaded in the data loader module.

<u>Result Logger:</u> This module was used to log into an ASCII file the results like number of alarms generated, number of incidents successfully detected, number of false alarms along with the control parameters.

5.6.2 Results

Appendix D provides the plots depicting the sensitivity of the detection-ratio to the different thresholds. The points in these plots are obtained by varying the values of a particular threshold while the other thresholds are restricted to marginal values such that their effect on the detection process is trivial. Table C.5 in Appendix C provides a summary of the results of iterations produced by varying the thresholds. The table provides the detection ratio versus false alarm rate data which is plotted in Figure 5.13. As can be seen in the plot, a detection ratio of 1, implying 100% detection, is obtained at a false alarm rate of 0.069 % as a good-case scenario and 0.11 % as an average-case scenario. These results compare favorably with the best results (using real data as opposed to simulated data) reported in the literature.

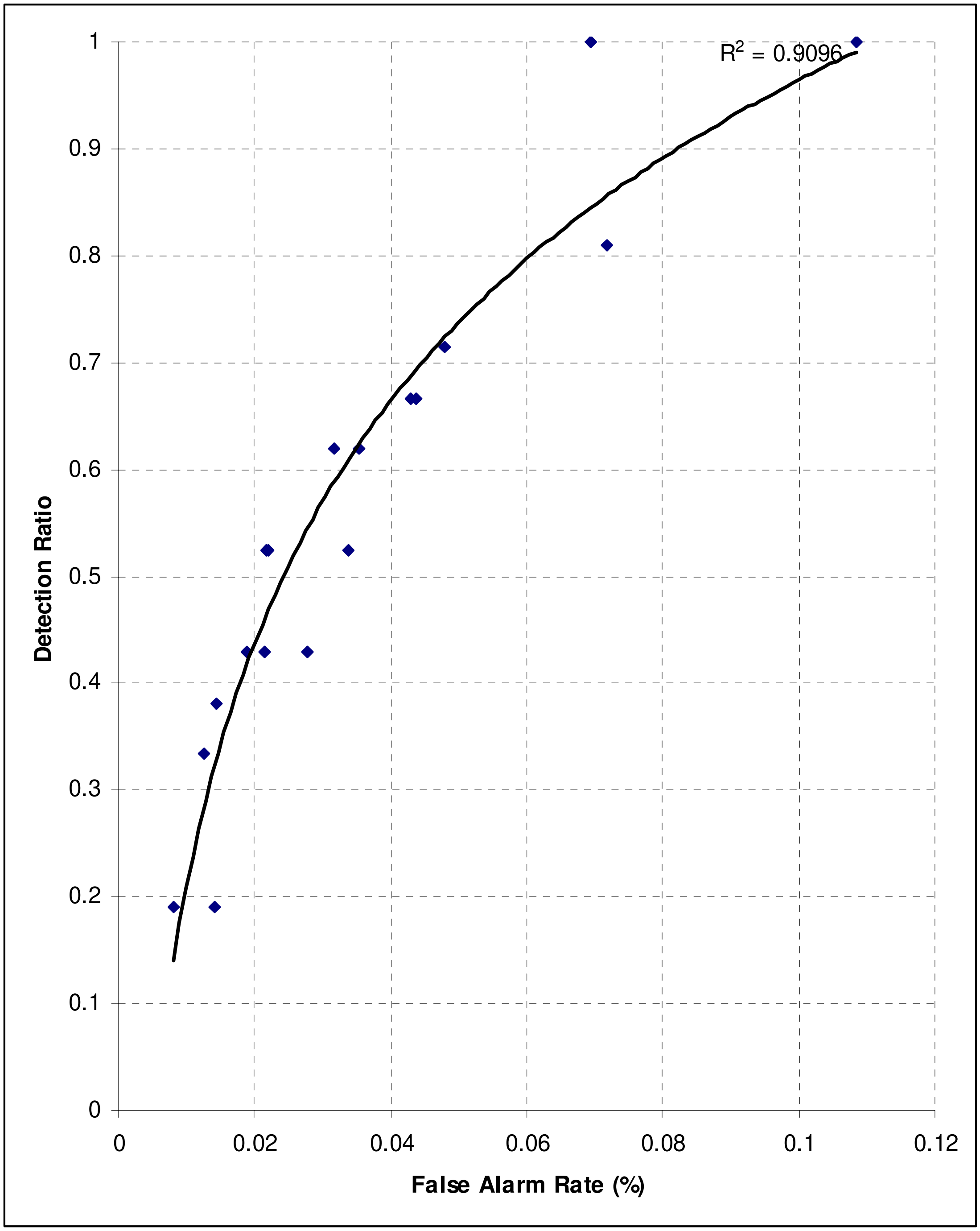

Figure 5.13: Detection Ratio Vs False Alarm Rate for DSPMID Algorithm

5.7 Comparative Evaluation

The evaluation of the algorithm would not be complete without a comparative evaluation against other contending algorithms.

5.7.1 Choice of Algorithms for Comparison

The following factors were considered while making a choice of algorithms for comparison:

- Use of algorithm for comparison in previous research
- Reported results of algorithm performance
- Deployment history of algorithm
- Ease of implementation of algorithm
- Calibration requirements of algorithm

The California algorithms, in their original form or in a modified form (All Purpose Incident Detection Algorithm), are the most widely implemented and deployed algorithms. Since they are among the oldest algorithms, the California algorithms have also been widely used as a benchmark for comparison. The logic for the California algorithms is very well documented and is easy to implement. California algorithm #8 was chosen based on the reports of its performance and false alarm suppression capabilities.

The McMaster algorithm is the other algorithm that is comparable to a large extent to the California algorithm in terms of use as a benchmark and frequency of deployment.

The logic for this algorithm and its implementation is also quite well documented. This ensures that the implementation of the algorithm does not involve any misinterpretation of the algorithm logic.

It was found desirable to compare the algorithm's performance against that of more recently developed algorithms. Due to the recentness of their development, none of these newer algorithms have a deployment history. The Fuzzy Wavelet based Radial Basis Function Neural Network algorithm was chosen among these algorithms. Not only did this algorithm report very high performance results, the documentation for the implementation of the algorithm was detailed enough to ensure a proper implementation, unlike the other algorithms that had detailed explanation of their logic but little documentation regarding their implementation details.

5.7.2 Implementation of Algorithms

All the algorithms were implemented on the same platform using the same test datasets to ensure conformity and congruity among them. As an addendum to the descriptions of the algorithms provided in Chapter II Section 2.5, some more implemented oriented details are provided in the following sub-sections for ease of reference.

5.7.2.1 California Algorithm # 8

The California algorithm uses 1-minute lane occupancy values averaged across all lanes for its computations. Four derived variables are used along with the primary variable. The descriptions and definitions using a set of symbols consistent with Payne and Tignor's usage are provided in Table 5.8. The definitions of the states used in the algorithm logic are provided in Table 5.9. The decision tree for California algorithm # 8 is shown in Figure 5.14.

The California algorithm # 8 employs a compression wave suppression technique for elimination of false alarms. States 1 through 5 as defined in Table 5.9 achieve this suppression for 5 minutes by incorporating information from last 5 successive data points. However, the data in the current study was available at 20 second intervals. This presented two options: (a) aggregate the data to 1 minute intervals for a direct implementation of the original California Algorithm #8; (b) increase the number of compression wave states to 15 so as to cover 5 minutes. The second option was chosen to allow a fair comparison of performance. The algorithm modified accordingly. The changes are reflected in Table 5.10 and Figure 5.15.

Table 5.8: Variable Definitions for California Algorithm # 8

Feature	*Description*	*Definition*
OCC(i , t)	Occupancy (percent) at station i, for time interval t	
DOCC(i , t)	Occupancy (percent) downstream of station i, for time interval t	OCC(i + 1 , t)
OCCDF(i , t)	Spatial difference in occupancies between station i and the downstream station	OCC(i , t) – OCC(i + 1 , t)
OCCRDF(i , t)	Relative spatial difference in occupancies between station i and downstream station	OCCDF(i , t) / OCC(i , t)
DOCCTD(i , t)	Relative temporal difference in downstream occupancy	(OCC(i + 1 , t – 2) - OCC(i + 1 , t)) / OCC(i + 1 , t – 2)

Table 5.9: State definitions for the California algorithm # 8

State	*Designates*
0	Incident-free
1	Compression wave downstream in this minute
2	Compression wave downstream 2 minutes ago
3	Compression wave downstream 3 minutes ago
4	Compression wave downstream 4 minutes ago
5	Compression wave downstream 5 minutes ago
6	Tentative incident
7	Incident confirmed
8	Incident continuing

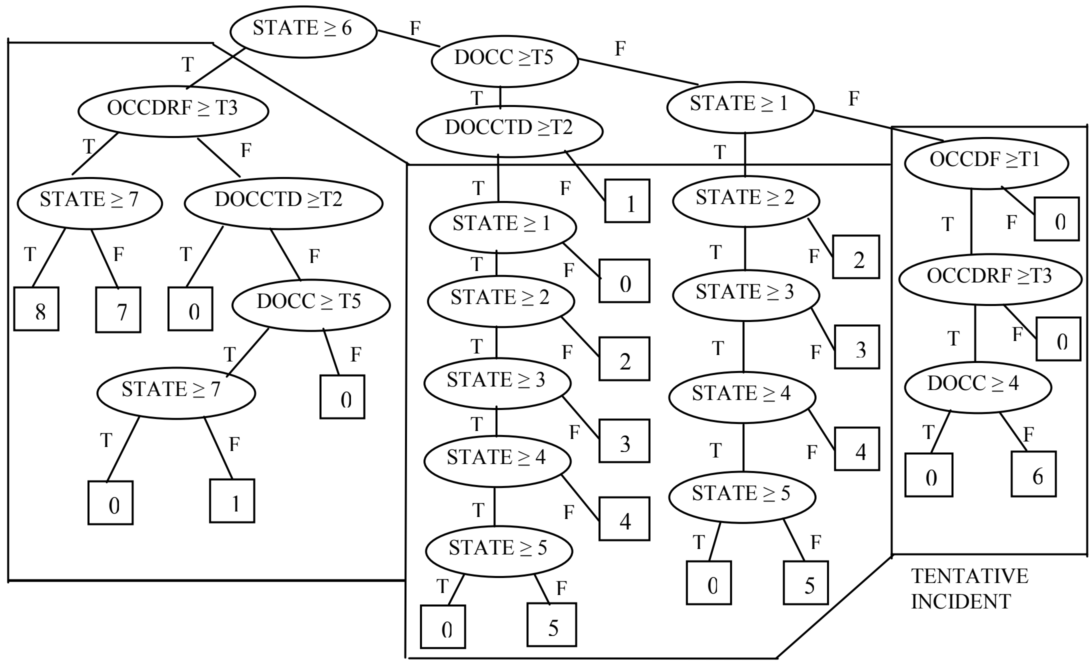

Figure 5.14: California Algorithm Decision Tree

Table 5.10: State definitions for the adapted California algorithm # 8

State	*Designates*
0	Incident-free
1	Compression wave downstream in this interval
1.33	Compression wave downstream in 40 seconds ago
1.66	Compression wave downstream 60 seconds ago
2, 2.33, 2.66	Compression wave downstream 80, 100 and 120 seconds ago respectively
3, 3.33, 3.66	Compression wave downstream 140, 160 and 180 seconds ago respectively
4, 4.33, 4.66	Compression wave downstream 200, 220 and 240 seconds ago respectively
5, 5.33, 5.66	Compression wave downstream 260, 280 and 300 seconds ago respectively
6	Tentative incident
7	Incident confirmed
8	Incident continuing

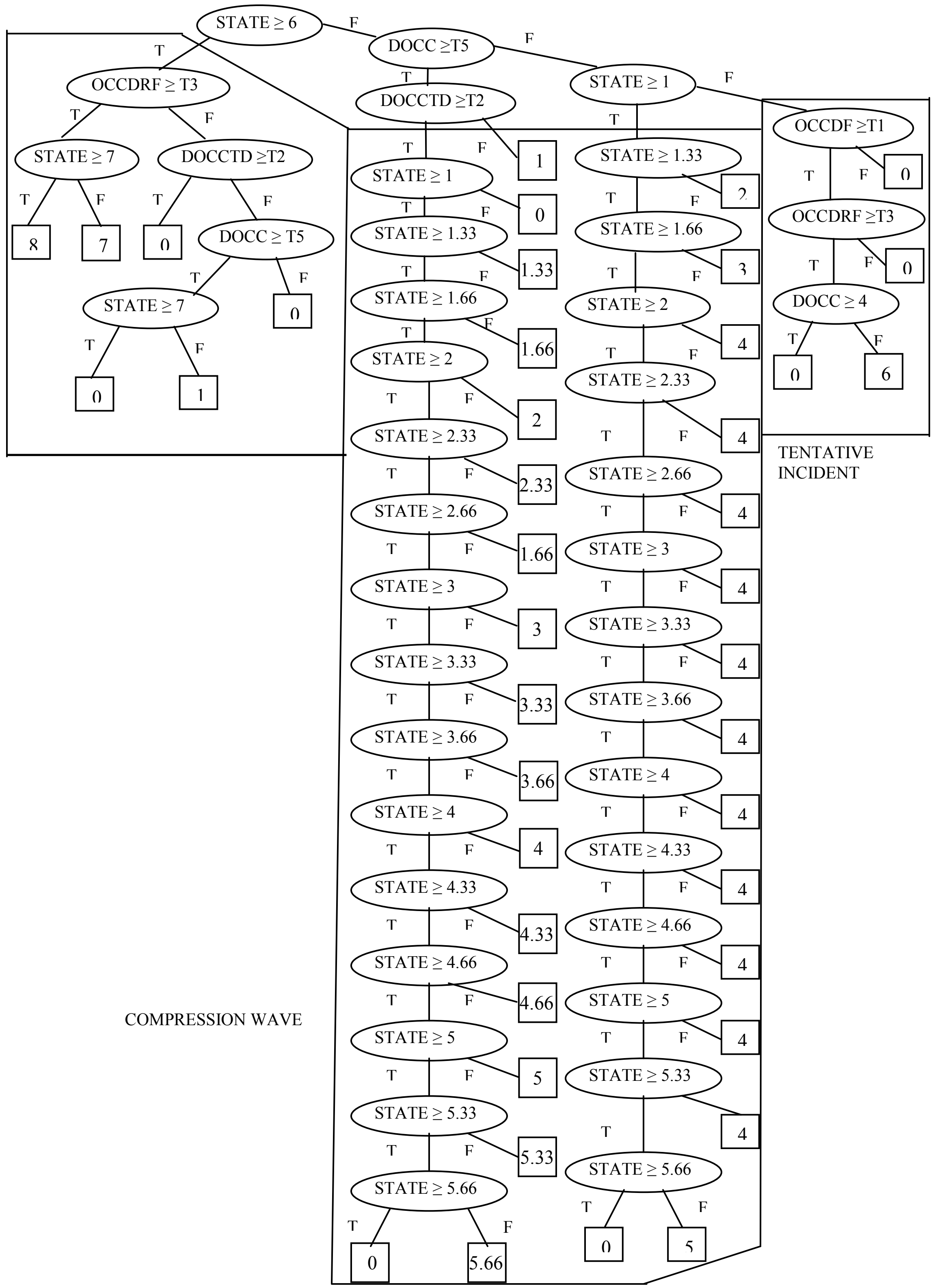

Figure 5.15: Adapted California Algorithm Decision Tree

5.7.2.1.1 Results

The California algorithm was tested with the same dataset as the DSPMID algorithm. The results of several iterations produced by varying the values of the several thresholds of the California Algorithm #8 are presented in the Figure 5.16. The data is pretty scattered and cannot as such be represented sufficiently with a curve. Two possible curves (albeit with sub-optimal fitting) are shown in the figure to illustrate the general trend of movement of the points in the Detection-Ratio versus False-Alarm-Rate space. It is worthwhile to note that the California algorithm succeeds in detecting most of the incidents like the DSPMID algorithm. This is in sharp contrast to the McMaster algorithm and the FWRBFNN algorithm as discussed in subsections 5.7.2.2.1 and 5.7.2.3.1.

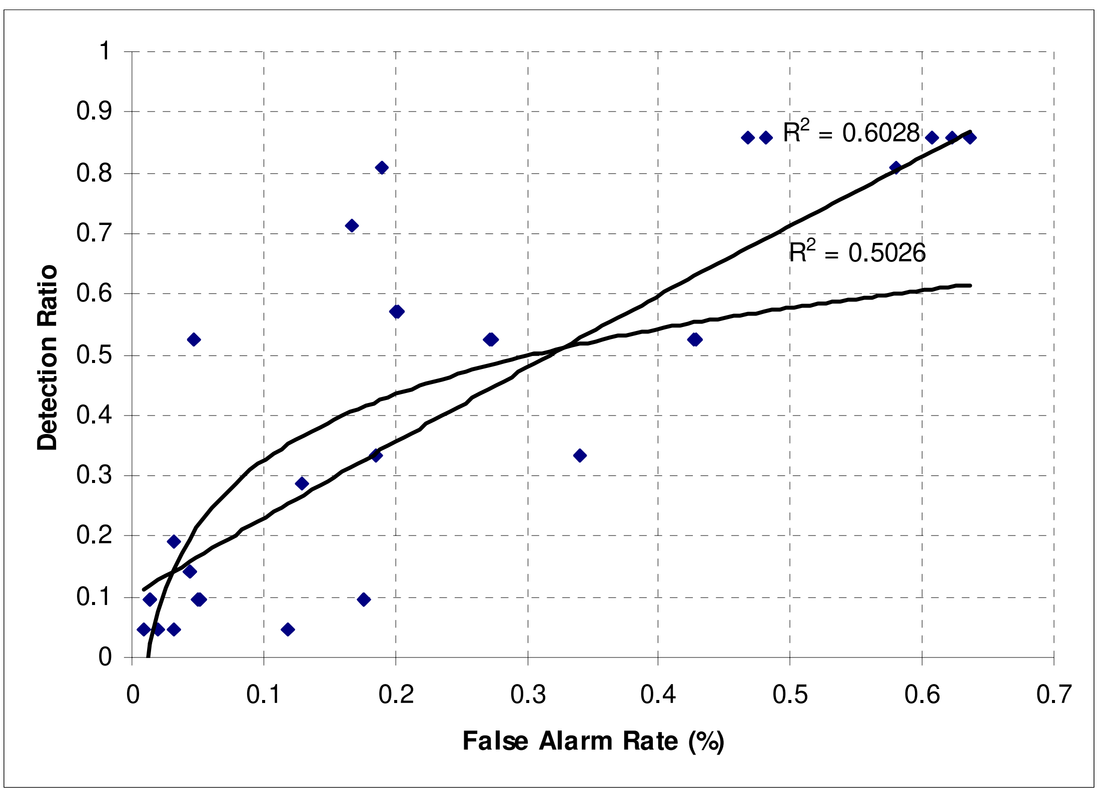

Figure 5.16: Detection Ratio Vs False Alarm Rate for California Algorithm

5.7.2.2 McMaster Algorithm

The McMaster algorithm uses a template such as the one shown in Figure 5.17. This template is calibrated for each station by calibrating the Critical Volume, Critical occupancy and *k*. The function *g(occ)*, derived from the catastrophe theory of traffic flow, represents the minimum predicted uncongested flow for station *i*. The template defines four states, state 1 represents uncongested flow, state 2 and 3 represent congested flow and state 4 represents bottleneck flow. The states are determined in the algorithm using the decision tree shown in Figure 5.18. The data is initially screened for missing data. If data is missing, data from the downstream station is used to act as the proxy data for the station. The data is then checked against the g(occ) function values and the critical volume (VCRIT) and critical occupancy (OCMAX) values for the given station. The decision logic for generating the alarms for an incident is shown in Figure 5.19. If the upstream station is congested and the downstream station is in state 1 or 2 (below critical occupancy), then the congestion is attributed to an incident. However if the downstream station is in bottleneck flow conditions, the upstream congestion is categorized as recurrent congestion. If the downstream station is in state 3, the state at the station downstream to it is used to determine the presence of an incident.

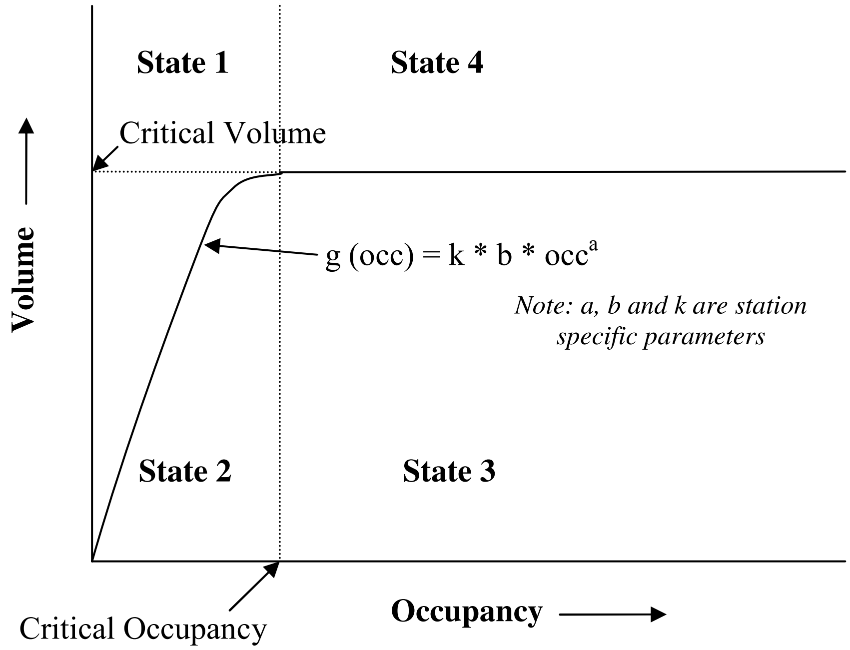

Figure 5.17: McMaster Template

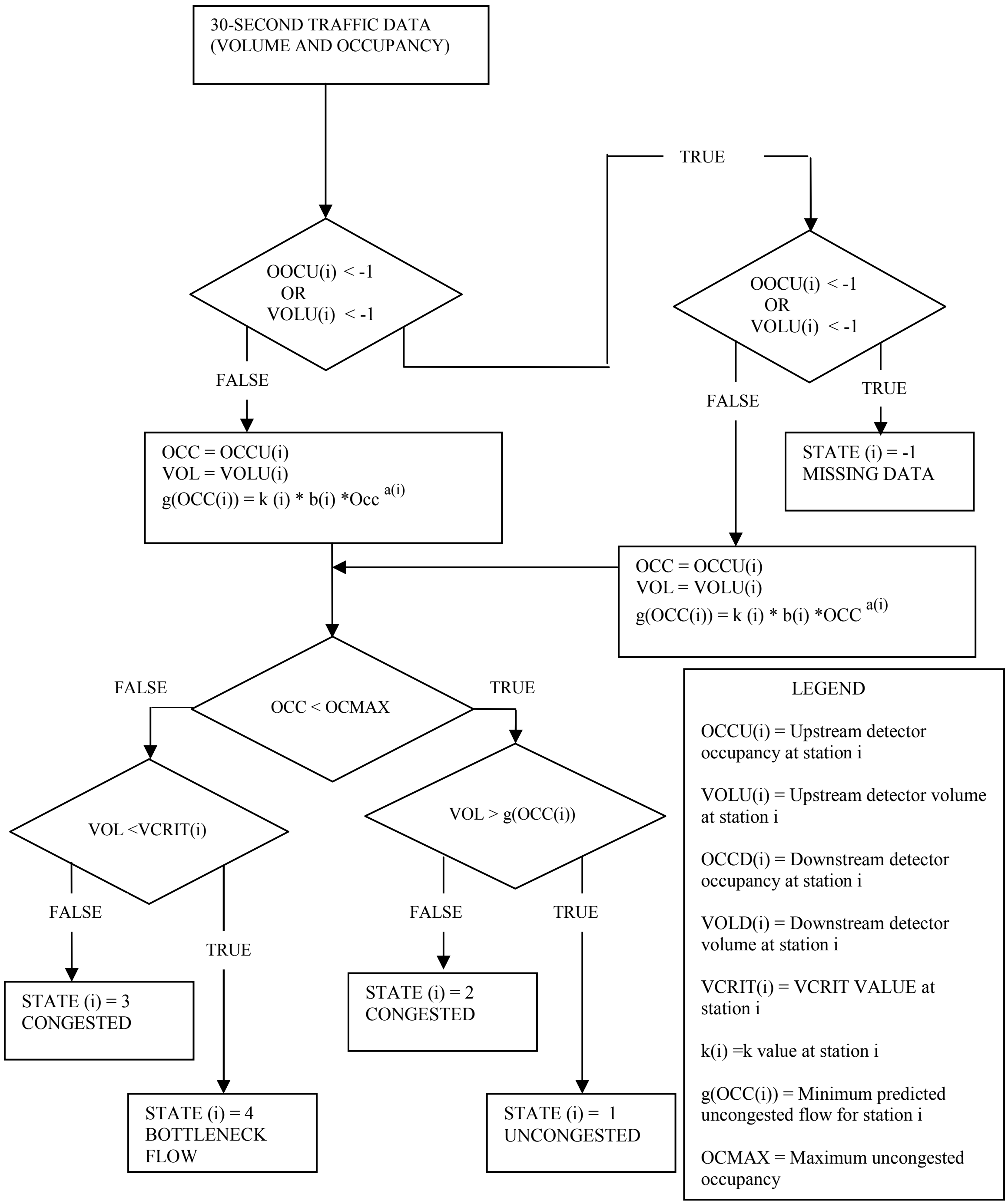

Figure 5.18: Decision Tree for Traffic State Classification in McMaster algorithm

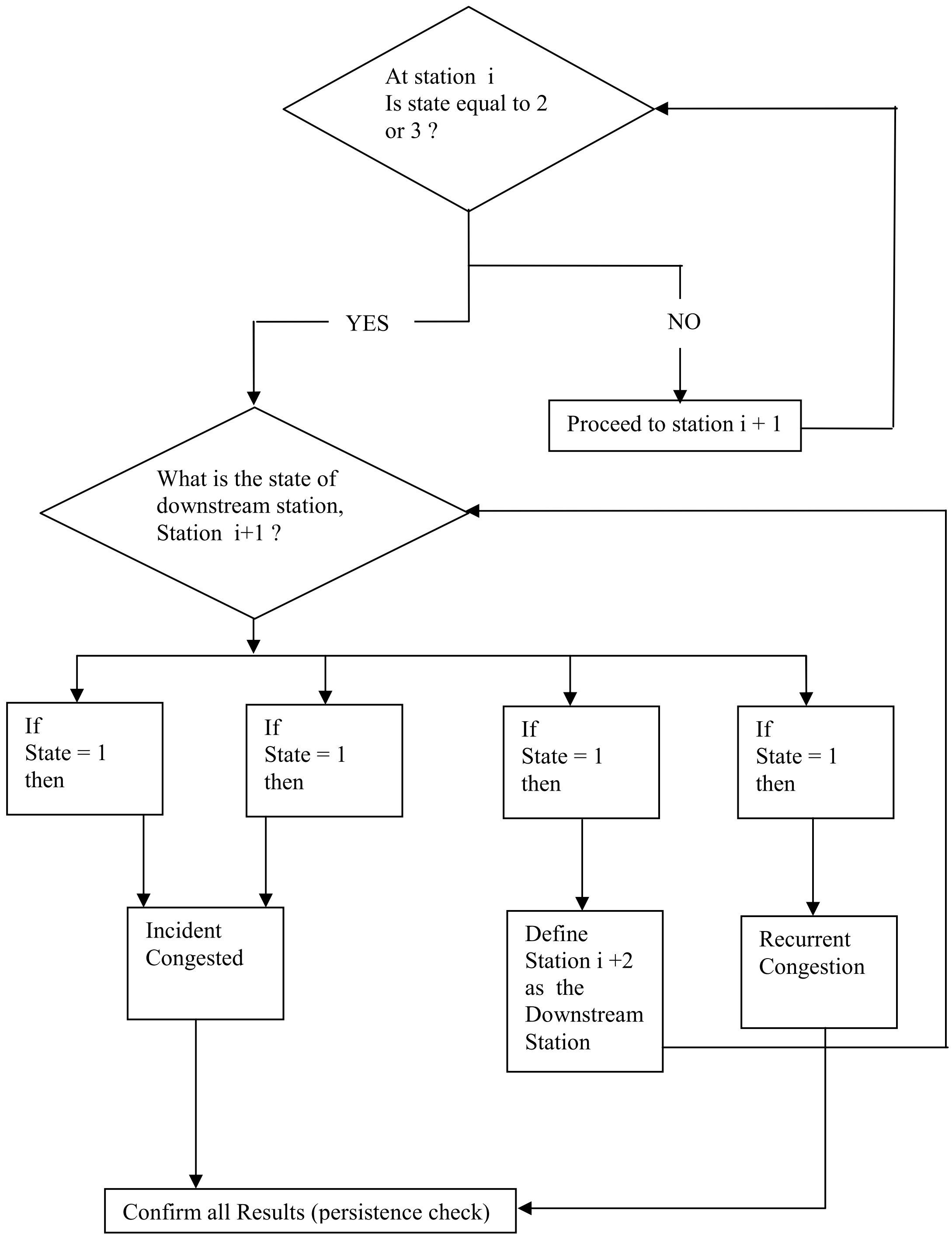

Figure 5.19: Flow Chart for Distinguishing between Recurrent and Incident Congestion in McMaster algorithm

5.7.2.2.1 Results

As can be seen in the detection-ratio versus false-alarm-rate plot in Figure 5.20, the McMaster algorithm did not respond actively to the thresholds in terms of the detection-ratio. The false-alarm-rate responded quite well to the thresholds. The algorithm produced a maximum detection ratio of 0.6 (which should ideally have been closer to 1.0) and failed to detect several of the incidents.[1]

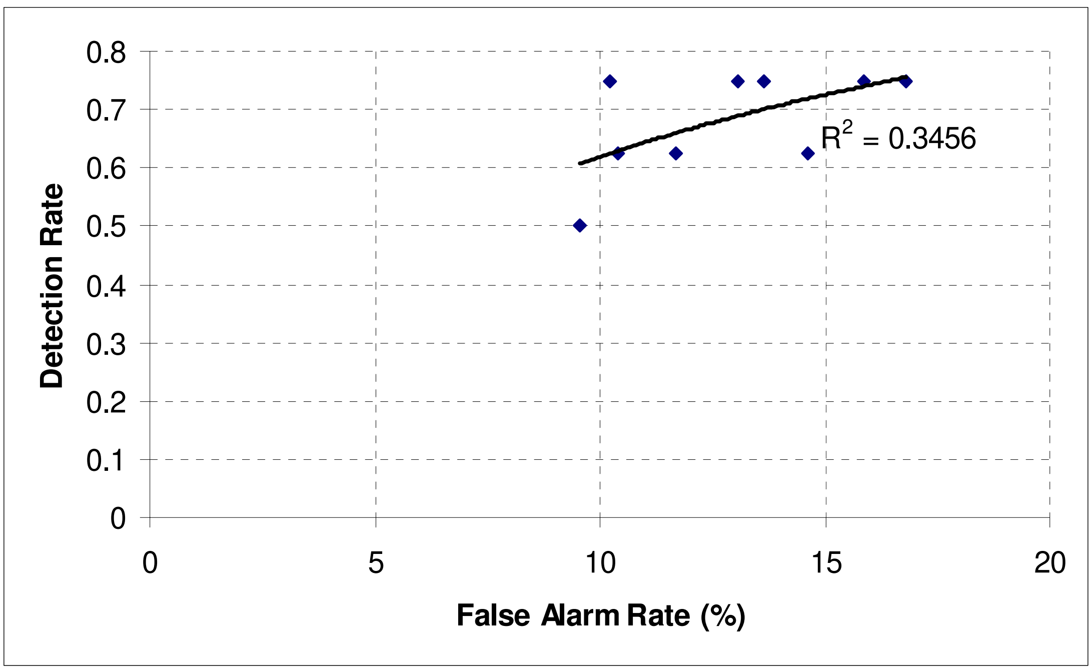

Figure 5.20: Detection Ratio Vs False Alarm Rate for McMaster Algorithm

[1] Further testing will be performed to investigate the response of this algorithm and the results presented during the defense, if not earlier.

5.7.2.3 FWRBFNN Algorithm

The logic of the Fuzzy Wavelet Radial Basis Function Neural Network Model algorithm has been explained in Section 2.5.18 of Chapter II. The algorithm implementation follows 5 steps – preprocessing, de-noising, clustering, classification and decision-making. The computations involved in each step, as identified by the author, are as follows:

Preprocessing: The 16 most recent data values for the lane occupancy (O[n]) and the lane speed (S[n]) are obtained. This is done in every time step by dropping the oldest reading in the sequence and adding the new reading to the sequence. The normalized sequences O′[n] and S′[n] are obtained from the data sequences O[n] and S[n] by dividing the values by the average of each sequence.

De-noising: This step involves three sub-steps:

a. The DWT of the normalized sequences O′[n] and S′[n] are computed using Daubechies wavelet system of length 8. The lowest scale resolved in each case is 2. For each sequence, the final number of scaling coefficients ($c_{2,k}$) obtained is 4 and the final number of wavelet coefficients ($d_{j,k}$) obtained is 12.

b. The wavelet coefficients ($d_{j,k}$) are filtered using the soft thresholding nonlinerarity $\eta(d) = \mathrm{sign}(d)(|d|-t)^+$ to remove noise, where $(.)^+$ is equal to (.) when (.) is positive and zero otherwise and the function sign(.) returns the sign of its argument. The threshold t is given by $t = \sqrt{2\log(N)}$ where N is the total number of data points.

c. If $d'_{j,k}$ is used to denote the filtered wavelet coefficients obtained from the previous step, the inverse DWT is computed with $c_{2,k}$ as the scaling coefficients and $d'_{j,k}$ as the wavelet coefficients to obtain the de-noised normalized sequences $\underline{O}[n]$ and $\underline{S}[n]$.

Clustering: The traffic pattern matrix of dimension 16 x 2 is formed by joining the sequences $\underline{O}[n]$ and $\underline{S}[n]$. The fuzzy c-mean algorithm is used to reduce the dimensionality of the two sequences from 16 x 2 to 4 x 2.

Classification: The eight data-points obtained from the previous step, which represent the de-noised and clustered pattern is used in a feed-forward radial basis function neural network.

Decision-making: The output from the neural network is compared against a preset threshold. If the output is greater than the threshold, an incident is indicated; otherwise non-incident conditions are indicated.

5.7.2.3.1 Results

The author tested the FWRBFNN algorithm with the same dataset as the DSPMID model. The training of the algorithm involved several incidents from the dataset for the Southbound direction. The testing of the algorithm was conducted over the incidents in the Northbound direction. As can be seen from Figure 5.21 the maximum detection rate achieved was generally low in the range studied. It should be noted that the algorithm was calibrated on the Southbound data and used for the Northbound data. This introduces the issues of transferability of algorithm. Although this would not be an issue for the DSPMID algorithm which usually responds critically to the nature of the data rather than the location characteristics, this Neural Network based algorithm, which is more calibration intensive can be expected to be more liable to failure with a change in location. Moreover, the algorithm was calibrated with real world data only. The real world data over 6 months cannot be expected to provide a comprehensive set of all possible incident scenarios. Consequently, the low detection rate is attributed to the lack of a comprehensive set of cases for calibration of the neural network and the poor spatial transferability of the algorithm. The author acknowledges the fact that the algorithm performance has possible room for improvement with more rigorous and site specific calibration.

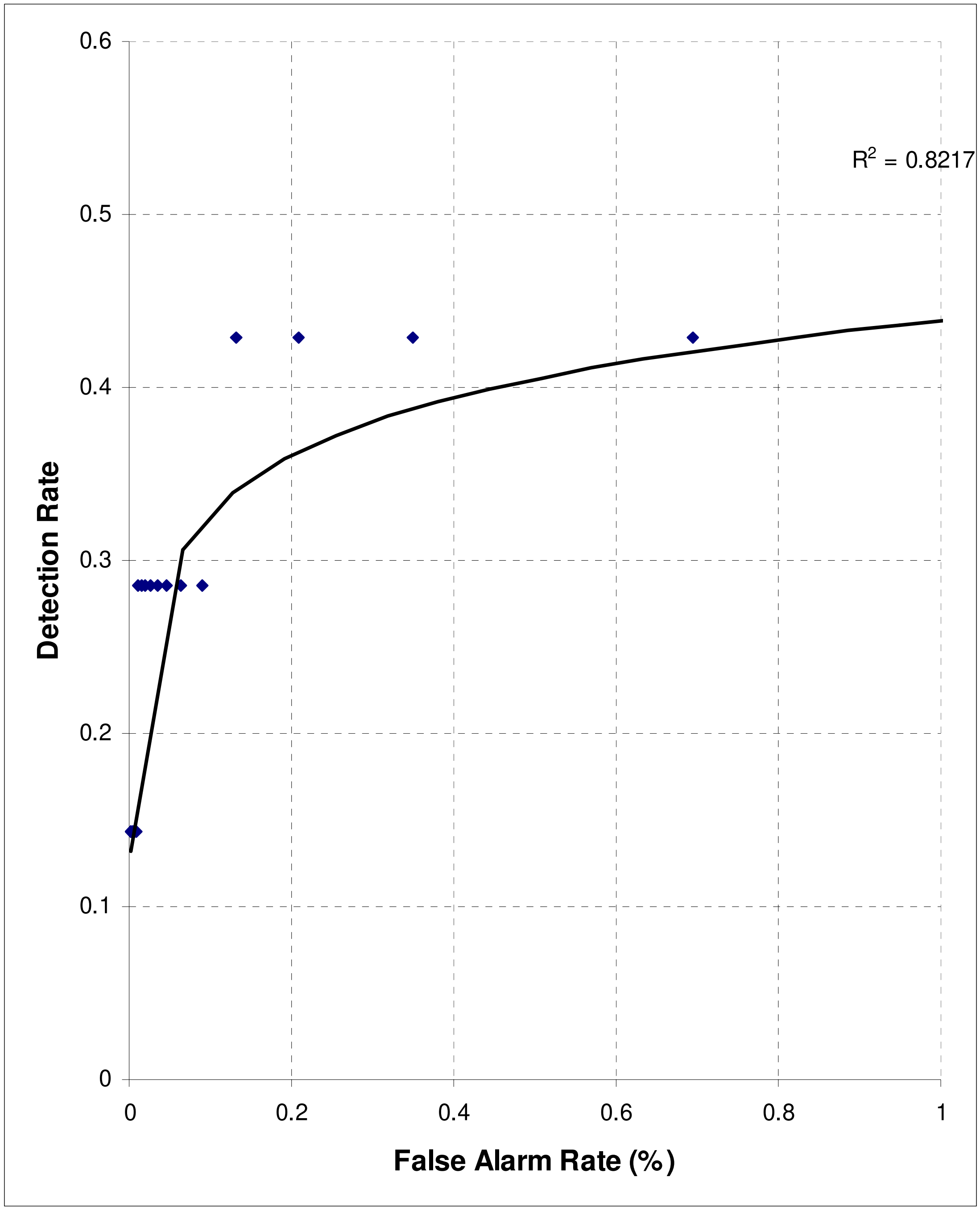

Figure 5.21: Detection Ratio Vs False Alarm Rate for FWRBFNN Algorithm

5.7.3 Comparison Results

All the four algorithms were tested over the same dataset to ensure a valid comparison. Figure 5.22 shows the plot of detection-ratio versus time-to-detect for all four algorithms. The x-axis of the McMaster algorithm plot had to be scaled (10:1) in order to fit it in the same range as the other algorithms. The plot shows that the McMaster algorithm is the only algorithm that performs superior to the DSPMID algorithm in terms of detection time.

Figure 5.23 shows the summary plot of detection-ratio versus false-alarm-rate for all the algorithms (presented earlier in separate plots) on the same graph. The x-axis of the McMaster algorithm plot had to be scaled (1:10) in order to fit it in the same range as the other algorithms. Keeping this in mind, it can be observed that the overall performance was best in the DSPMID algorithm, followed by the California algorithm, the FWRBFNN algorithm and the McMaster algorithm.

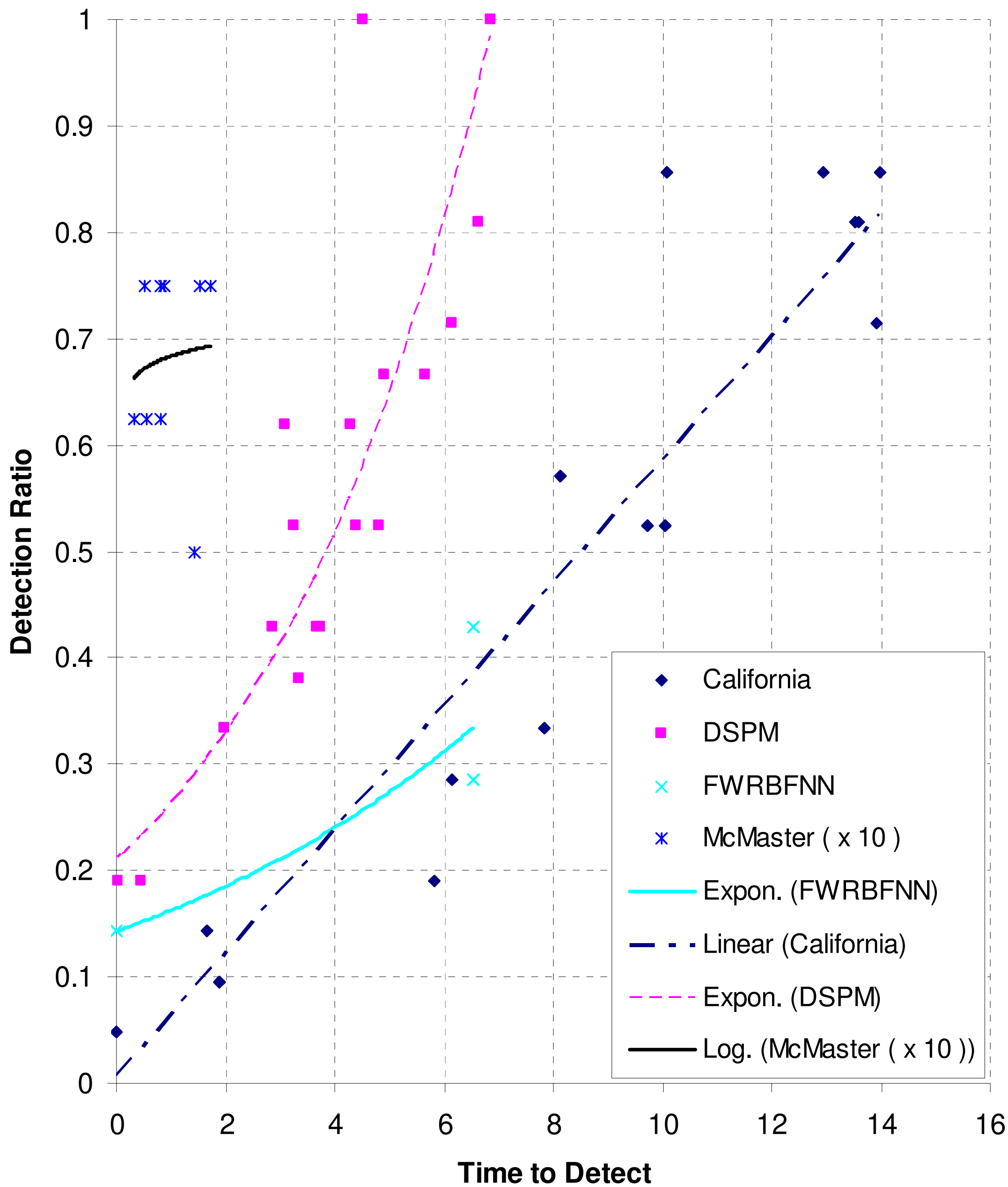

Figure 5.22: Detection-Ratio Vs Time-to-Detect for Four Algorithms

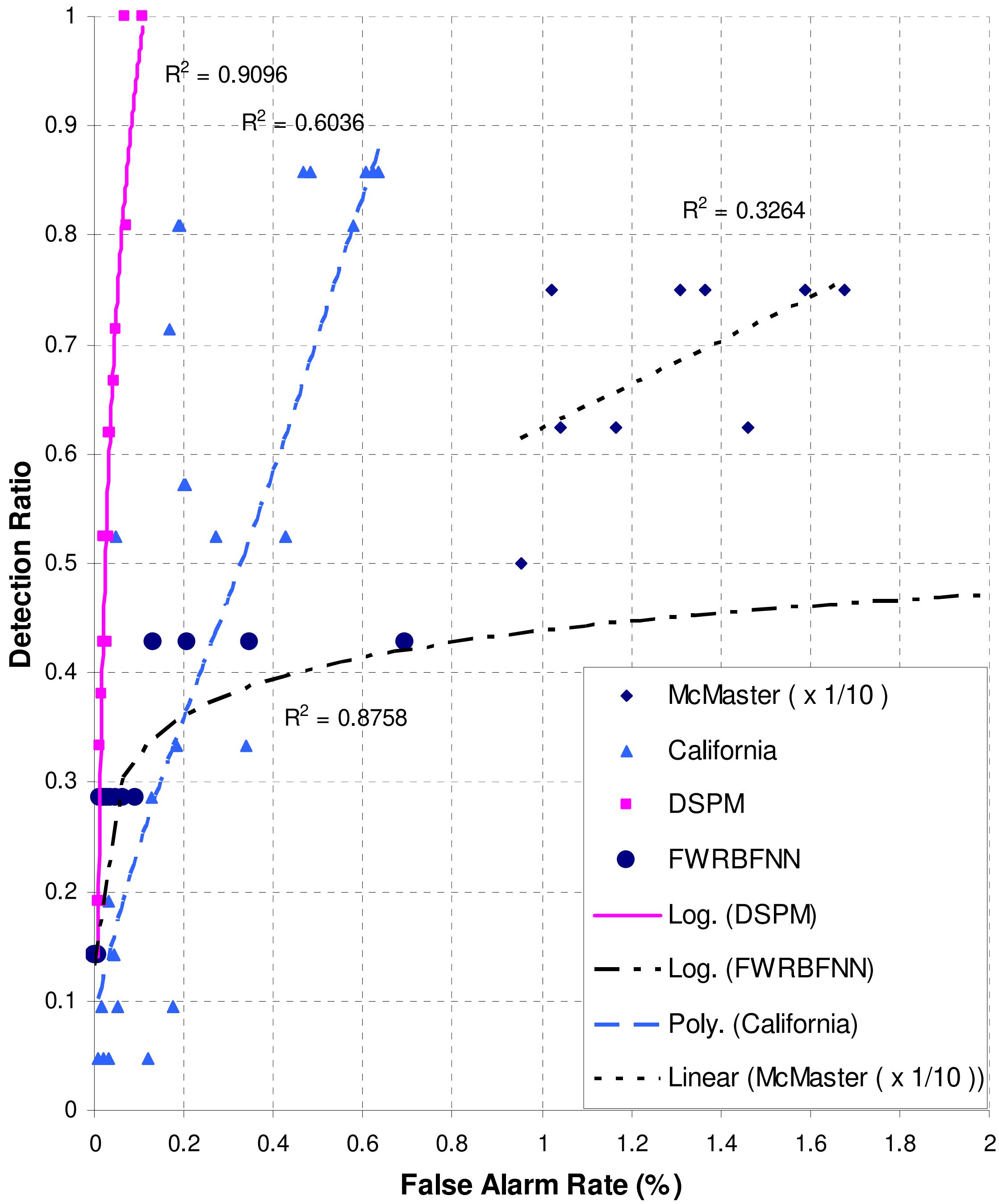

Figure 5.23: Detection-Ratio Vs False-Alarm-Rate for Four Algorithms

5.8 Summary

This chapter outlined the implementation of the incident detection algorithm methodology developed in the previous chapter. As is common in studies like this, the availability of data and the characteristics of the data play a critical role. Therefore the site-selection procedures, the meta-data information and the limitations and assumptions regarding the data were clearly laid out in Section 5.3. The processes involved in cleaning up and formatting of the data were also presented to ensure that the study is easily replicable.

Section 5.5 presented the evaluation of the core prediction model. A comparison of the DSPM model with the LCT model demonstrated the superiority of performance of the DSPM model in the given scenario. The different model options presented in Chapter IV were all valid theoretically. An empirical evaluation, however, showed that Model C provided the best performance. This model option was therefore used for the subsequent algorithm evaluation. The implementation of the DSPM model involved some implementation specific enhancements. Since the DSPM model depended on the determination of the traffic flow regime, the different strategies of regime separation for the model were studied. Speed was observed to be a more favorable criterion for detecting change of traffic conditions from congested to uncongested regime and vice versa. A dynamic pace updating policy for automatic adjustment of the model to the surrounding conditions proved to be demonstrably superior to a static calibration policy.

The algorithm evaluation results showed the effectiveness of the algorithm in successfully identifying incidents. The high detection rate achieved by this algorithm provided the proof of validity of the hypothesis presented in Section 5.1.

Three algorithms – the California algorithm #8, the McMaster algorithm and the FWRBFNN algorithm – were identified for comparison with the developed DSPMID algorithm. Section 5.7.2 presented the design as well as implementation details of these algorithms. The results of testing these algorithms were presented as detection-ratio versus false alarm rate plots.

All three algorithms used for comparison produced more false alarms than the DSPMID algorithm for a given detection ratio. The McMaster algorithm gave a lower detection-time, but the false-alarm-rate was very high – thereby severely limiting the overall performance of that algorithm. Moreover, all these algorithms gave overall lower detection rates than the DSPMID algorithm. The analysis of the results thus demonstrated the superior capabilities of the DSPMID algorithm as compared to these existing algorithms.

In summary, this Chapter successfully applied the methodology developed in Chapter IV, and demonstrated its capability for detecting incidents using operations data. The successful implementation proved the research hypothesis presented in Section 5.1 and achieved the design objectives identified in Section 4.3.

CHAPTER VI

SUMMARY, FINDINGS AND RECOMMENDATIONS

This chapter provides a summary of the research work presented in this thesis, highlights its findings and conclusions and delineates recommendations for future research.

6.1 Summary

This dissertation presented a new methodology for detecting incidents using operations data. In essence, this methodology involves an accurate one step prediction of traffic parameters followed by a comparison between the observed and predicted parameters to identify incidents.

The one-step predictions were obtained by using the DSPM macroscopic traffic model. The DSPM model developed in this research employs a methodology whereby it integrates spatial as well as temporal changes in road geometry and their influences on traffic into the prediction procedure. This model estimates traffic conditions at a point based on the temporally and spatially adjacent measured traffic states. This approach to one-step macroscopic traffic predictions is unique and provides significant conceptual enhancement to previously developed models (Daganzo, 1999) by introducing a procedure that provides predictions that can be compared directly with future observations without making any spatial or temporal adjustments. The limitation of the model in modeling traffic under incident conditions was effectively used to track the shift of traffic conditions into the incident conditions regime. Therefore, the design objectives 1 and 2, as presented in Section 4.3 of Chapter IV, were successfully achieved by the developed DSPMID methodology.

Chapter V presented the calibration and validation process of the methodology. The developed DSPMID methodology was applied in a case study involving a portion of the network covered under the Georgia Navigator, Georgia DOT's ATMS. The operations data was obtained from the ATMS system. The incident information data that was required for the calibration and validation was obtained from Georgia DOT's TMC in Atlanta. Chapter V outlined the procedures for processing and analysis of the data. Calibration of the incident detection algorithm was performed with half of the dataset and validation was performed with the other half to ensure that the validation results are not inflated by over-calibration. The successful implementation of the DSPMID methodology achieved design objective 3 presented in Section 4.3 of Chapter IV. The results of the validation process proved the research hypothesis stated in Section 4.2 of Chapter IV.

6.2 Findings

The following is a summary of the main findings of this research:

- The successful development and implementation of the DSPMID methodology proved the research hypothesis and achieved its original design objectives.

- Estimation of traffic parameters from spatially and temporally adjacent traffic conditions is a viable means of accurately predicting traffic conditions in the short term (less than or equal to a minute).

- The use of a comparison between modeled and observed behavior of traffic is a viable means of detecting incidents.

- A self calibration scheme for a traffic prediction model, based on one of the traffic variables (speed is used to update the pace in this case study) can provide significant accuracy enhancements to the model. While it introduces some instability in the prediction model in the presence of bad detector data (which of course can be filtered out with any simple filtering scheme) it provides significant benefit in terms of minimizing the manual calibration effort.

- The DSPMID methodology for incident detection provides significant performance advantages over the existing incident detection algorithms in a testing environment with limitations in size of calibration data. In addition to a high overall detection ratio, the detection-ratio versus the false-alarm-rate curve is better optimized as compared to the other algorithms.

- Low-cum-medium-pass digital signal processing filters provide a robust means of eliminating noise from high-resolution traffic data. A medium-pass filter is capable of eliminating the high-frequency noise, while preserving the features of the data that are required for incident detection.

- Attempting to relate past incident information with operations data observation station location can be challenging, given that the Georgia DOT stores location information relative to the interchanges only, and not with reference to the observation stations.

- Speed was found to be a better choice than density for separating congested traffic conditions from uncongested conditions.

- The contiguity of a point in the time-space domain was found to have a direct effect on the accuracy of predictions as seen from the comparison of different model alternatives

6.3 Recommendations for Future Research

Future research based on this work has several possibilities. Apart from the direct use of the developed algorithm in traffic operations, the concepts developed during this research can be useful in several different fields like traffic data management, work-zone management, evacuation planning, congestion hot-spot detection etc. The research presented in this dissertation can be extended in the following directions:

- An online testing of the detection algorithm involving a real time application of the algorithm in an ATMS can be performed to test the viability of use of the algorithm in traffic operations.

- Testing of the algorithm with data from different detection technology (e.g. loop detectors) would test the viability of the algorithm for use across different technologies and different ATMSs.

- Further exploration of the lane model needs to be performed. Since some effects on traffic are expected to be smoothed out when an averaging is performed across lanes, the individual lane model is expected to be more sensitive to all incidents in general and to shoulder incidents in particular. The author abandoned the use of the individual lane model because of the lack of a satisfactory lane changing model at the macroscopic level, especially at the interchanges. A combinatorial model using the individual lane model in basic freeway sections and the cumulative lane model near interchanges could prove to be an improvement over the current model.

- A confidence value based output from the rule-based filters that are implemented can be used to give an overall confidence value for each incident alarm. This would provide the operators with a handy tool for varying the sensitivity of the algorithm in real time without the need for rigorous fine tuning of the thresholds.

- The algorithm can be used as a detection tool for identifying malfunctioning detectors. Cumulative statistics such as the mean absolute percentage difference of the predictions from the observations, or the percentage of data-points where the difference of predictions from the observations was over a pre-specified threshold, can be used for detecting malfunctions.

- The DSPM model can be used for replacing missing or erroneous detector data in real time.

- The incident detection algorithm can be used as an offline tool for identifying un-identified bottlenecks. Locations which present incident like conditions in the absence of real incidents can be identified as problematic sections that need some congestion alleviation measures.

- Several instances exist where macroscopic traffic flow models have been tested with aggregated data because the high-resolution data was considered too noisy. The possibility of applying the data processing techniques used in this research for creating high-resolution datasets for such model testing needs to be explored.

- One of the fallouts of this research effort was the creation of an archive for high-resolution traffic operations data at Georgia Tech for a portion of Georgia Navigator. Given the success of implementation of the low-maintenance archive, the Georgia DOT should be encouraged to provided

Georgia Tech the full network wide data for archival. The possible benefits of such an archive are well known to the research community.

- Given the uncertainties in time and location information in the incident database, the Georgia DOT should be encouraged to record more detailed and objective location information (e.g. station numbers instead of road names). This would significantly benefit future incident-detection, incident modeling and traffic modeling studies.

APPENDIX A

Aerial Photo of Study Site

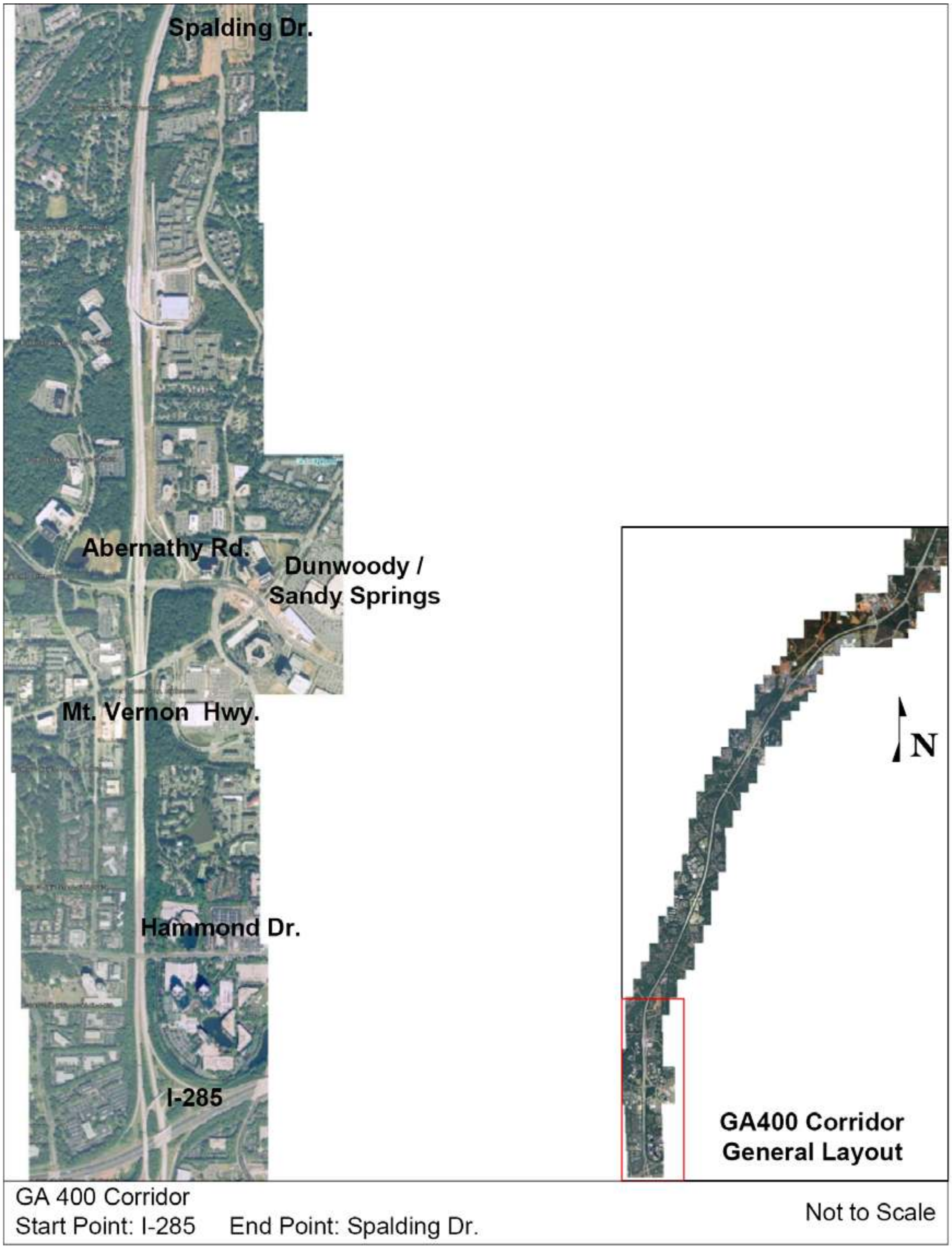

Figure A.1: Aerial Photo of Study Site (1 of 5)

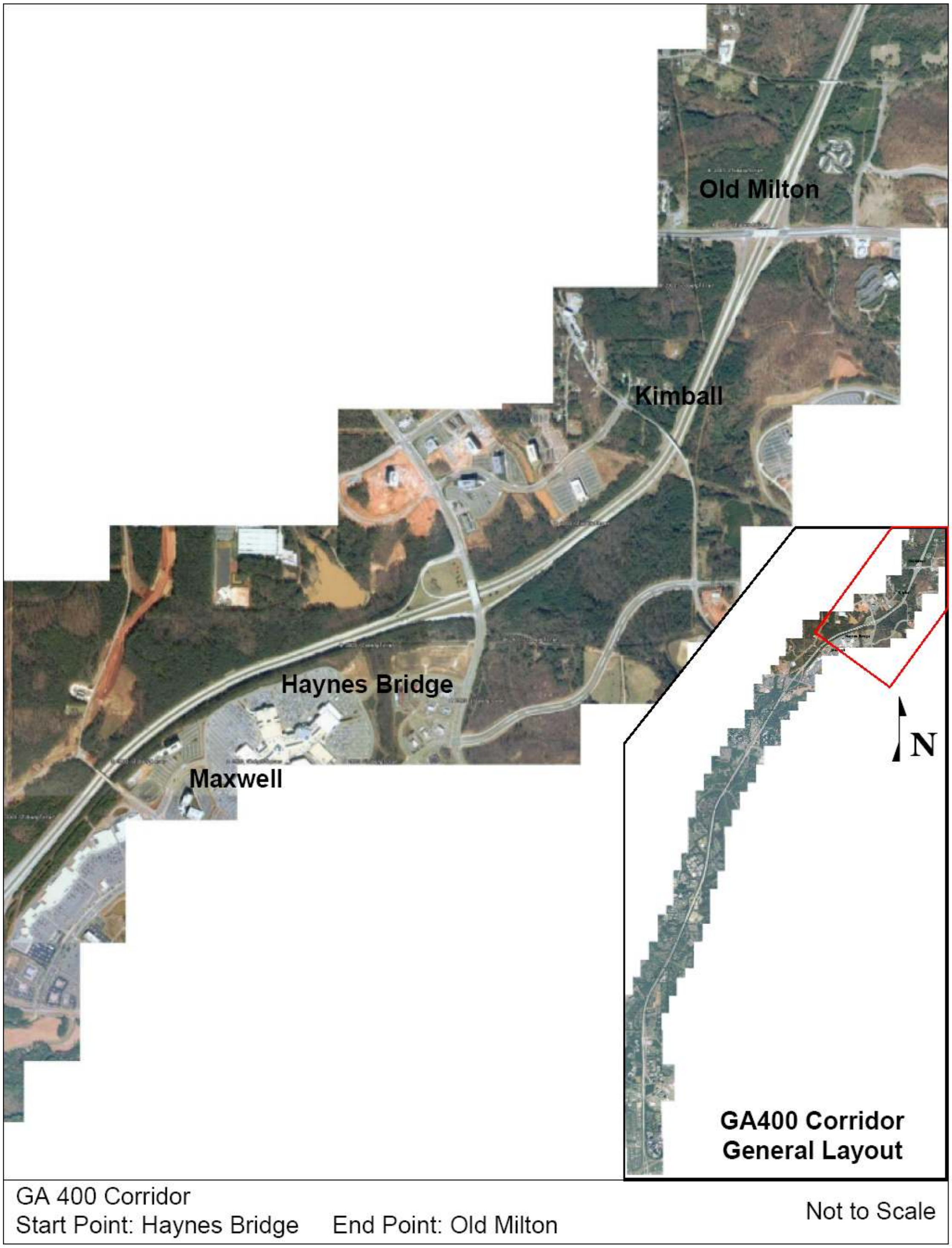

Figure A.2: Aerial Photo of Study Site (2 of 5)

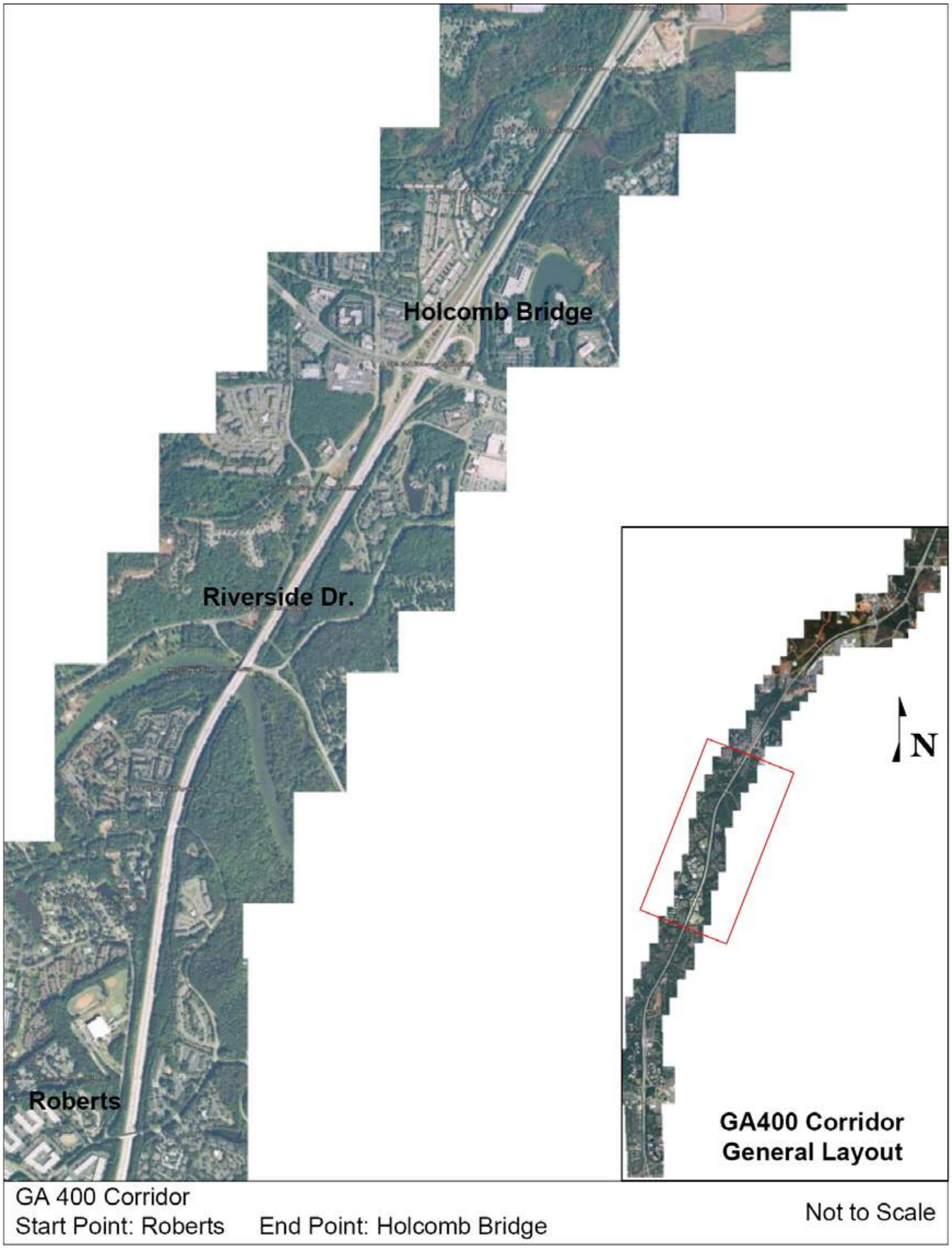

Figure A.3: Aerial Photo of Study Site (3 of 5)

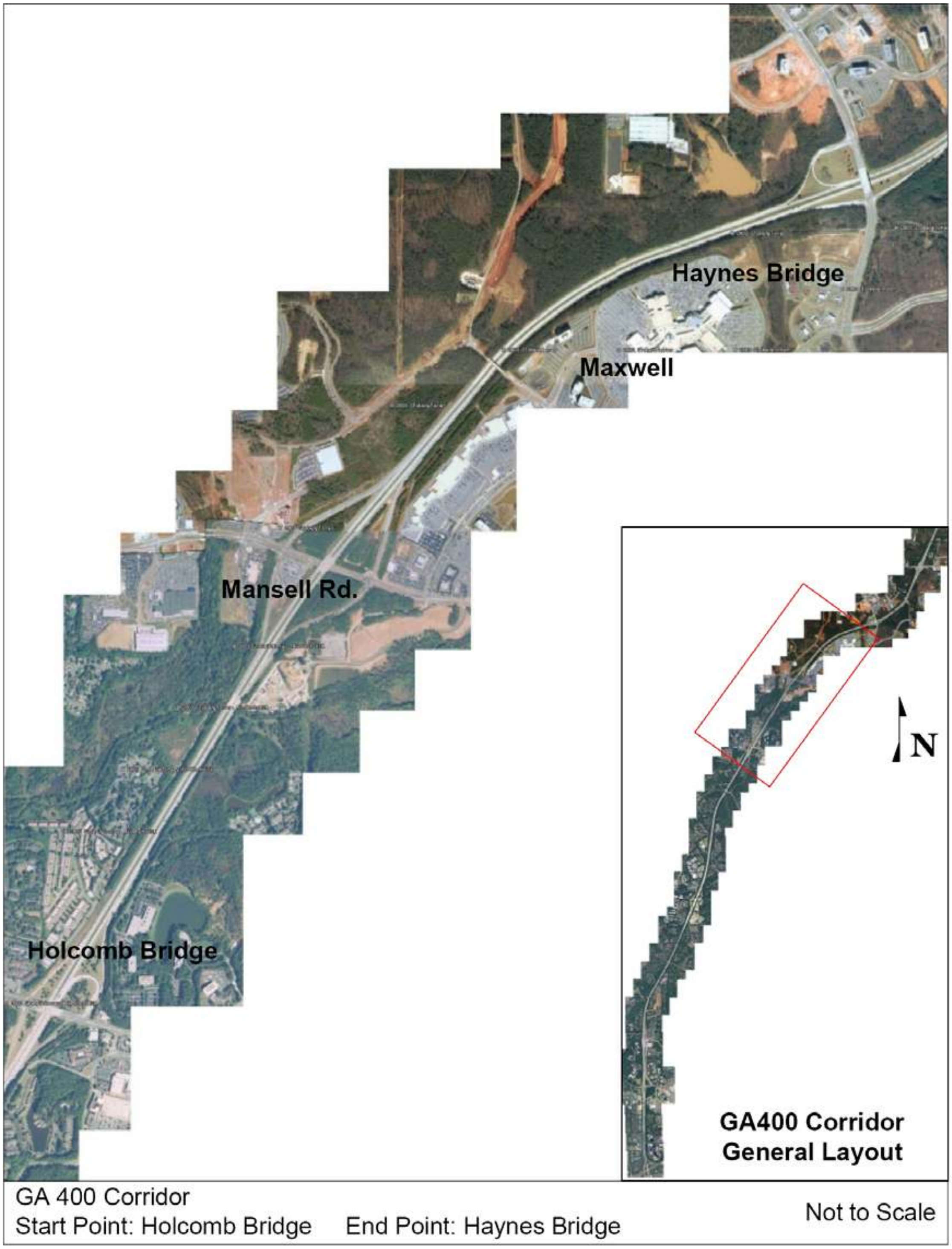

Figure A.4: Aerial Photo of Study Site (4 of 5)

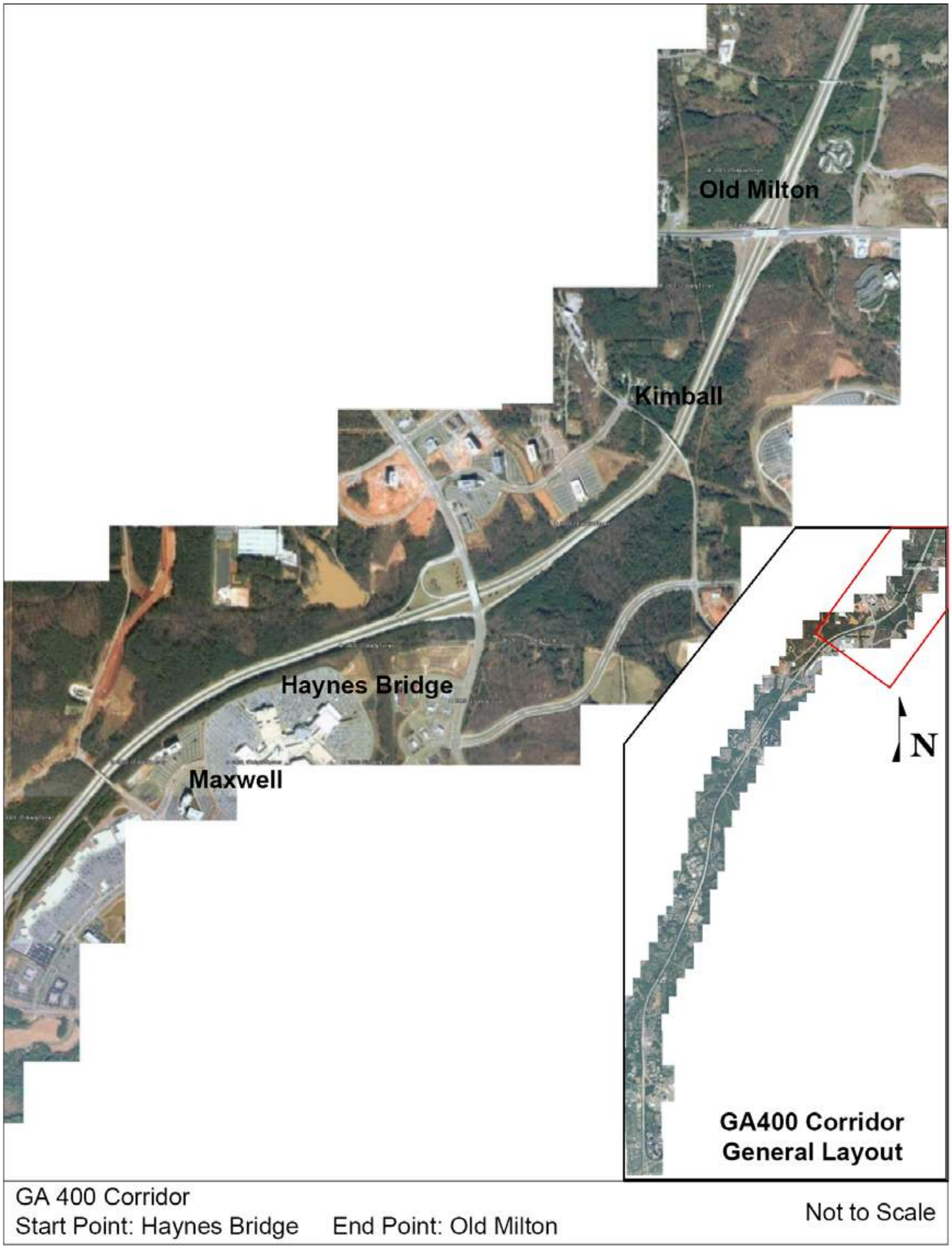

Figure A.5: Aerial Photo of Study Site (5 of 5)

APPENDIX B

Schematic of Study Site

KEY:
Detector ID
Station ID
Mile Post
Lane Number
DetectorClass

	\ / \ / V	\ / \ / V	/\ / \ / \	/\ / \ / \			
	400500 **4001101** 19.84 1 Mainline	400501 **4001101** 19.84 2 Mainline					GEORGIA 400 SOUTH NEAR N OF OLD MILTON PKWY
400502 **4006101** 19.780001 1 Exit			400248 **4000063** 19.780001 1 Mainline	400249 **4000063** 19.780001 2 Mainline	400250 **4005010** 19.780001 1 Entrance		N OF OLD MILTON PKWY.
	400504 **4001102** 19.559999 2 Mainline	400503 **4001102** 19.559999 1 Mainline	400246 **4000062** 19.58 1 Mainline	400247 **4000062** 19.58 2 Mainline			N OF OLD MILTON PKWY.
400505 **4005101** 19.379999 1 Entrance					400245 **4006010** 19.379999 1 Exit		AT OLD MILTON PKWY
	400507 **4001103** 19.360001 2 Mainline	400506 **4001103** 19.360001 1 Mainline	400243 **4000061** 19.27 1 Mainline	400244 **4000061** 19.27 2 Mainline			N OF KIMBALL BR RD
	400509 **4001104** 18.940001 2 Mainline	400508 **4001104** 18.940001 1 Mainline	400241 **4000060** 18.92 1 Mainline	400242 **4000060** 18.92 2 Mainline			AT KIMBALL BR RD
	400511 **4001105** 18.629999 2 Mainline	400510 **4001105** 18.629999 1 Mainline	400237 **4000059** 18.59 1 Mainline	400238 **4000059** 18.59 2 Mainline	400239 **4000059** 18.59 3 Mainline		N OF HAYNES BR RD
400514 **4006102** 18.200001 1 Exit	400513 **4001106** 18.23 2 Mainline	400512 **4001106** 18.23 1 Mainline	400234 **4000058** 18.280001 1 Mainline	400235 **4000058** 18.280001 2 Mainline	400236 **4005009** 18.290001 1 Entrance		AT HAYNES BR RD
400515 **4005102** 17.99 1 Entrance	400517 **4001107** 17.98 2 Mainline	400516 **4001107** 17.98 1 Mainline	400230 **4000057** 17.950001 1 Mainline	400231 **4000057** 17.950001 2 Mainline	400232 **4000057** 17.950001 3 Mainline	400233 **4006009** 17.969999 1 Exit	S HAYNES BR RD
400520 **4001108** 17.65 3 Mainline	400519 **4001108** 17.65 2 Mainline	400518 **4001108** 17.65 1 Mainline	400227 **4000056** 17.610001 1 Mainline	400228 **4000056** 17.610001 2 Mainline	400229 **4000056** 17.610001 3 Mainline		1/2 MILE OF N OF MAXWELL RD

		400523 **4001109** 17.33 3 Mainline	400522 **4001109** 17.33 2 Mainline	400521 **4001109** 17.33 1 Mainline	400224 **4000055** 17.299999 1 Mainline	400225 **4000055** 17.299999 2 Mainline	400226 **4000055** 17.299999 3 Mainline			N OF MAXWELL RD
		400526 **4001110** 17.049999 3 Mainline	400525 **4001110** 17.049999 2 Mainline	400524 **4001110** 17.049999 1 Mainline	400221 **4000054** 17.02 1 Mainline	400222 **4000054** 17.02 2 Mainline	400223 **4000054** 17.02 3 Mainline			S OF MAXWELL RD
	400530 **4006103** 16.719999 1 Exit	400529 **4001111** 16.719999 3 Mainline	400528 **4001111** 16.719999 2 Mainline	400527 **4001111** 16.719999 1 Mainline	400216 **4000053** 16.690001 1 Mainline	400217 **4000053** 16.690001 2 Mainline	400218 **4000053** 16.690001 3 Mainline	400219 **4005008** 16.690001 1 Entrance	400220 **4005008** 16.690001 2 Entrance	N OF MANSELL RD
		400533 **4001112** 16.379999 3 Mainline	400532 **4001112** 16.379999 2 Mainline	400531 **4001112** 16.379999 1 Mainline	400213 **4000052** 16.41 1 Mainline	400214 **4000052** 16.41 2 Mainline	400215 **4000052** 16.41 3 Mainline			AT MANSELL RD
	400537 **4005103** 16.08 1 Entrance	400536 **4001113** 16.08 3 Mainline	400535 **4001113** 16.08 2 Mainline	400534 **4001113** 16.08 1 Mainline	400209 **4000051** 16.040001 1 Mainline	400210 **4000051** 16.040001 2 Mainline	400211 **4000051** 16.040001 3 Mainline	400212 **4006008** 16.040001 1 Exit		S MANSELL RD
		400540 **4001114** 15.67 3 Mainline	400539 **4001114** 15.67 2 Mainline	400538 **4001114** 15.67 1 Mainline	400206 **4000050** 15.64 1 Mainline	400207 **4000050** 15.64 2 Mainline	400208 **4000050** 15.64 3 Mainline			1/2 MI OF N OF HOLCOMB BR RD
	400544 **4006104** 15.2 1 Exit	400543 **4001115** 15.25 3 Mainline	400542 **4001115** 15.25 2 Mainline	400541 **4001115** 15.25 1 Mainline	400203 **4000049** 15.25 1 Mainline	400204 **4000049** 15.25 2 Mainline	400205 **4000049** 15.25 3 Mainline	400202 **4005007** 15.24 1 Entrance		N OF HOLCOMB BR RD
								400200 **4006007** 15.02 1 Exit	400201 **4006007** 15.02 2 Exit	
		400547 **4001116** 14.97 3 Mainline	400546 **4001116** 14.97 2 Mainline	400545 **4001116** 14.97 1 Mainline	400196 **4000048** 14.99 1 Mainline	400197 **4000048** 14.99 2 Mainline	400198 **4000048** 14.99 3 Mainline	400199 **4000048** 14.99 4 Mainline		AT HOLCOMB BR RD
400549 **4005104** 14.75 2 Entrance	400548 **4005104** 14.75 1 Entrance	400552 **4001117** 14.75 3 Mainline	400551 **4001117** 14.75 2 Mainline	400550 **4001117** 14.75 1 Mainline	400190 **4000047** 14.71 1 Mainline	400191 **4000047** 14.71 2 Mainline	400192 **4000047** 14.71 3 Mainline	400193 **4000047** 14.71 4 Mainline	400195 **4006006** 14.73 1 Exit	S OF HOLCOMB BR RD
	400556 **4001118** 14.32 4 Mainline	400555 **4001118** 14.32 3 Mainline	400554 **4001118** 14.32 2 Mainline	400553 **4001118** 14.32 1 Mainline	400186 **4000046** 14.24 1 Mainline	400187 **4000046** 14.24 2 Mainline	400188 **4000046** 14.24 3 Mainline	400189 **4000046** 14.24 4 Mainline		3/4 MI S OF HOLCOMB BR RD

	400560 **4001119** 13.96 4 Mainline	400559 **4001119** 13.96 3 Mainline	400558 **4001119** 13.96 2 Mainline	400557 **4001119** 13.96 1 Mainline	400182 **4000045** 13.89 1 Mainline	400183 **4000045** 13.89 2 Mainline	400184 **4000045** 13.89 3 Mainline	400185 **4000045** 13.89 4 Mainline		S OF RIVERSIDE RD
	400564 **4001120** 13.65 4 Mainline	400563 **4001120** 13.65 3 Mainline	400562 **4001120** 13.65 2 Mainline	400561 **4001120** 13.65 1 Mainline	400178 **4000044** 13.62 1 Mainline	400179 **4000044** 13.62 2 Mainline	400180 **4000044** 13.62 3 Mainline	400181 **4000044** 13.62 4 Mainline		1 MI N OF ROBERTS RD
	400568 **4001121** 13.33 4 Mainline	400567 **4001121** 13.33 3 Mainline	400566 **4001121** 13.33 2 Mainline	400565 **4001121** 13.33 1 Mainline	400174 **4000043** 13.3 1 Mainline	400175 **4000043** 13.3 2 Mainline	400176 **4000043** 13.3 3 Mainline	400177 **4000043** 13.3 4 Mainline		HALF MILE N OF ROBERTS DR
	400572 **4001122** 13.01 4 Mainline	400571 **4001122** 13.01 3 Mainline	400570 **4001122** 13.01 2 Mainline	400569 **4001122** 13.01 1 Mainline	400170 **4000042** 12.97 1 Mainline	400171 **4000042** 12.97 2 Mainline	400172 **4000042** 12.97 3 Mainline	400173 **4000042** 12.97 4 Mainline		N OF ROBERTS DR
	400576 **4001123** 12.7 4 Mainline	400575 **4001123** 12.7 3 Mainline	400574 **4001123** 12.7 2 Mainline	400573 **4001123** 12.7 1 Mainline	400166 **4000041** 12.69 1 Mainline	400167 **4000041** 12.69 2 Mainline	400168 **4000041** 12.69 3 Mainline	400169 **4000041** 12.69 4 Mainline		AT ROBERTS DR
	400580 **4001124** 12.37 4 Mainline	400579 **4001124** 12.37 3 Mainline	400578 **4001124** 12.37 2 Mainline	400577 **4001124** 12.37 1 Mainline	400161 **4000040** 12.33 1 Mainline	400162 **4000040** 12.33 2 Mainline	400163 **4000040** 12.33 3 Mainline	400164 **4000040** 12.33 4 Mainline	400165 **4005006** 12.33 1 Entrance	N OF NORTHRIDGE RD
400585 **4001125** 11.99 5 Mainline	400584 **4001125** 11.99 4 Mainline	400583 **4001125** 11.99 3 Mainline	400582 **4001125** 11.99 2 Mainline	400581 **4001125** 11.99 1 Mainline	400156 **4000039** 12.05 1 Mainline	400157 **4000039** 12.05 2 Mainline	400158 **4000039** 12.05 3 Mainline	400159 **4000039** 12.05 4 Mainline	400160 **4006005** 12.1 1 Exit	AT NORTHRIDGE RD
400586 **4006105** 11.93 1 Exit										
400587 **4005105** 11.78 1 Entrance	400591 **4001126** 11.77 4 Mainline	400590 **4001126** 11.77 3 Mainline	400589 **4001126** 11.77 2 Mainline	400588 **4001126** 11.77 1 Mainline	400152 **4000038** 11.76 1 Mainline	400153 **4000038** 11.76 2 Mainline	400154 **4000038** 11.76 3 Mainline	400155 **4000038** 11.76 4 Mainline		S OF NORTHRIDGE RD
	400595 **4001127** 11.47 4 Mainline	400594 **4001127** 11.47 3 Mainline	400593 **4001127** 11.47 2 Mainline	400592 **4001127** 11.47 1 Mainline	400148 **4000037** 11.49 1 Mainline	400149 **4000037** 11.49 2 Mainline	400150 **4000037** 11.49 3 Mainline	400151 **4000037** 11.49 4 Mainline		N OF PITTS RD
	400599 **4001128** 11.1 4 Mainline	400598 **4001128** 11.1 3 Mainline	400597 **4001128** 11.1 2 Mainline	400596 **4001128** 11.1 1 Mainline	400144 **4000036** 11.08 1 Mainline	400145 **4000036** 11.08 2 Mainline	400146 **4000036** 11.08 3 Mainline	400147 **4000036** 11.08 4 Mainline		AT PITTS RD

400603 **4001129** 10.77 4 Mainline	400602 **4001129** 10.77 3 Mainline	400601 **4001129** 10.77 2 Mainline	400600 **4001129** 10.77 1 Mainline	400140 **4000035** 10.73 1 Mainline	400141 **4000035** 10.73 2 Mainline	400142 **4000035** 10.73 3 Mainline	400143 **4000035** 10.73 4 Mainline		S OF PITTS RD
400607 **4001130** 10.44 4 Mainline	400606 **4001130** 10.44 3 Mainline	400605 **4001130** 10.44 2 Mainline	400604 **4001130** 10.44 1 Mainline	400136 **4000034** 10.42 1 Mainline	400137 **4000034** 10.42 2 Mainline	400138 **4000034** 10.42 3 Mainline	400139 **4000034** 10.42 4 Mainline		N OF SPALDING DR
400611 **4001131** 10.11 4 Mainline	400610 **4001131** 10.11 3 Mainline	400609 **4001131** 10.11 2 Mainline	400608 **4001131** 10.11 1 Mainline	400132 **4000033** 10.12 1 Mainline	400133 **4000033** 10.12 2 Mainline	400134 **4000033** 10.12 3 Mainline	400135 **4000033** 10.12 4 Mainline		AT SPALDING DR
400615 **4001132** 9.78 4 Mainline	400614 **4001132** 9.78 3 Mainline	400613 **4001132** 9.78 2 Mainline	400612 **4001132** 9.78 1 Mainline	400128 **4000032** 9.75 1 Mainline	400129 **4000032** 9.75 2 Mainline	400130 **4000032** 9.75 3 Mainline	400131 **4000032** 9.75 4 Mainline		S OF SPALDING DR
400619 **4001133** 9.42 4 Mainline	400618 **4001133** 9.42 3 Mainline	400617 **4001133** 9.42 2 Mainline	400616 **4001133** 9.42 1 Mainline	400124 **4000031** 9.39 1 Mainline	400125 **4000031** 9.39 2 Mainline	400126 **4000031** 9.39 3 Mainline	400127 **4000031** 9.39 4 Mainline		1/2 MI S OF SPALDING DR
400623 **4001134** 9.11 4 Mainline	400622 **4001134** 9.11 3 Mainline	400621 **4001134** 9.11 2 Mainline	400620 **4001134** 9.11 1 Mainline	400120 **4000030** 9.07 1 Mainline	400121 **4000030** 9.07 2 Mainline	400122 **4000030** 9.07 3 Mainline	400123 **4000030** 9.07 4 Mainline		1/2 MI N OF ABERNATHY ROAD
400627 **4001135** 8.78 4 Mainline	400626 **4001135** 8.78 3 Mainline	400625 **4001135** 8.78 2 Mainline	400624 **4001135** 8.78 1 Mainline	400116 **4000029** 8.75 1 Mainline	400117 **4000029** 8.75 2 Mainline	400118 **4000029** 8.75 3 Mainline	400119 **4000029** 8.75 4 Mainline		NORTH OF ABERNATHY ROAD
400631 **4001136** 8.45 4 Mainline	400630 **4001136** 8.45 3 Mainline	400629 **4001136** 8.45 2 Mainline	400628 **4001136** 8.45 1 Mainline	400112 **4000028** 8.41 1 Mainline	400113 **4000028** 8.41 2 Mainline	400114 **4000028** 8.41 3 Mainline	400115 **4000028** 8.41 4 Mainline	Exit and Entrance Ramps (No data available)	AT ABERNATHY ROAD
400635 **4001137** 8.12 4 Mainline	400634 **4001137** 8.12 3 Mainline	400633 **4001137** 8.12 2 Mainline	400632 **4001137** 8.12 1 Mainline	400108 **4000027** 8.08 1 Mainline	400109 **4000027** 8.08 2 Mainline	400110 **4000027** 8.08 3 Mainline	400111 **4000027** 8.08 4 Mainline		S OF MT VERNON HWY
400639 **4001138** 7.74 4 Mainline	400638 **4001138** 7.74 3 Mainline	400637 **4001138** 7.74 2 Mainline	400636 **4001138** 7.74 1 Mainline	400104 **4000026** 7.7 1 Mainline	400105 **4000026** 7.7 2 Mainline	400106 **4000026** 7.7 3 Mainline	400107 **4000026** 7.7 4 Mainline		N OF HAMMOND DR
400643 **4001139** 7.32 4 Mainline	400642 **4001139** 7.32 3 Mainline	400641 **4001139** 7.32 2 Mainline	400640 **4001139** 7.32 1 Mainline	400100 **4000025** 7.28 1 Mainline	400101 **4000025** 7.28 2 Mainline	400102 **4000025** 7.28 3 Mainline	400103 **4005005** 7.28 1 Entrance		S OF HAMMOND DR

APPENDIX C

Mean Absolute Prediction Error Data

Table C.1: Prediction Errors using DSPM Model C on Filtered and Raw Data

Station Number	*Mean Absolute Percentage Error*	
	Filtered	***Raw***
4000027	1.784	4.778
4000029	8.386	11.539
4000030	3.755	12.437
4000031	2.414	5.972
4000032	3.405	6.976
4000033	3.841	6.375
4000034	2.522	9.104
4000035	1.115	3.672
4000036	1.122	4.024
4000037	1.123	3.919
4000038	1.395	5.158
4000039	4.504	6.063
4000040	2.146	6.038
4000041	2.674	4.863
4000042	2.359	5.499
4000043	1.438	4.301
4000044	1.593	5.399
4000045	1.614	5.525
4000046	1.555	4.763
4000047	3.767	7.046
4000048	5.506	9.082
4000049	10.709	15.452
4000050	5.691	10.850
4000051	6.900	16.317
4000052	2.074	6.953
4000053	2.635	8.063
4000054	3.627	8.669
4000055	1.957	7.644
4000056	3.033	11.232
4000057	2.384	8.713
4000058	23.484	29.487
4000059	4.605	9.172
4000060	10.245	19.020
4000061	4.073	12.260
4000062	18.181	30.289

Table C.2: Prediction Errors using Different Models with Raw Data

Station Number	*Mean Absolute Percentage Error*			
	Model D	*Model B*	*Model C*	*LCT*
4000027	4.622	4.647	4.778	4.824
4000029	11.434	11.434	11.539	11.044
4000030	10.904	11.397	12.437	8.687
4000031	6.027	7.411	5.972	6.391
4000032	6.777	6.824	6.976	7.593
4000033	7.709	7.752	6.375	7.184
4000034	8.609	8.667	9.104	7.085
4000035	3.686	5.878	3.672	6.083
4000036	4.073	4.731	4.024	4.388
4000037	3.633	3.648	3.919	3.719
4000038	5.050	5.569	5.158	7.533
4000039	6.162	6.578	6.063	8.986
4000040	5.799	8.556	6.038	7.936
4000041	4.877	5.935	4.863	5.410
4000042	5.487	5.922	5.499	6.557
4000043	4.278	6.134	4.301	5.248
4000044	5.297	6.276	5.399	5.763
4000045	5.400	5.449	5.525	6.850
4000046	4.710	6.560	4.763	5.225
4000047	7.060	7.073	7.046	7.212
4000048	8.753	8.978	9.082	11.004
4000049	14.019	18.812	15.452	21.243
4000050	9.793	9.798	10.850	10.834
4000051	14.425	14.429	16.317	14.290
4000052	6.735	8.840	6.953	8.684
4000053	8.031	9.232	8.063	9.647
4000054	9.111	9.560	8.669	10.086
4000055	7.571	9.785	7.644	9.934
4000056	10.635	11.080	11.232	12.678
4000057	8.982	9.061	8.713	9.296
4000058	28.880	29.548	29.487	30.795
4000059	9.416	10.124	9.172	10.410
4000060	17.580	17.530	19.020	17.590
4000061	11.747	12.115	12.260	13.024
4000062	28.531	30.085	30.289	28.786

Table C.3: Prediction Errors using Different Regime Separation Strategies

Station Number	***Mean Absolute Percentage Error***	
	Speed Cutoff	***Density Cutoff***
4000027	1.782	1.678
4000029	8.412	8.584
4000030	3.645	3.661
4000031	2.409	2.330
4000032	3.404	3.618
4000033	3.841	3.909
4000034	2.662	2.769
4000035	1.031	1.042
4000036	1.124	1.073
4000037	1.107	1.132
4000038	1.438	1.398
4000039	4.560	4.686
4000040	1.849	1.910
4000041	2.687	2.691
4000042	2.296	2.350
4000043	1.475	1.471
4000044	1.561	1.555
4000045	1.636	1.544
4000046	1.578	1.649
4000047	3.770	3.822
4000048	5.486	5.374
4000049	9.316	9.752
4000050	5.636	5.886
4000051	6.765	6.852
4000052	2.064	2.052
4000053	2.732	2.545
4000054	3.653	3.786
4000055	1.906	1.893
4000056	2.996	3.051
4000057	2.386	2.674
4000058	23.463	23.730
4000059	5.670	5.799
4000060	10.165	10.399
4000061	4.060	4.086
4000062	18.030	18.162

Table C.4: Prediction Errors using Different Models with Filtered Data

Station Number	***Mean Absolute Percentage Error***			
	ModelD	***ModelB***	***ModelC***	***LCT***
4000027	1.773	1.773	1.784	2.578
4000029	8.365	8.365	8.386	6.064
4000030	3.640	3.668	3.755	3.689
4000031	2.401	3.241	2.414	2.680
4000032	3.377	3.377	3.405	4.487
4000033	4.022	4.022	3.841	4.562
4000034	2.648	2.474	2.522	2.747
4000035	1.027	2.527	1.115	3.723
4000036	1.114	1.291	1.122	1.850
4000037	1.097	1.097	1.123	1.231
4000038	1.438	1.496	1.395	3.098
4000039	4.545	4.411	4.504	7.437
4000040	1.825	5.617	2.146	2.823
4000041	2.678	2.984	2.674	3.224
4000042	2.300	2.926	2.359	1.780
4000043	1.450	2.352	1.438	2.081
4000044	1.556	2.282	1.593	2.438
4000045	1.620	1.578	1.614	1.644
4000046	1.571	2.032	1.555	2.000
4000047	3.769	3.769	3.767	3.384
4000048	5.504	5.649	5.506	2.859
4000049	9.199	14.502	10.709	14.962
4000050	5.628	5.628	5.691	7.674
4000051	6.747	6.747	6.900	6.176
4000052	2.040	2.463	2.074	4.496
4000053	2.720	2.767	2.635	3.315
4000054	3.643	3.664	3.627	7.570
4000055	1.908	4.041	1.957	2.728
4000056	2.995	3.100	3.033	3.840
4000057	2.380	2.385	2.384	4.730
4000058	23.484	23.083	23.484	23.139
4000059	5.681	3.108	4.605	6.256
4000060	10.171	10.169	10.245	7.487
4000061	4.059	4.068	4.073	5.027
4000062	18.095	19.565	18.18121	19.209

Table C.5: Detection Ratio and False Alarm Rates for DSPM algorithm

False Alarm Rate	***Detection Ratio***
0.10836	1.00000
0.04805	0.71429
0.07166	0.80952
0.03389	0.52381
0.04374	0.66667
0.02174	0.52381
0.06931	1.00000
0.03179	0.61905
0.04308	0.66667
0.02158	0.42857
0.02769	0.42857
0.01435	0.38095
0.03541	0.61905
0.01885	0.42857
0.02200	0.52381
0.01251	0.33333
0.01416	0.19048
0.00810	0.19048

APPENDIX D

Threshold Sensitivity Plots

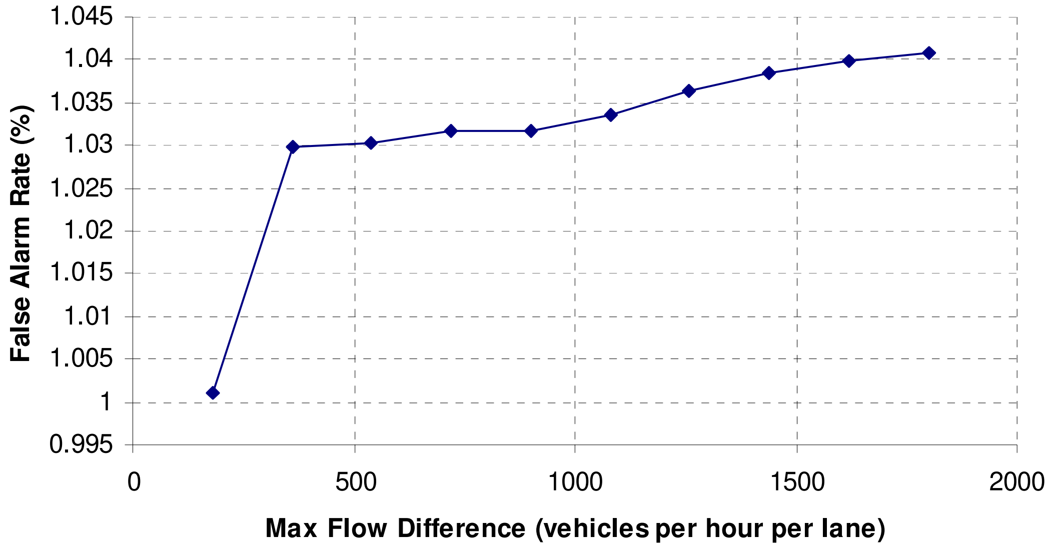

Figure D.1: Sensitivity of False Alarms to Threshold for Maximum Temporal Difference of Flow

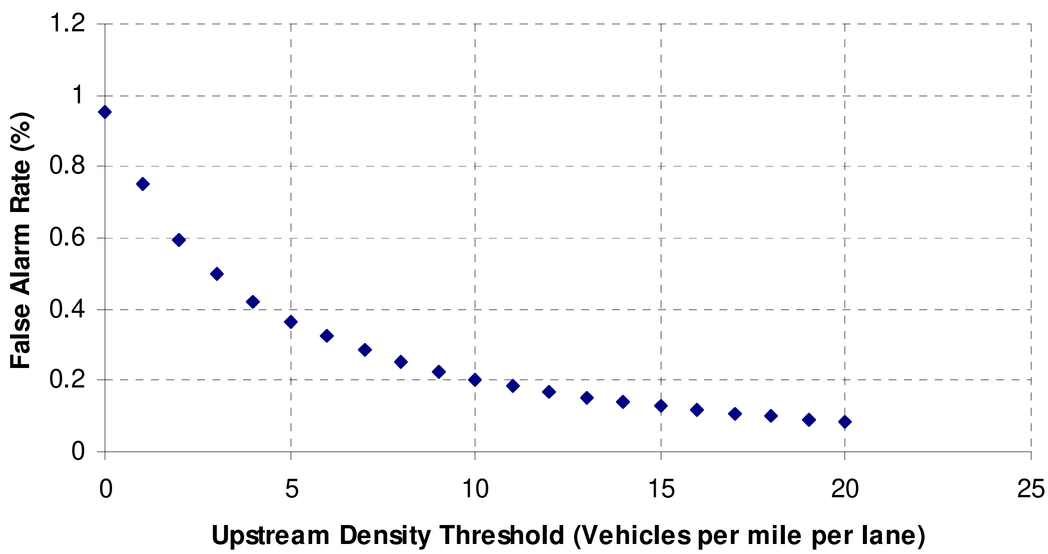

Figure D.2: Sensitivity of False Alarms to Threshold for Upstream Density Difference

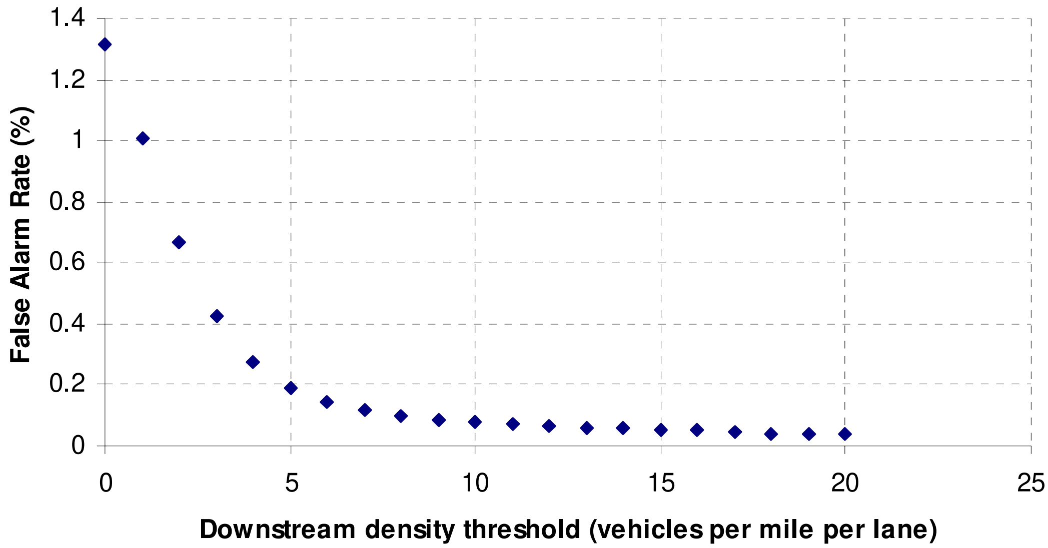

Figure D.3: Sensitivity of False Alarms to Threshold for Downstream Density Difference

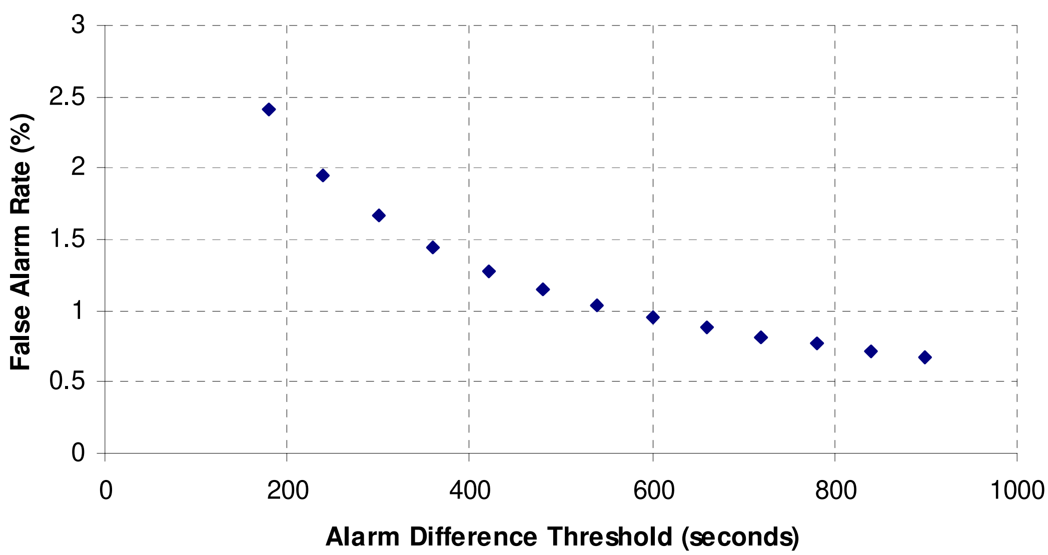

Figure D.4: Sensitivity of False Alarms to Threshold for Time Difference Between Successive Alarms

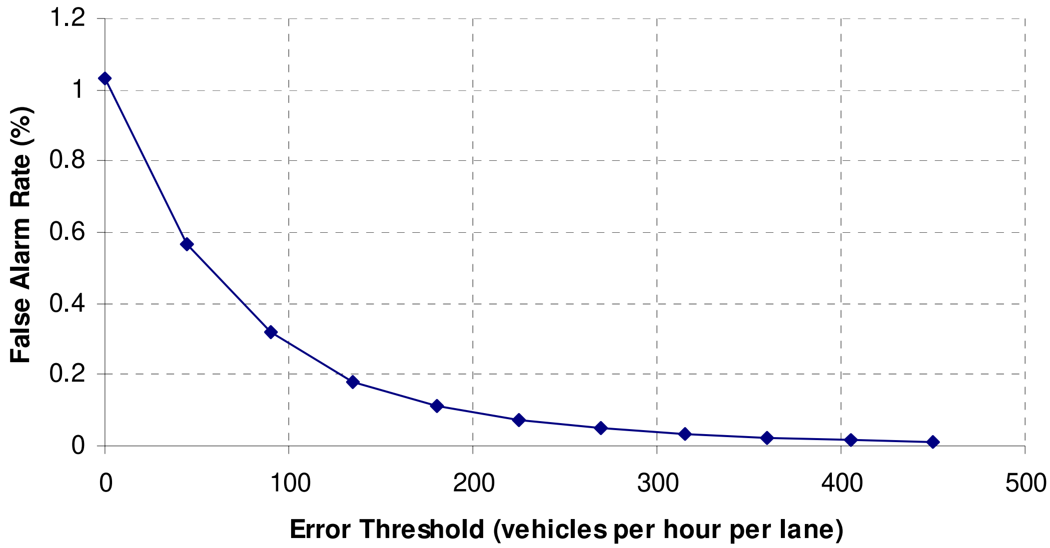

Figure D.5: Sensitivity of False Alarms to Threshold for Maximum Prediction Error

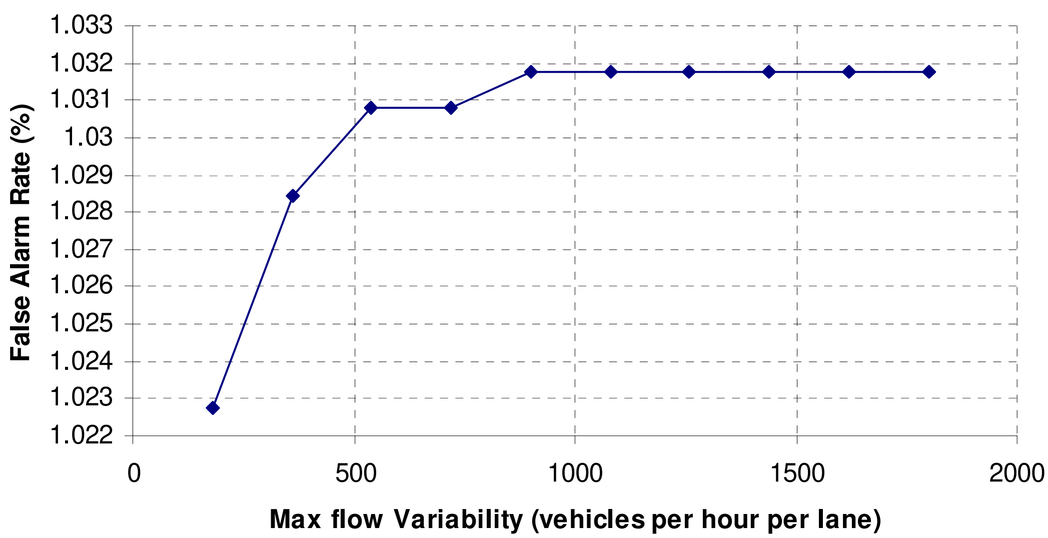

Figure D.6: Sensitivity of False Alarms to Threshold for Maximum Difference of Flow from 5-Minute Moving-Average

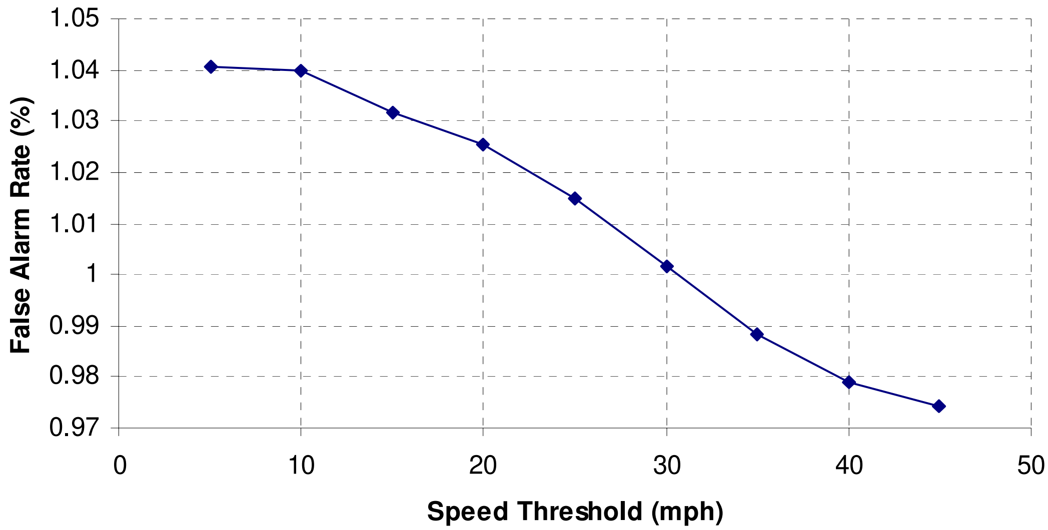

Figure D.7: Sensitivity of False Alarms to Threshold for Speed Cutoff for Stop-and-Go Traffic

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