A MATHEMATICAL MODEL FOR FREEWAY INCIDENT DETECTION AND CHARACTERIZATION: A FUZZY APPROACH

by

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A DISSERTATION

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ABSTRACT

Automatic incident detection and characterization have been examined through the three articles included in this dissertation. The sample for each analysis consists of data supplied through the South Carolina Department of Transportation (SCDOT). The dissertation consists of a general introduction, Article One, Article Two, Article Three, and a general conclusion. The Alabama Freeway Incident Detection System- Incident Detection Module (AFIDS-IDM) was presented in Article One as a means of automatic incident detection in evacuation scenarios. A characterization module and a re-routing module were presented in Article Two supporting AFIDS-IDM. Article Three compares AFIDS-IDM to a group of comparison algorithms to determine the creditability of the proposed methodology.
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<td>ACC</td>
<td>Accuracy of Characterization Metrics</td>
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<tr>
<td>AID</td>
<td>Automatic Incident Detection</td>
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<td>AFIDS</td>
<td>Alabama Freeway Incident Detection System</td>
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<tr>
<td>AFIDS-ICM</td>
<td>Alabama Freeway Incident Detection System- Incident Characterization Module</td>
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<td>AFIDS-IDM</td>
<td>Alabama Freeway Incident Detection System-Incident Detection Module</td>
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<tr>
<td>AFIDS-RM</td>
<td>Alabama Freeway Incident Detection System-Rerouting Module</td>
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<tr>
<td>AR</td>
<td>Accurate Re-Routing Percentage</td>
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<td>ATR</td>
<td>Automatic Traffic Recorder</td>
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<tr>
<td>$c_j$</td>
<td>Capacity for Road Section</td>
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<td>DR</td>
<td>Detection Rate</td>
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<td>DOCC</td>
<td>Downstream Occupancy</td>
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<tr>
<td>DOCCTD</td>
<td>Relative Downstream Temporal Occupancy Measurement</td>
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<tr>
<td>ES</td>
<td>Exponential Smoothing Algorithm</td>
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<tr>
<td>$f_i^d$</td>
<td>Downstream Traffic Count</td>
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<tr>
<td>$F_p$</td>
<td>Time Lag Index</td>
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<tr>
<td>$f_p$</td>
<td>AFIDS-IDM Adjustment Factor for Time of Day</td>
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<tr>
<td>$f_i^u$</td>
<td>Upstream Traffic Count</td>
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<td>Acronym</td>
<td>Description</td>
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<tr>
<td>FAR</td>
<td>False Alarm Rate</td>
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<tr>
<td>FCR</td>
<td>False Characterization Rate</td>
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<tr>
<td>FHWA</td>
<td>Federal Highway Administration</td>
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<tr>
<td>I</td>
<td>Total Number of Adjacent Lanes</td>
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<tr>
<td>IVHS</td>
<td>Intelligent Vehicle Highway Systems Program</td>
</tr>
<tr>
<td>ISTEIA</td>
<td>Intermodal Surface Transportation Efficiency Act of 1991</td>
</tr>
<tr>
<td>$\omega_m$</td>
<td>AFIDS-IDM Fuzzy Set Membership Value</td>
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<tr>
<td>GLR</td>
<td>Dynamic Model Algorithm</td>
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<tr>
<td>HCP</td>
<td>Highway Capacity Manual</td>
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<tr>
<td>ID</td>
<td>Road Identification Number</td>
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<tr>
<td>ITS</td>
<td>Intelligent Transport Systems Journal</td>
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<td>JTR</td>
<td>Journal of Transportation Research</td>
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<td>$(\lambda)$</td>
<td>AFIDS-IDM Comparison Value Lambda</td>
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<td>LOC</td>
<td>Level of Congestion</td>
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<td>LOC$_\text{Index}$</td>
<td>Level of Congestion Index</td>
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<tr>
<td>LOS</td>
<td>Level of Service</td>
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<tr>
<td>NCHPP</td>
<td>National Cooperative Highway Research Program</td>
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<td>$o_i^d$</td>
<td>Downstream Occupancy</td>
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<td>$o_i^u$</td>
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<tr>
<td>OCC</td>
<td>Occupancy at Downstream Detector Station</td>
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<td>OCCDF</td>
<td>Spatial Occupancy Difference</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>OCCRDF</td>
<td>Relative Spatial Occupancy Difference</td>
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<tr>
<td>$\mu_{SR}$</td>
<td>Degree of Belongingness of the $s^{th}$ Object to the $r^{th}$ Cluster</td>
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<tr>
<td>RGY</td>
<td>Red-Green-Yellow Color Scheme</td>
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<tr>
<td>SAFETEA-LU</td>
<td>Safe, Accountable, Flexible, and Efficient Transportation Equity Act: A Legacy for Users</td>
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<td>SCDOT</td>
<td>South Carolina Department of Transportation</td>
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<td>SF</td>
<td>Service Flow Rate for AFIDS-IDM LOC</td>
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<td>$T_n$</td>
<td>Predetermined Threshold Value</td>
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<tr>
<td>$T$</td>
<td>Time Lag between Upstream and Downstream Sensors</td>
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<tr>
<td>TCRP</td>
<td>Transit Cooperative Research Program</td>
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<tr>
<td>TEA-21</td>
<td>Transportation Equity Act for the 21st Century</td>
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<tr>
<td>TMC</td>
<td>Traffic Management Center</td>
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<td>TRB</td>
<td>Transportation Research Board</td>
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<tr>
<td>TTC$_C$</td>
<td>Time to Characterize a Cleared Incident</td>
</tr>
<tr>
<td>TTC$_O$</td>
<td>Time to Characterize an Incident Occurrence</td>
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<td>TTD</td>
<td>Time to Detect an Incident Occurrence</td>
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<td>$\nu$</td>
<td>AFIDS-IDM Decision Variable</td>
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INTRODUCTION TO THE DISSERTATION

Problem Statement

In the U.S., evacuations of hundreds of subjects take place every two to three weeks from disasters such as chemical spills, inclement weather, and terrorist attacks. Major threats from hurricanes and other natural disasters happen every one to three years, requiring the evacuation of millions of subjects over short periods of time (TRB No. 29, 2008). Under ideal conditions, these evacuations are carried out in an orderly manner across pre-planned and well maintained evacuation routes. However, increased congestion from normal freeway usage has created an environment where the major thoroughfares normally set aside for evacuation purposes become stressed as evacuation traffic levels approach near design capacities (Nowakowski, et al., 1999). These result in traffic patterns overwhelmed by the magnitude of vehicles leaving the affected area, having detrimental effects on the safety and mobility of vehicles de-departing the evacuation area.

Hindering the evacuation process, even more, is the potential for non-recurring traffic incidents. Non-recurring traffic incidents are defined as any incident causing a reduction of roadway capacity or an abnormal increase in demand, and require first responders to be dispatched (Coifman, 2007). These incidents further congest the traffic stream by both causing delays in clean-up efforts by first-responders and increasing the
time frame necessary to evacuate subjects from the affected area. Further, they lead to potential secondary incidents, which result in higher fatality rates.

The combinations of stressed traffic streams and non-recurring and secondary traffic incidents create delays and backups that result in:

- Increased response time by first responders
- Lost time resulting in a wider evacuation window
- Increased fuel consumption
- Reduced air quality and other adverse environmental conditions
- Increased potential for more serious secondary incidents resulting from rear end collisions, traffic exiting the route, or exiting to the shoulder of the road
- Increased potential for *struck by* incidents involving personal responding to traffic incidents
- Negative public image of first responders involved in incident management activities

**Proposed Solution**

This study proposes the Alabama Freeway Incident Detection System (AFIDS) as an automated decision support system for the recognition and characterization with re-routing support of non-recurring incidents in evacuation scenarios. The system offers near immediate incident recognition while providing traffic monitors with a characterization, or priority, scheme coupled with a re-routing module.
AFIDS was developed as an alternative to existing systems after an exhaustive search of current research related to incident detection and characterization was performed. The proposed system was deemed necessary due to the need for automatic incident detection that could both operate with a minimum amount of historical data and be put in place quickly with a minimum expenditure of time and hardware.

The literature review indicated a trend in the escalating usage of freeway systems resulting in many freeways operating at near capacity during peak periods (Nowakowski, Green, and Kojima, 1999). The ensuing traffic patterns associated with these levels of congestion result in recurrent compression waves that form and break apart over varying periods of time, making the identification of naturally forming congestion categories somewhat fuzzy. For this reason, fuzzy set theory, which identifies set membership through degrees of belongingness and allowing belongingness to multiple sets simultaneously, was determined to be the most appropriate methodology for real-time incident detection using real data.

AFIDS differs from other automated incident detection systems in that it combines actual field research reported in the *Highway Capacity Manual* (HCP) (TRB, 2008) with concepts of fuzzy cluster analysis. The HCP is a regularly updated composite of multiple years of research performed by the *National Cooperative Highway Research Program* (NCHPP), *Federal Highway Administration* (FHWA), *Transit Cooperative Research Program* (TCRP), and *Transportation Research Board* (TRB). HCP contains concepts, guidelines, and computational procedures for computing the capacity and quality of service of various highway facilities.

Fuzzy cluster analysis has been used effectively in data categorization and can be viewed as an improved clustering methodology (Bezdek, 1973; Hall et. al., 1992; Sugeno and Yasukawa, 1993). This approach to clustering differs from classical clustering techniques in that a given
data point can be included in multiple groups with the degree of belongingness between 0 and 1. Classical clustering is defined as the partitioning of a set of \( S \) objects into \( R \) mutually exclusive clusters, and can be expressed through an \( S \times R \) matrix \( U = [\mu_{SR}] \), where \( \mu_{SR} = 1 \) if object \( s \) belongs to the cluster \( r \) else \( \mu_{SR} = 0 \).

The discontinuity of clusters, as well as the assurance that clusters are not empty, is insured in classical clustering techniques through the satisfaction of two conditions:

\[
\sum_{r=1}^{R} \mu_{sr} = 1, \quad s = 1, \ldots, S, \tag{1}
\]

\[
\mu_{sr} \in \{0, 1\}, \quad s = 1, \ldots, S; \quad r = 1, \ldots, R. \tag{2}
\]

Fuzzy clustering recognizes that exclusive clusters are not necessarily appropriate for naturally occurring subgroups. In these cases Equation 2 is replaced with Equation 3:

\[
\mu_{sr} \in [0, 1], \quad s = 1, \ldots, S; \quad r = 1, \ldots, R. \tag{3}
\]

Where:

the natural subgroup is considered a fuzzy subset of a set of objects

\( \mu_{sr} \) = the degree of belongingness of the \( s^{th} \) object to the \( r^{th} \) cluster

When applied to freeway incident detection, fuzzy clustering offers the flexibility to explain the compression waves or irregular changes in patterns of data attributes that take place across multiple time frames. This allows the grouping of patterns of lane traffic variables into
comparatively like patterns in response to non-recurrent incident effects on real-time freeway traffic patterns.

Fundamental to fuzzy cluster analysis is the concept of natural subgroups. When the spatial and temporal relationships of natural subgroups are examined, both the value of fuzzy cluster analysis and the need for inapproachable spatial and temporal traffic patterns becomes clear. In this study, this is accomplished by combining fuzzy cluster analysis techniques with the spatial and temporal traffic patterns and relationships defined in the *Highway Capacity Manual* (TRB, 2008).

**Current Studies**

As part of The University of Alabama College of Engineering, The Aging Infrastructure Systems Center of Excellence funded the development of the Alabama Freeway Incident Detection System (AFIDS). AFIDS is a decision support system supporting non-recurrent incident detection, characterization, and re-routing efforts in Traffic Management Centers (TMCs).

The three articles in this dissertation define different aspects of the research and evaluation of the AFIDS project. At the time of this dissertation, a prototype of the system using a modified version of the incident detection logic has been developed by the Intergraph Corporation. However, the system has not been implemented in any actual or real setting.

This dissertation is a collection of three articles with introduction and conclusion sections that summarize the research. Each article is a standalone effort supported with its own literature review, methodology, and discussion sections. While there is a well-defined partition separating the three works, each article is related to the others through their association with AFIDS.
Article One- Traffic Incident Detection Algorithm for Emergency Evacuation Using Real Data

This article introduces the Alabama Freeway Incident Detection System-Incident Detection Module (AFIDS-IDM) as a methodology for the detection of freeway incidents. AFIDS-IDM invokes fuzzy cluster analysis in the identification of lane blocking incidents from comparisons of time varying patterns of incident induced and incident free traffic states. Lane traffic counts and density, collected at successive traffic sensors, are the two primary types of input data. State variables are defined from the spatial and temporal relationships of the raw data, and then evaluated quantitatively and qualitatively to determine the decision variables necessary for the determination of lane blocking incidents. The specified decision variable is then compared to a fuzzy cluster analysis algorithm to determine the existence of a lane blocking incident.

Article Two- Incident Characterization and Re-routing After Automatic Incident Detection

Article Two defines the Alabama Freeway Incident Detection System- Incident Characterization Module (AFIDS-ICM) as a methodology for the characterization of previously identified freeway incidents. The method characterizes incidents through the firing of a series of fuzzy based rules to determine both partial and full blockage of highway freeways. Freeway incidents are characterized as “green”, “yellow”, or “red” to indicate severity of traffic conditions, with red conditions consider the highest priority. When incidents are characterized as a red condition AFIDS-ICM initiates a computerized rerouting module, the Alabama Freeway Incident Detection System-Rerouting Module (AFIDS-RM), for the selection of alternate routes.
using Geo-Media and Geo-Media Web Map. AFIDS-ICM continues to evaluate yellow and red traffic conditions until a “green” condition exists.

**Article Three- Comparison of Five Algorithms for Automatic Freeway Incident Detection**

It is the purpose of Article Three to survey current literature related to Automatic Incident Detection (AID) and to list present methods in this field of study. Further, this article evaluates each method against a set of criteria to short-list algorithms that are applicable to field practice. The latter are then implemented using real data collected by the South Carolina Department of Transportation (SCDOT) to determine the number and location of traffic incidents identified by each algorithm. The five algorithms selected for comparison are the California Algorithm #8, the Exponential Smoothing Algorithm, the McMaster Incident Detection Algorithm, the Shue Algorithm, and the Alabama Freeway Incident Detection System- Incident Detection Module Algorithm.

**Significance and Limitations of the Studies**

This initiative will provide traffic officials with relevant insights and expertise to detect and characterize situations that may drastically impair appropriate responses during a potential eventuality such as a chemical spill, a terrorist attack, or a natural disaster. The study is limited to data collected and supplied by the South Carolina Department of Transportation (SCDOT). As such, only bulk data collected in hourly increments were used. While this impacts the immediacy of the results, it does not diminish the value of the tool, which applies equally with data collected at lesser time intervals. The insights of this study are critical to homeland security and
emergency management personal who are charged with insuring the safety and security of numerous individuals through preparedness planning and evacuation.
ARTICLE ONE

Traffic Incident Detection Algorithm for Emergency Evacuation Using Real Data

1.1. Introduction

The response to a potential disaster can require the evacuation of personnel from a specified area. Generally, such efforts are restricted to the orderly mass departure of individuals across preplanned and well maintained transportation routes. In the U.S., evacuations of up to 1,000 subjects take place every two to three weeks, with more extreme evacuations involving two million or more every one to three years (TRB, 2008).

While evacuation routes are designed to accommodate normal traffic movements, congestion and gridlock can occur as the design capacity of the road system is overwhelmed by the magnitude of vehicles leaving the affected area. The resulting traffic patterns affect the safety and mobility of subjects moving to more secure areas. Adding to this disarray, potential non-recurring incidents congest traffic patterns even more. Estimates indicate that between fifty and sixty-five percent of traffic congestion is caused by non-recurring traffic incidents with an additional ten percent related to construction and weather (Coifman, 2007). A non-recurring traffic incident is any event that both causes a reduction of roadway capacity or an abnormal increase in demand, and requires
first responders to be dispatched. Stalled vehicles, roadway debris, spilled loads, and crashes fall into this category of incidents.

Non-recurring traffic incidents can cause secondary traffic incidents. These incidents further congest the traffic stream and cause delays in clean-up efforts by first-responders. Studies indicate that twenty percent of traffic incidents are secondary incidents, with one out of five resulting in a fatality. In addition to crashes, secondary incidents can include overheated vehicles, out of fuel conditions, and engine stalls.

The delay and traffic gridlock associated with traffic incidents is compounded during the evacuation process due to the large numbers of subjects leaving the affected area. These delays and backups result in:

- Increased response time by first responders
- Lost time resulting in a wider evacuation window
- Increased fuel consumption
- Reduced air quality and other adverse environmental conditions
- Increased potential for more serious secondary incidents resulting from rear end collisions, traffic exiting the route, or exiting to the shoulder of the road
- Increased potential for *struck by* incidents involving personal responding to traffic incidents
- Negative public image of first responders involved in incident management activities.
1.2. Background Studies

Early detection of traffic incidents can both reduce the time to return traffic to normal rates of flow and reduce the potential for secondary incidents (Busch, 1987), thus increasing the number of vehicles leaving the affected area. It would be expected, therefore, that the real-time reporting of traffic data would have dramatic effects on the reduction of the impact of traffic incidents in emergency evacuations.

A number of methods, both human-based and automated, have been proposed to manage and regulate traffic movement along freeways (Williams and Guin, 2007). Human-based methods rely on technologies such as cell phones, call boxes, passing motorists, and first responder patrols (Monahan, 2007). While these methods are reliable, they are accompanied by a triggering delay which increases the response time of emergency personnel, further inhibiting efforts to restore normal traffic movement (Singliar and Hauskrecht, 2006).

Automatic incident detection (AID) is generally founded on a series of algorithms intended for the detection of freeway incidents. Studies indicate that the effectiveness of AID is, at best, poor (Parkany and Xie, 2002). The lack of AID operational effectiveness is primarily related to unacceptably high false alarm rates and complex calibration procedures.

For a period of time, the poor performance of AID was of no consequence, since traffic management centers (TMCs) were able to provide marginal detection capability through human-based systems (Sobhi and Kelly, 1999). However, with an estimated 17% of freeways often experiencing congestion levels at or above capacity, the increasing size and range of freeway transportation networks are growing at rates faster than human-based resources are capable of monitoring, bringing a new focus to AID (Nowakowski et al., 1999). It would be expected that freeway congestion during evacuation would be at or near design capacity, rendering human-
based methods incapable of delivering the response time necessary for the significant reduction of traffic slowdowns related to secondary incidents.

Since the 1960’s, AID has seen a number of advancements. However, inputs have remained fairly consistent with remotely sensed traffic data as the primary source of input. Data are zone specific, collected at upstream and downstream sensors for each zone. The primary metric for most AID algorithms is lane occupancy with others using speed and vehicle count (Williams and Guin, 2007).

Early efforts in AID were statistical and pattern-based algorithms. These efforts can be summarized in four categories: comparative algorithms, statistical algorithms, time-series and filtering based algorithms, and traffic theory based algorithms (Dudek et al., 1974).

Comparative algorithms are characterized by their reliance on pattern recognition for the identification of patterns of behavior of specific variables known to be associated with incident conditions. The California algorithm family is an example of this category of algorithms (Courage and Levin, 1968; Payne and Tignor, 1978). The California family consists of 10 algorithms developed using real traffic data from the Los Angeles freeway system. The California #8 is one of the more popular algorithms from this group. The algorithm uses decision tree logic to identify traffic incidents. California algorithms are often used as benchmarks to evaluate other algorithms.

Statistical algorithms use standard statistical techniques to identify sudden changes in behavior in variables such as lane occupancy and rate of speed, known to indicate the existence of an incident (Payne and Tignor, 1978). The Standard Normal Deviate (SND) and Bayesian Algorithm are examples of these algorithms (Dudek et al., 1974, Courage and Levin, 1968, Levin and Krause, 1978).
Time series and filtering algorithms rely on concepts of time-series to track decision variables. Incidents are recognized when a decision variable deviates from the modeled time-series behavior. The Auto-Regressive Integrated Moving Average (ARIMA) based algorithm, the Exponential Smoothing Algorithm (Cook and Cleveland, 1974), and the Kalman Filtering based Algorithm are included in this category of algorithms (Chow et al., 1977; Cook and Cleavland, 1974).

The Exponential Smoothing algorithm was developed for use from data collected from the John C. Lodge Freeway in Detroit. This method uses double exponential smoothing to generate a tracking variable that is further processed to recognize a traffic blocking incident.

Traffic theory based algorithms recognize the relationship between the traffic variables as a means of analysis. The McMaster Algorithm (Persaud et al., 1990; Hall et al., 1993) based on catastrophe theory, falls in this category. The GLR, a dynamic model algorithm, also falls in this category. This algorithm is designed to make full use of all information about the dynamic and stochastic evolution of traffic variables in time and space (Chow et al., 1977, Gall and Hall, 1989; Greene et al., 1977; Kurkijian et al., 1977).

The McMaster Algorithm was developed using data from Queen Elizabeth Way, Mississauga, Ontario. The basic McMaster Algorithm is a congestion detection algorithm. It uses a catastrophe theory model for description of the flow-occupancy-speed relationship. Incidents are detected based on positioning on a flow-density chart.

More recently, AID research and development have moved in the direction of artificial intelligence and soft computing techniques, ushering in a fifth category of incident algorithms. Among these are fuzzy logic/fuzzy set theory (Hsiao, Lin, and Cassidy, 1994; Chang and Wang, 1994; Lin and Chang, 1998; Shue, 2002), artificial neural networks (Dia and Rose, 1997), fuzzy
logic in conjunction with neural networks (Ishak and AlDeek, 1998a, Ishak and Al-Deek, 1998b, Srinivasan et al, 2001), fuzzy expert systems (Lin and Chang (1998), wavelet transformations (Samant and Adeli, 2000), and genetic algorithm over neural networks (Roy and Abdulhai, 2003). This group of algorithms is referred to as advanced incident detection algorithms.

The development of fuzzy logic/fuzzy set theory algorithms is most promising in that they do not necessarily rely on complex calibration procedures, but rather on the appraisal of existing traffic conditions. Additionally, they are principally prepared to deal with the fuzziness of the complex temporal relationships of ever changing traffic patterns. While advances in this area of study have been made by Shue (2002), the current state of fuzzy logic/fuzzy set algorithms have only been tested in simulation and have not been modified to fit real time traffic data.

The large number of approaches to AID indicates an inability of Traffic Management Center’s (TMC) to settle on one single approach to traffic management. In many cases, the calibration procedures of more modern algorithms demand technology not available to their intended users. While issues related to the effectiveness of AID have been addressed in algorithms developed since the 1990’s, current collection methods employed make these methodologies difficult to implement.

1.3. Research Objectives and Scope

This paper proposes the Alabama Freeways Incident Detection System- Incident Detection Module (AFIDS-IDM), an automated method for freeway incident detection, as a necessary tool for real time incident detection during evacuation processes. AFIDS-IDM is the incident detection module of the Alabama Incident Detection System (AFIDS). AFIDS is a three module system consisting of incident detection, incident characterization, and traffic re-routing modules.
The proposed system is based on fuzzy set theory. This tool is different from similar tools on the market in that it is intended for use exclusively in an evacuation process. This increases the value of the tool by decreasing the complexity of necessary calculations, eliminating the need for elaborate calibration, and reducing the number of false alarms associated with other automatic methods. Since the tool is automated, it is expected to reduce the trigger time associated with the deployment of first responders to traffic incidents. The tool is designed for use with available TMC technology.

1.3.1 Detection Process

The Alabama Freeway Incident Detection System Incident Detection Module (AFIDS-IDM) identifies lane blocking incidents from comparisons of time varying patterns of incident induced and incident free traffic states. Decision variables are defined from the spatial and temporal relationships of the raw data, and then evaluated quantitatively and qualitatively to establish inputs for the algorithmic determination of freeway blocking incidents.

The AFID-IDM logic is a continuous loop process carried out in seven steps. These steps are indicated in Table 1-1. In the event an incident is detected, the system continues to monitor the location until the incident is cleared up. When no incident is detected, the system continues to the next time step. This procedure is depicted graphically in Figure 1-1.

1.3.1.1 Data Set

Data for this study was made available by the South Carolina Department of Transportation (SCDOT). Vehicle speed and traffic counts from successive upstream and
Table 1-1. AFID-IDM Incident Detection Process

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Input data</td>
</tr>
<tr>
<td>2</td>
<td>Determination of a Level of Congestion Index (LOC Index)</td>
</tr>
<tr>
<td>3</td>
<td>Determination of the Level of Congestion (LOC) from the index</td>
</tr>
<tr>
<td>4</td>
<td>Determination of the decision variable $v^d$ associated with the specified LOC</td>
</tr>
<tr>
<td>5</td>
<td>Determination of the comparison variable lambda ($\lambda$) associated with the input data and posted speed limit</td>
</tr>
<tr>
<td>6</td>
<td>Determination of the fuzzy set membership, $\omega_m$, associated with the specified $v^d$</td>
</tr>
<tr>
<td>7</td>
<td>A lane blocking incident exists when $\omega_m &gt; \lambda$.</td>
</tr>
</tbody>
</table>

downstream sensors, or Automatic Traffic Recorders (ATR), collected at hourly intervals were the primary inputs. Together, the two ATR’s form detection zone. Occupancy values were calculated mathematically from the data.

The SCDOT data set consisted of data collected over a period of one calendar year from 269 ATR’s across South Carolina. Twelve detection zones, representing continuous sections of the highway, were selected from this data. Table 1-2 depicts the format in which the collected data was made available for the study. ID is the road identification number. Hour refers to the particular hour of the day the data was reported. There are 5 lanes considered for a particular section of the road. Bin numbers identify the number of vehicles traveling at a given speed. Total Volume is the summation of the number of vehicles in all the Bins.

Road sections under study, Figure 1-2, were primarily north and south of Greenville along Interstate Highway 185, north and south of Spartanburg along Interstate Highway 85, and north and south of Laurens County, along Interstate 385. Data was collected over a period of two and a half months by SCDOT.
Start

Input Data

Determine Level of Congestion Index (LOC\textsubscript{Index})

Determine Level of Congestion from LOC\textsubscript{Index} (Table 3)

Determine Decision Variable $\nu^*$

Determine Comparison Variable $\lambda$

Determine Fuzzy Set Membership $\omega_m(k)$

$\omega_m(k) > \lambda$

YES

Initiate Characterization Module

NO

Figure 1-1. System Flowchart
Table 1-2. Sample of Collected Traffic Data

<table>
<thead>
<tr>
<th>ID</th>
<th>ATR_ID</th>
<th>HOUR</th>
<th>LANE</th>
<th>Bin_0_5</th>
<th>Bin_11_5</th>
<th>Total Volume</th>
<th>ID1</th>
</tr>
</thead>
<tbody>
<tr>
<td>137085</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>237</td>
<td>1</td>
</tr>
<tr>
<td>137086</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>150</td>
<td>2</td>
</tr>
<tr>
<td>137087</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>31</td>
<td>3</td>
</tr>
<tr>
<td>137088</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>137089</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>87</td>
<td>5</td>
</tr>
</tbody>
</table>

Figure 1-2. Road Sections Considered
1.3.1.2 Determination of Level of Congestion Index

The determination of the Level of Congestion Index (LOC\textsubscript{Index}), Equation 1-1, is the first step in the identification of a lane blocking incident. A single algorithm, resulting in a value between 0 and 1, is necessary to determine the LOC\textsubscript{Index} at the upstream and downstream sensors:

$$\text{LOC}\textsubscript{Index}_{,ijk} = \frac{SF_{jk}}{c_j} \times \frac{1}{f_p}$$

Where:

\text{LOC}\textsubscript{Index}_{,ijk} = Level of congestion for i lane of traffic in evacuation route j at time period k

\(SF = \) Service flow rate for LOC\textsubscript{i} under prevailing roadway and traffic conditions for I lanes in one direction, in vehicles per hour. This value is obtained from the input data, and is the total number of actual vehicles across all bin numbers for that ATR for that hourly update.

\(c_j = \) Capacity for the road section under study. This value is obtained from the Capacity field in the ATR data.

\(\frac{SF_{jk}}{c_j}\) = Utilization at time factor \(k\).

\(f_p\) = factor for further adjustments due to time of day (Table 1-3).

<table>
<thead>
<tr>
<th>Traffic Stream Type</th>
<th>Factors, (f_p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekday or Commuter</td>
<td>1.0</td>
</tr>
<tr>
<td>Other</td>
<td>0.75-0.90\textsuperscript{a}</td>
</tr>
</tbody>
</table>

\textsuperscript{a} Engineering judgment and/local data must be used in selecting the exact value

\textsuperscript{b} Reprinted from the Highway Capacity Manual
1.3.1.3 Determination of Level of Congestion (LOC)

The LOC index is applied to Table 1-4 to determine the Level of Congestion (LOC). Posted speed limit and LOC index are the two variables in determining the LOC. Congestion categories are rated as: a) low, b) moderate, c) heavy, and d) over congested.

LOC Categories are derived from Level of Service Categories (LOS) A through F, described in the Transportation Research Board’s publication Highway Capacity Manual, where:

- LOC Category Low = LOS Categories A and B
- LOC Category Moderate = LOS Categories C and D
- LOC Category High = LOS Category E
- LOC Category Over Congestion = LOS Category F.

<table>
<thead>
<tr>
<th>LOC Category</th>
<th>50 mph</th>
<th>60 mph</th>
<th>70 mph</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOC Category</td>
<td>LOC</td>
<td>LOC</td>
<td>LOC</td>
</tr>
<tr>
<td>Low</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mpvh</td>
<td>1,100</td>
<td>1,000</td>
<td>850</td>
</tr>
<tr>
<td>Index</td>
<td>0.00-0.54</td>
<td>0.00-0.69</td>
<td>0.00-0.66</td>
</tr>
<tr>
<td>Moderate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mpvh</td>
<td>1,850</td>
<td>1,700</td>
<td>1,650</td>
</tr>
<tr>
<td>Index</td>
<td>0.55-0.93</td>
<td>0.70-0.84</td>
<td>0.67-0.83</td>
</tr>
<tr>
<td>High</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mpvh</td>
<td>2,000</td>
<td>2,000</td>
<td>1,900</td>
</tr>
<tr>
<td>Index</td>
<td>0.94-1.00</td>
<td>0.85-1.00</td>
<td>0.84-1.00</td>
</tr>
<tr>
<td>Over Congestion</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Highly variable, unstable

1.3.1.4 Determination of Decision variable $v^s$

Decision variable $v^s$ is determined through the application algorithms $v^l$, $v^m$, and $v^h$, each representing the LOC’s low, moderate, and high, respectively.
\[ v_i^1(k) = \frac{o_i^{u(k-n)} - o_i^d(k)}{o_i^u(k-n)} \]  
\[ v_i^2(k) = \left\{ \left[ \frac{f_i^d(k)}{I} \right] - f_i^d(k) \right\} - \{f_i^d(k)/I\} \]  
\[ v_i^3(k) = \{f_i^d(k) \ast \text{Min}(1.0, F_p)\} - \{o_i^u(k_{k-n}) \ast (C_{f_i})\} - (f_i^d(k)/I) \]

Where:

\( f_i^u(k) \) and \( f_i^d(k) \) = the upstream and downstream traffic counts collected at target lane \( i \) and time step \( k \),

\( o_i^u(k) \) and \( o_i^d(k) \) = collected occupancies,

\( I \) = total number of adjacent lanes,

\( T \) = the maximum time lag predetermined for consideration of the travel time taken from the upstream detector station to the downstream detector station on the relationship between the upstream and downstream traffic data,

\( F_p \) = time lag index defined as the posted speed limit / distance between \( f_i^u(k) \) and \( f_i^d(k) \).

### 1.3.1.5 Determination of Comparison Variable Lambda

Comparison variable \( \lambda \) is determined by offsetting the traffic count at the upstream ATR by a correction factor adjusting for the minimum speed expected to navigate each detection zone based on the appropriate LOC. The minimum expected speed values are indicated in Table 1-5.
Table 1-5. Min. Expected Speed at Posted Speed Limits at LOC’s High, Moderate, and Low

<table>
<thead>
<tr>
<th>Posted Speed (mph)</th>
<th>30</th>
<th>35</th>
<th>40</th>
<th>45</th>
<th>50</th>
<th>55</th>
<th>60</th>
<th>65</th>
<th>70</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>26</td>
<td>32</td>
<td>38</td>
<td>42</td>
<td>45</td>
<td>48</td>
<td>51</td>
<td>54</td>
<td>57</td>
</tr>
<tr>
<td>Moderate</td>
<td>25</td>
<td>32</td>
<td>37</td>
<td>38</td>
<td>40</td>
<td>41</td>
<td>43</td>
<td>44</td>
<td>46</td>
</tr>
<tr>
<td>High</td>
<td>23</td>
<td>25</td>
<td>26</td>
<td>27</td>
<td>28</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Over Congestion</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
</tbody>
</table>

* Highly variable, unstable

The comparison value, \( \lambda \), is arrived through the following equation:

\[
\lambda = (\text{Upstream traffic count at ATR}_i) \times (C_{fs})
\]  

Where:

- Upstream traffic count at ATR\(_i\) is the vehicle count at time period \( k \) determined from the upstream ATR;
- \( C_{fs} \) is a correction factor derived from dividing the minimum expected speed for a detection zone at a specified LOC by the posted speed for the detection zone.

1.3.1.6 Determining Fuzzy Set Membership

Fuzzy set membership is determined by applying Equation1-6:

\[
\omega_m(k) = 1 - (v^s(k - f_p) - \mu_m)
\]  

(1-6)
Where:

\( \omega_m \) = Fuzzy set membership value,

\( \mu_m \) = pattern of the decision variable pre clustered on the basis of historical traffic data associated with attribute \( m \), values are as follows:

- Low Congestion = 0.75
- Moderate congestion = 0.90
- Heavy congestion = 1.0

1.3.1.7 Recognition of Lane Blocking Incident

AFIDS-IDM recognizes a lane blocking incident when the following fuzzy rule is fired:

IF \( \omega_m(k) > \lambda \)
THEN a lane blocking incident with attribute \( m \) is recognized at time step \( k \)
ELSE \( k = k+1 \) and go back to previous procedure

Where:

\( m \) = low, moderate, or high level of congestion category,

\( k \) = Specified time frame

1.4. Numerical Tests and Results

Performance tests of the AFIDS-IDM algorithm were conducted with the SCDOT data set. The results, presented in Table 1-6, indicate that the algorithm successfully identified traffic incidents in each of the road sections tested.
Table 1-6. Performance Results by ATR

<table>
<thead>
<tr>
<th>Road Section</th>
<th>Total Number of Incidents</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATR 194-196</td>
<td>5</td>
</tr>
<tr>
<td>ATR 196-197</td>
<td>39</td>
</tr>
<tr>
<td>ATR 242-243</td>
<td>3</td>
</tr>
<tr>
<td>ATR 243-244</td>
<td>2</td>
</tr>
</tbody>
</table>

The total of traffic incidents on road section bounded by ATR’s 196 and 197 were significantly higher than other road sections. This is attributed to both an overall heavier traffic count than other road sections and a higher speed limit. The road section bounded by ATR’s 243 and 244 reported the least number of incidents. This section of road was characterized by a much lower volume of congestion, which explains the lower number of traffic incidents.

1.5. Conclusion and Recommendations

AID research has evolved with the introduction of one technique after another, with no single methodology assuming a dominate role in incident detection. This is, in some ways, attributed to the development of many algorithms which take place in simulated environments where actual traffic conditions were designed to fit the algorithm, giving a greater degree of control of the experiment than would be found in actual implementation. And where, in other algorithms, AID methodologies are defined by complex calibrations based on calibration parameters have to be fine tuned in practice.

This paper introduces the AFIDS-IDM as an alternate methodology for automatic incident detection based on fuzzy cluster analysis. The algorithm presented was founded in fuzzy
clustering and developed around field research defined in the TRB’s *Highway Capacity Manual* (2008). The algorithm was tested with real data supplied through the SCDOT. AFIDS-IDM differs from others in that it is not dependent on the calibration of parameters from historical data.

Performance tests indicate that the algorithm is capable of determining traffic incident occurrence across a number of different road sections. While the data set provided sufficient information to allow testing on multiple levels of congestion, it did not provide weather data, which would have provided greater insight into the performance of the algorithm. This limitation provides direction for future performance testing for the algorithm.

A limitation of the study was in the data set itself, which was made available in bulk form at hourly increments. While this is representative of real collection methodologies, this greatly impaired the evaluation of the algorithm, further providing direction for future research.
REFERENCES


2.1. Introduction

Quick and responsive freeway incident detection decreases traffic congestion, fuel consumption, and environmental pollution. It also reduces the response time of emergency vehicles, increasing the survival rate of any seriously injured individuals, and minimizes traffic congestion which can lead to secondary incidents (Lomax et al., 2003). It has, in recent years, taken on added significance by reducing delays and increasing the number of vehicles evacuated from hazardous areas. Incident detection in itself, however, is not enough to meet the needs of stressed highway systems. Characterization and re-routing systems are necessary to organize and expedite the identification of an existing incident, the determination of its location, and, to identify alternate routes to alleviate potential traffic buildup (Han and May, 1990).

2.2. Background Studies

Incident detection is classified into two categories: human-based and automatic incident detection (Williams and Guin, 2007). Human-based technologies are primarily dependent on the reporting of traffic incidents through a number of low tech capabilities such as cell phones and radios by a number of sources including passing motorists, law enforcement agencies, and Department of Transportation (DOT) employees (Monahan,
These technologies, along with their predominant initiating sources, are outlined in Table 2-1. While considered highly reliable, there is a considerable delay between the occurrence of an incident and the initiation of a traffic management response where low tech technologies are engaged (Singliar and Hauskrecht, 2006).

**Table 2-1. Human-Based Incident Detection Technologies**

<table>
<thead>
<tr>
<th>Technology</th>
<th>Initiating Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cellular Phone Calls</td>
<td>Passing Motorists</td>
</tr>
<tr>
<td>Freeway Service Patrols</td>
<td>Police and Other Official Vehicles</td>
</tr>
<tr>
<td>Peak Period Patrols</td>
<td>Law Enforcement Agencies</td>
</tr>
<tr>
<td>Fleet Operators</td>
<td>DOT Patrol Agents</td>
</tr>
<tr>
<td>Closed Circuit TV</td>
<td>Traffic Center Employees</td>
</tr>
<tr>
<td>Motorist Call Boxes</td>
<td>Passing Motorists</td>
</tr>
<tr>
<td>Aircraft Patrols</td>
<td>Law Enforcement and DOT</td>
</tr>
<tr>
<td>Fixed Observers</td>
<td>Law Enforcement and DOT</td>
</tr>
<tr>
<td>CB Radio Monitoring</td>
<td>Law Enforcement Agencies</td>
</tr>
</tbody>
</table>

Automatic incident detection (AID) is generally founded in a series of algorithms intended for the recognition of freeway incidents. While this approach has been around since the beginning of intelligent transportation systems, studies indicate that the effectiveness of AID is, at best, poor (Parkany and Xie, 2002). The lack of AID operational usefulness is primarily related to an unacceptably high false alarm rate, resulting in many automatic incident alarms being either disabled or ignored.

For a period of time, the poor performance of AID was of no consequence, since traffic management centers (TMCs) were able to provide marginal detection capability through human-based systems (Sobhi and Kelly, 1999). However, the increasing size and range of freeway transportation networks under the management of TMCs are growing at rates faster than human-
based resources are capable of monitoring, with an estimated 17% of freeways often experiencing traffic levels at or above capacity (Nowakowski et al., 1999). This along with the high cost of building new freeway systems and the passage of bills such as the Safe, Accountable, Flexible, And Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU) has caused TMCs to face the realization that human-based methods will not meet future incident detection needs, thereby refocusing attention on AID.

SAFETEA-LU is a bill that governs federal surface road spending (US Government Printing Office, 2005). It was set in law in August 2005, and will expire in September, 2009. It is the successor of the Transportation Equity Act for the 21st Century (TEA-21) which followed the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA). ISTEA established the Intelligent Vehicle Highway Systems Program (IVHS). IVHS recognizes the need to link vehicles and freeways through advanced information systems and the development of Advanced Traffic Management Systems such as AID (Chen and Galler 1990). This group of bills recognizes the constraints placed on the further expansion of freeway systems and places a priority on the maximization of system efficiency and preservation. They also lay out guidelines for congestion and air quality management.

One of the more progressive aspects of SAFETEA-LU is the recognition of the need for AID. SAFETEA-LU goes further to recommend that AID be combined with human based systems. It is expected that this mixture of approaches to incident detection will help overcome AID shortcomings.

AID is accomplished algorithmically from data collected at sensors strategically located throughout the control area. The algorithms can be classified through five categories that explain
the general nature of the algorithm (Dudek and Messer, 1974): a) pattern recognition, b) time series and filtering, c) statistical, d) traffic theory, and e) advanced algorithms.

Pattern recognition algorithms compare tracking variables against pre-determined threshold values to identify anomalies. The tracking variable is typically a traffic parameter or a variable derivative of the traffic parameter (Eisele and Lomax, 2004). Occupancy is the most common traffic parameter in this class of algorithms. These algorithms are sometimes referred to as comparative algorithms due to the comparative nature of the variables under consideration. The California Algorithm family is the most commonly used pattern recognition algorithm (Courage and Levin, 1968).

In time series and filtering algorithms, the tracking variable is treated as a time-series variable. In this group of algorithms, an incident is recognized when there is a deviation of the tracking variable from the modeled time-series behavior. An example of this algorithm is the exponential smoothing algorithm (Chow et. al., 1977).

Statistical algorithms use typical statistical analysis to identify unexpected changes and atypical behavior in the tracking variable to identify incidents. Algorithms in this group are based on the argument that the reverse of a situation is an indication of an incident. Traffic flow, average speed, and lane occupancy are often used as tracking variables. The Standard Normal Deviate and the Bayesian define this category of algorithms (Payne and Tignor, 1978).

Traffic theory algorithms rely on relationships between traffic variables for analysis. The most common of this type of algorithm is the McMaster catastrophe theory algorithm which determines the state of traffic variables based on its position in a flow-density plot (Chow et al, 1977).
Advanced algorithms include a number of algorithms with techniques founded in advanced mathematical formulae. This category of algorithms integrates inexact reasoning and uncertainty into the decision logic. Artificial Intelligence methods (AI) are able to recognize specific patterns and learn from data collected at upstream and downstream sensors, much like the structure of human thought. AI algorithms are generally founded on either fuzzy logic or neural networks or combinations of the two (Ishak and Al-Deek, 1998).

The Shue algorithm (Shue, 2002) is a fuzzy clustering based approach to identify lane blocking incidents from comparisons of time varying patterns of incident induced and incident free traffic states that was developed in simulation mode. Shue’s approach first recognizes the existence of a lane blocking incident followed by the characterization of the incident.

The Alabama Freeway Incident Detection System (AFIDS) is an approach to incident detection similar to the Shue but adapted to the use of real data and specifically designed for use in evacuation processes. AFIDS consists of three modules: a) incident detection, b) incident characterization, and b) re-routing. AFIDS is different from other incident detection algorithms in that it recognizes the slower more congested traffic patterns found in evacuation processes. And, it was designed around data collection methods in use in Department of Transportation’s (DOT) around the U.S.

2.3. Research Objective and Scope

It is the purpose of this paper to provide overviews of the AFIDS system and then describe the AFIDS Incident Characterization (AFIDS-ICM) and re-routing (AFIDS-RM) modules. AFIDS-ICM and AFIDS-RM are described through the application of real-time data supplied through the South Carolina Department of Transportation (SCDOT). The AFIDS incident
detection module (AFIDS-IDM) is summarized to provide coherency leading to AFIDS-ICM and AFIDS-RM.

2.3.1 Overview of AFIDS System

The Alabama Freeway Incident Detection System (AFIDS) consists of a three module automated freeway incident detection, characterization, and re-routing decision support system employed under emergency evacuation conditions. Alabama Freeway Incident Detection System-Incident Detection Module (AFIDS-IDM) continuously monitors traffic conditions in multiple detection zones. Input data, supplied from traffic sensor stations, are processed for the determination of lane blocking incidents through a fuzzy-clustering algorithm. In the event an incident is detected, The Alabama Freeway Incident Detection System- Incident Characterization Module (AFIDS-ICM) is employed. The recognition of an incident causes a change in detection zone status from normal traffic conditions to a low incident priority. Incidents that persist for more than one time period are assigned a high priority status; otherwise they are recognized as cleared and re-assigned a normal condition. When incidents are assigned a high priority status, GeoMedia Web Map is evoked through the Alabama Freeway Incident Detection System-Re-routing Module (AFIDS-RM). The module allows Traffic Management Center (TMC) monitors access to graphical representations of pre-determined routings. These routings represent alternate routes to alleviate potential traffic congestion caused by the recognized incident. The decision to re-route traffic along identified routings is at the discretion of TMC monitors. Access to routings is manually available through lower priority conditions at the discretion on traffic Managers. An overview of the AFIDS system is depicted graphically in Figure 2-1.
2.3.2 Summary of AFIDS-IDM

AFIDS-IDM incorporates a fuzzy cluster approach to incident detection with research findings identified and reported through the *Highway Capacity Manual* (TRB, 2008). AFIDS-IDM follows a seven step approach to incident detection defined in Table 2-2.
Table 2-2. AFID-IDM Incident Detection Process

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Input data</td>
</tr>
<tr>
<td>2</td>
<td>The determination of a Level of Congestion Index (LOC \text{Index})</td>
</tr>
<tr>
<td>3</td>
<td>The determination of the Level of Congestion (LOC) from the index</td>
</tr>
<tr>
<td>4</td>
<td>The determination of the decision variable ( v' ) associated with the specified LOC</td>
</tr>
<tr>
<td>5</td>
<td>The determination of the comparison variable lambda (( \lambda )) associated with the input data and posted speed limit</td>
</tr>
<tr>
<td>6</td>
<td>The determination of the fuzzy set membership, ( \omega_m ), associated with the specified ( v' )</td>
</tr>
<tr>
<td>7</td>
<td>A lane blocking incident exists when ( \omega_m &gt; \lambda ).</td>
</tr>
</tbody>
</table>

Step 1 is data input. From the data, the LOC \text{Index} is determined in Step 2, from Equation 2-1.

\[
LOC_{ijk} = \left( \frac{SF_{ik}}{c_j} \right) \times \left( \frac{1}{f_p} \right) \tag{2-1}
\]

Where:

- \( LOC_{ijk} \) = Level of congestion for \( i \) lane of traffic in evacuation route \( j \) at time period \( k \),
- \( SF \) = Service flow rate for LOC \( i \) under prevailing roadway and traffic conditions for \( I \), lanes in one direction, in vehicles per hour. This value is obtained from the input data, and is the total number of actual vehicles across all bin numbers for that ATR for that hourly update,
- \( c_j \) = Capacity for the road section under study. This value is obtained from the Capacity field in the ATR data,
- \( \left( \frac{SF_{ik}}{c_j} \right) \) = Utilization at time factor \( k \),
- \( f_p \) = factor for further adjustments due to time of day determined from a look-up table.
The LOC Index is applied to a look-up table to determine the Level of Congestion (LOC). Posted speed limit and LOC Index are the two variables in determining the LOC. Congestion categories are rated as: a) low, b) moderate, c) heavy, and d) over congested.

LOC Categories are derived from Level of Service Categories (LOS) A through F, described in the Transportation Research Board’s publication Highway Capacity Manual, where:

- LOC Category Low = LOS Categories A and B
- LOC Category Moderate = LOS Categories C and D
- LOC Category High = LOS Category E
- LOC Category Over Congestion = LOS Category F.

A decision variable \( v^i \) and comparison variable \( \lambda \) are then defined. Decision variable \( v^i \) is determined through the application algorithms \( v^1 \), \( v^2 \), and \( v^3 \), each representing the LOC’s low, moderate, and high, respectively.

\[
v^1_i(k) = \frac{o_u^i(k-n) - o_d^i(k)}{o_d^i(k-n)} \quad (2-2)
\]
\[
v^2_i(k) = \left\{ \left\lceil \frac{f_d^i(k)}{I} \right\rceil - f_d^i(k) \right\} - \{ f_d^i(k)/I \} \quad (2-3)
\]
\[
v^3_i(k) = \{ f_d^i(k) * Min(1.0, F_p) \} - \{ f_u^i(k_{k-n}) * (C_{fs}) \} - (f_d^i(k))/I \quad (2-4)
\]

Where:

- \( f_u^i(k) \) and \( f_d^i(k) \) = the upstream and downstream traffic counts collected at target lane \( i \) and time step \( k \),
- \( o_u^i(k) \) and \( o_d^i(k) \) = collected occupancies,
- \( I \) = total number of adjacent lanes,
$T =$ the maximum time lag predetermined for consideration of the travel time taken from the
upstream detector station to the downstream detector station on the relationship between the
upstream and downstream traffic data,

$F_p =$ time lag index defined as the posted speed limit / distance between $f_{i}^{u}(k)$ and $f_{i}^{d}(k)$.

Comparison variable $\lambda$ is determined by offsetting the traffic count at the upstream ATR
by a correction factor adjusting for the minimum speed expected to navigate each detection zone
based on the appropriate LOC.

The comparison value, $\lambda$, is arrived through the following equation:

$$\lambda = (\text{Upstream traffic count at ATR}_i) \times (C_{fs}) \quad (2-5)$$

Where:

Upstream traffic count at ATR$_i$ is the vehicle count at time period $k$ determined from the
upstream ATR;

$C_{fs}$ is a correction factor derived from dividing the minimum expected speed for a detection zone
at a specified LOC by the posted speed for the detection zone.

Fuzzy set membership is then determined by applying Equation 2-6:

$$\omega_m(k) = 1 - (v^p(k - f_p) - \mu_m) \quad (2-6)$$
Where:

\[ \omega_m = \text{Fuzzy set membership value}, \]

\[ \mu_m \text{ pattern of the decision variable pre clustered on the basis of historical traffic data associated} \]

with attribute \( m \).

AFIDS-IDM recognizes a lane blocking incident when the following fuzzy rule is fired:

\[
\text{IF } \omega_m(k) > \lambda \\
\text{THEN a lane blocking incident with attribute } m \text{ is recognized at time step } k \\
\text{ELSE } k = k+1 \text{ and go back to previous procedure}
\]

2.3.3 AFIDS-ICM

AFIDS-ICM is an automated decision support system designed to provide support to TMC monitors through a visual display of traffic condition characterizations for traffic management, or detection, zones monitored by the TMC. Traffic conditions are characterized by a red-green-yellow (RGY) color scheme where “green” indicates a normal traffic condition, “yellow” indicates a low priority incident, and “red” indicates a high priority incident. Initial characterization is a “green” or normal traffic condition. Preliminary detection of freeway incidents changes the characterization to “yellow” at time step \( k \). Incidents not cleared by \( k+1 \) are re-characterized as “red”. An either, “yellow” or “red” characterization is returned to “green” if incidents are cleared before the next successive time step. Incident characterization is incorporated into AFIDS-IDMs IF-THEN-ELSE incident detection logic:
CHARACTERIZATION= Green
IF \( \omega_m(k) > \lambda \) at time step \( k \)
    THEN a lane blocking incident with attribute \( m \) is recognized at time step \( k \)
    ELSE \( k = k + 1 \) and go back to previous procedure
CHARACTERIZATION= Yellow
IF \( \omega_m(k+1) > \lambda \) at time step \( k+1 \)
    THEN a lane blocking incident with attribute \( m \) is recognized at time step \( k+1 \)
    ELSE \( k+1 = k + 2 \) and go back to previous procedure
CHARACTERIZATION= Red

AFIDS-ICM logic is depicted graphically in Figure 2-2.

Traffic characterizations are conveyed to TMC monitors in the form of a visual output file relying on RGY color schemes. The outputs file (Figure 2-3) is a continuous display monitoring multiple detection zones with user interface. Clicking on individual RGY color status fields brings up detailed information associated with the corresponding ATR such as ATR names and locations (obtained from the revised ATR table) report date, hour (from the ATR data table) and the traffic congestion status (Figure 2-4). “Red”, or high priority, color fields display a proposed alternate route, from GeoMedia Web Map.

2.3.4 AFIDS-RM

When incidents are assigned a “Red”, or high priority, traffic congestion status, GeoMedia Web Map is evoked through the Alabama Freeway Incident Detection System-Re-routing Module (AFIDS-RM). The module works in conjunction with the AFIDS-ICM Traffic Zone Congestion Status Screen (Figure 2-4) to allow Traffic Management Center (TMC) monitors access to graphical representations of pre-determined alternate routings. AFIDS-RM is designed to support TMC monitors by providing alternate routes to alleviate potential traffic congestion
Figure 2-2. AFIDS-ICM Flowchart
Figure 2-3. AFIDS-ICM Output File

Figure 2-4. Detailed AFIDS-ICM Traffic Zone Congestion Status Screen
caused by the recognized incident. Access to routings is manually available through lower priority conditions at the discretion of traffic Managers.

AFIDS-RM is based on the concept of traffic management, or detection, zones. Automatic Traffic Recorders (ATR) collect data from upstream and downstream ATR’s to form a single zone. The data collection network is expanded by adding successive ATR’s where the downstream ATR for a detection zone becomes the upstream ATR for the next detection zone in succession. AFIDS-RM establishes the identification and location of ATR’s and their respective boundaries through a zone layout table (Table 2-3).

The zone table catalogs GIS reference fields (e.g. Fnode, Tnode, and EdgeID) for use as GIS references for GeoMedia Web Map. And, to support the color-coding of roadway segments based on their traffic congestion levels (Figure 2-3 and 2-4).

<table>
<thead>
<tr>
<th>Zone #</th>
<th>Fnode</th>
<th>Tnode</th>
<th>FromATRID</th>
<th>ToATRID</th>
<th>EdgeID</th>
<th>Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>194</td>
<td>196</td>
<td>1</td>
<td>South</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2</td>
<td>197</td>
<td>195</td>
<td>1</td>
<td>North</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>5</td>
<td>196</td>
<td>441</td>
<td>7</td>
<td>South</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>1</td>
<td>440</td>
<td>197</td>
<td>7</td>
<td>North</td>
</tr>
<tr>
<td>5</td>
<td>7</td>
<td>6</td>
<td>345</td>
<td>256</td>
<td>5</td>
<td>East</td>
</tr>
<tr>
<td>6</td>
<td>8</td>
<td>7</td>
<td>257</td>
<td>346</td>
<td>5</td>
<td>West</td>
</tr>
</tbody>
</table>

2.3.5 Data

Data input to AFIDS-ICM was supplied by the South Carolina Department of Transportation. Vehicle speed and traffic counts from successive upstream and downstream
sensors collected at hourly intervals were the primary inputs. Occupancy values were calculated mathematically from the data.

The SCDOT data set consisted of data collected over a period of one calendar year from 269 ATR’s across South Carolina. Twelve detection zones, representing continuous sections of the highway, were selected from this data. Table 2-4 depicts the format in which the collected data was made available for the study.

ID is the road identification number. Hour refers to the particular hour of the day the data was reported. There are 5 lanes considered for a particular section of the road. Bin numbers identify the number of vehicles traveling at a given speed. Total Volume is the summation of the number of vehicles in all the Bins.

### Table 2-4. Sample of Collected Traffic Data

<table>
<thead>
<tr>
<th>ID</th>
<th>ATR_ID</th>
<th>HOUR</th>
<th>LANE</th>
<th>Bin_0_5</th>
<th>Bin_11_5</th>
<th>Total Volume</th>
<th>ID1</th>
</tr>
</thead>
<tbody>
<tr>
<td>137085</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>237</td>
<td>1</td>
</tr>
<tr>
<td>137086</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>150</td>
<td>2</td>
</tr>
<tr>
<td>137087</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>31</td>
<td>3</td>
</tr>
<tr>
<td>137088</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>137089</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>87</td>
<td>5</td>
</tr>
</tbody>
</table>

Road sections under study, Figure 2-5, were primarily north and south of Greenville along Interstate Highway 185, north and south of Spartanburg along Interstate Highway 85, and north and south of Laurens County, along Interstate 385.

SCDOT data did not include real time traffic incident data. Incidents were predicted for the study using a multi-algorithmic approach. This approach predicts traffic incidents through a triangulation of the California #8, Exponential Smoothing, and McMaster algorithms.
For this study, two data sets were formed to predict traffic incident data. Each data set represented data collected in successive 39 day periods of time. Results of the California Algorithm was used with the first data set to determine a quadratic equation necessary to perform the McMaster algorithm. The quadratic equation was then used with the second data set to predict incidents. The quadratic equation was then determined through the Exponential

Figure 2-5. Road Sections Considered
Smoothing Algorithm using the second data set. The resulting quadratic equation was used to predict incidents in the first data set. This approach was followed to train the McMaster Incident Detection Algorithm with the first data set, and use the McMaster Algorithm to detect incidents with the second data set.

2.3.6. Numerical Tests, and Results

Results of characterization and re-routing algorithms fit eight categories:

1. Correct recognition and assignment of “green” traffic congestion conditions.
2. Incorrect recognition and assignment of “green” traffic congestion conditions.
3. Correct recognition and assignment of “yellow” traffic congestion conditions.
4. Incorrect recognition and assignment of “yellow” traffic congestion conditions.
5. Correct recognition and assignment of “red” traffic congestion conditions.
6. Incorrect recognition and assignment of “red” traffic congestion conditions.
7. Correct identification of alternate traffic routes.
8. Incorrect identification of alternate traffic routes.

AFIDS-ICM and AFIDS-RM results are defined through three objectives:

1. Maximize the correct characterization of real-time incidents
2. Minimize the number of false characterizations
3. Maximize the correct number of alternate routes reported
Objectives are evaluated through three metrics: FCR, DR, and AR. The FCR is the false characterization rate, which reports the percentage of incorrect characterizations as a percentage of total characterizations. The DR is the detection rate. Reported as a percentage, the DR is an indicator of the number of characterizations that remain undetected. The AR is the correct number of re-routings reported by AFIDS-RM. The AR is expressed as a percentage.

The accuracy of FCR, DR, and AR are indicated by the ACC. The ACC (Equation 2-7) is expressed as a percentage of correct assignments and places the FCR, DR, and AR on a common scale.

\[
\text{ACC}_n = \left( \frac{\text{Number of Correct Assignments}}{\text{Total Number of Assignments}} \right) \times 100
\]  

A fourth metric, the time to characterize (TTC\(_n\)) is introduced as a means to distinguish the time to characterize occurring incident across levels of congestion from the time to characterize an incident that has cleared. The time to characterize an incident that has occurred (TTC\(_O\)) is the time to detect and characterize an incident from the time the incident occurs until it is detected and characterized. The time to characterize a cleared incident (TTC\(_C\)) is the time to recognize the characterization of a cleared incident from the time it is cleared until it is no longer recognized as an incident.

Tables 2-5 through 2-7 summarize AFIDS-ICM performance data for road sections I-185, I-385, and I-85; described in Section 2.5 and indicated in Figure 2-5. The performance data is grouped by the LOC’s low, moderate, and high; representing the various levels of congestion acknowledged by the study. Table 2-8 represents the average performance data for all levels of congestion by road section.
Table 2-5 AFIDS-ICM Performance Data by Road Section for Low Congestion

<table>
<thead>
<tr>
<th>LOC</th>
<th>TTC₀</th>
<th>TTCₐ</th>
<th>DR (%)</th>
<th>FCR (%)</th>
<th>AR (%)</th>
<th>ACC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rd. Sec.</td>
<td>(m)</td>
<td>(m)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
</tr>
<tr>
<td>I-85</td>
<td>12.8</td>
<td>32.2</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>I-185</td>
<td>13.8</td>
<td>31.2</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>I-385</td>
<td>13.8</td>
<td>31.2</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 2-6 AFIDS-ICM Performance Data by Road Section for Moderate Congestion

<table>
<thead>
<tr>
<th>LOC</th>
<th>TTC₀</th>
<th>TTCₐ</th>
<th>DR (%)</th>
<th>FCR (%)</th>
<th>AR (%)</th>
<th>ACC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rd. Sec.</td>
<td>(m)</td>
<td>(m)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
</tr>
<tr>
<td>I-85</td>
<td>12.9</td>
<td>31.1</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>I-185</td>
<td>13.8</td>
<td>31.2</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>I-385</td>
<td>13.8</td>
<td>31.2</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 2-7 AFIDS-ICM Performance Data by Road Section for High Congestion

<table>
<thead>
<tr>
<th>LOC</th>
<th>TTC₀</th>
<th>TTCₐ</th>
<th>DR (%)</th>
<th>FCR (%)</th>
<th>AR (%)</th>
<th>ACC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rd. Sec.</td>
<td>(m)</td>
<td>(m)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
</tr>
<tr>
<td>I-85</td>
<td>24.4</td>
<td>20.6</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>I-185</td>
<td>24.9</td>
<td>20.1</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>I-385</td>
<td>24.9</td>
<td>20.1</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 2-8 AFIDS-ICM Cumulative Performance Data by Road Section

<table>
<thead>
<tr>
<th>LOC</th>
<th>TTC₀</th>
<th>TTCₐ</th>
<th>DR (%)</th>
<th>FCR (%)</th>
<th>AR (%)</th>
<th>ACC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rd. Sec.</td>
<td>(s)</td>
<td>(s)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
</tr>
<tr>
<td>All Rd. Sec.</td>
<td>17.2</td>
<td>27.65</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>
Results indicated in Tables 2-5 through 2-7, and summarized in 2-8, support the use of AFIDS-ICM and AFIDS-RM as a means of characterization of traffic incidents and the identification of alternate routes as an integral part of traffic related decision support. Using a computer based platform, the methodologies described result in characterization and re-routing within 24.4 minutes for low and high priority incidents. And, 32.2 minutes for cleared incidents.

ACC results support that all three objectives of the study were obtained and that the two modules operate at maximum efficiency. This is somewhat expected due to the incorporation of computer logic into the process that all but eliminates the possibility for error.

The TTCₙ is relatively high compared to other approaches. However, this relates to the efficiency of the AFIDS-IDM, which is tuned for maximum identification of incidents with limited tolerance for false alarms. Such tuning is achieved through a calculation process that waits longer to make a decision, but is less prone to error.

There is a noticeable difference between the times to characterize a cleared incident (TTCₙ) and the time to characterize an incident that has occurred (TTC₀). This is explained on the basis of fuzzy clustering theory where an incident can only be declared “cleared” when the decision variable reaches an incident free state. That is the degree of belongingness associated with the incident-free membership is greater than the degree of belongingness associated with the incident membership. This, greater than relationship, can only be obtained at the expense of increased time.

2.5. Conclusion and Recommendations

Advances in AID have lead to a number of approaches to automatic incident detection. These approaches were generally restricted to incident detection and stopped short of incident
characterization and re-routing options. This has created a void in traffic control and management efforts, leading to increased legislation directed toward the creation of advanced information systems linked to freeways and vehicles.

This paper introduces AFIDS-ICM as the incident characterization module of the AFIDS decision support system. The system is augmented with a re-routing module, AFIDS-RM, employed when high priority incidents are recognized. The modules presented engage traffic management personnel through a series of user friendly computer screens that are color coded to simplify the recognition and characterization of traffic incidents.

Performance tests of the two modules indicate that the modules meet their intended objectives through the:

1. Maximization of the real time characterization of traffic incidents
2. Minimization of the number of false characterizations
3. Maximization of the correct number of correct alternate routes reported

In comparison to alternative approaches to incident characterization and re-routing, the two modules described offer two relative advantages:

1. The two modules presented are accompanied with an incident detection capability. Working in unison, the three modules form a complete decision support system directed toward the identification and characterization of traffic incidents, supported with re-routing capability.
2. The two modules are supported with color coded computer graphic output for incident
detection and graphical mapping for re-routing.

Current efforts are underway to enhance the computer graphic capability of the two
modules. Through these efforts, traffic managers will be able to access additional screens
detailing historical data, weather conditions, traffic flows in areas surrounding the incident, and
weather conditions surrounding the incident. This is expected to increase the value of the tool by
providing additional decision support data.
REFERENCES


ARTICLE THREE
Comparison of Five Algorithms for Automatic Freeway Incident Detection

3.1. Introduction

Non-recurring traffic incidents can be costly, resulting in increased traffic congestion, fuel consumption, and environmental pollution. Some estimates place these costs in excess of $35 billion per year (Lindley, 1996). Early recognition can help control the escalation of costs by both reducing the time frame to clear an incident and reducing the potential for secondary incidents (Busch, 1987). It is not unexpected that a considerable body of research has evolved on quick detection methodologies centered on automatic incident detection (Williams and Guin, 2007).

3.2. Background Studies

The beginnings of Automatic Incident Detection (AID) can be traced back to the 1960’s with early approaches restricted to the development of statistical and pattern-based algorithms (Dudek and Messer, 1974; Courage and Levin, 1968; Levin and Krause, 1978). Since that time, other efforts, based on numerous approaches, have evolved. These include comparative algorithms (Payne and Tignor, 1978), time series and filtering algorithms (Chow et al. 1977; Cook and Cleveland, 1974), and traffic theory based algorithms (Chow et al. 1977; Gall and Hall, 1989; Greene et al., 1977; Kurkijian et al., 1977).
More recently, AID research has centered on artificial intelligence and soft computing techniques producing a number of methodologies including fuzzy logic/fuzzy set theory (Hsiao et al., 1994; Chang and Wang, 1994; Lin and Chang, 1998; Shue, 2002), artificial neural networks (Dia and Rose, 1997), fuzzy logic in conjunction with neural networks (Ishak and Al-Deek, 1998; Srinivasan et al, 2001), fuzzy expert systems (Lin and Chang, 1998), wavelet transformations (Samant and Adeli, 2000), and generic algorithms over neural networks (Roy and Abdulhaid, 2003).

AID research has evolved with the introduction of one technique after another, with no single methodology assuming a dominate role in incident detection. This can be somewhat perplexing for traffic management practitioners who must distinguish the applicability of one approach over another in actual field applications. Compounding the issue further is that many methods were developed in simulated environments where actual traffic conditions were designed to fit the algorithm, giving a greater degree of control of the experiment than would be found in actual implementation. Further, AID methodologies are generally presented as standalone approaches rather than as comparisons against baseline values.

One barrier to comparison by field practitioners is the complex calibrations that many AID are based on. The calibration parameters have to be fine-tuned in practice. Failure to do so properly can result in poor performance and abnormally high false alarm rates (Balke, 1993).

Data collection appears to be the single commonality to AID. Lane traffic counts and density, collected at successive traffic sensors, are the two primary types of input data. Capacity is then calculated mathematically from inputs.

The evaluation of incident detection algorithms is a somewhat time consuming process, due to the need to calculate threshold values for each methodology. However, since incident
detection algorithms seldom perform at the levels they were developed under (Abdulhai and Ritchie, 1999), it is a necessary undertaking. The standard approach that has evolved to meet this need produces three metrics (Dia et al., 996): a) detection rate (DR), false alarm rate (FAR), and time to detect (TTD). The Comparison of AID’s between detection zones is through a methodology assigning weighted priorities to each of the three metrics.

3.3. Research Objectives and Scope

It is the purpose of this paper to survey current literature related to AID and to list present methods in this field of study. Further, this paper evaluates each method against a set of criteria to short-list algorithms that are applicable to field practice. The latter are then implemented using real data collected by the South Carolina Department of Transportation (SCDOT) to determine the FAR, DR, and TTD.

3.3.1 Identification of Current Algorithms

The literature search included a wide variety of electronic and print resources to identify algorithms for inclusion in this study, including the Transportation Research Board (TRB), the Journal of Transportation Research (JTR), and the Intelligent Transport Systems Journal (ITS). Additionally, holdings from seven university libraries and Dissertation Abstracts International were searched along with reference sections of the innumerable studies that were collected were reviewed to identify other potential pertinent research. Finally, several researchers and practitioners, currently working in the field, were contacted and asked to provide pertinent research or to identify sources of studies.

A total of twenty-two algorithms, indicated in Table 3-1, were identified from the
Table 3-1. AID Algorithms Identified Through Literature Search

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Normal Deviate Algorithm</td>
<td>Exponential Smoothing Algorithm</td>
</tr>
<tr>
<td>Low Volume Algorithm</td>
<td>Dynamic Model (MM and GLR)</td>
</tr>
<tr>
<td>The California Algorithms</td>
<td>Bayesian</td>
</tr>
<tr>
<td>Decision Logic Units-based Algorithm</td>
<td>HIOCC and PATREG</td>
</tr>
<tr>
<td>ARIMA</td>
<td>Multi-Layer Feed-Forward</td>
</tr>
<tr>
<td>DELOS</td>
<td>Image Processing</td>
</tr>
<tr>
<td>Fuzzy Logic</td>
<td>Principal Component Analysis</td>
</tr>
<tr>
<td>Cumulative Sum of Occupancy</td>
<td>Probabilistic Neural Network Algorithm</td>
</tr>
<tr>
<td>Fuzzy Radial Neural Network Algorithm</td>
<td>Adaptive ANN-Wavelet Algorithm</td>
</tr>
<tr>
<td>Wavelet Energy-Radial Basis Algorithm</td>
<td>Discrete Wavelet Transform Algorithm</td>
</tr>
<tr>
<td>CUSUM based Algorithm</td>
<td>Support Vector Machine</td>
</tr>
</tbody>
</table>

literature review. Inclusion criteria for the initial list centered on its ability to recognize traffic incidents and not on its applicability to TMC’s.

3.3.2 Short-List of Applicable Algorithms

The twenty-two algorithms were examined for five unique identifiers to determine if they met criteria for inclusion in the study. The criteria, listed below, identify those algorithms that can be implemented with real traffic data:

- Over-saturation is not included as a category of analysis
- The capability to analyze bulk data on an hour-by-hour basis
- Incidents are predicted within a specific zone at a given point in time
- No traffic incident data was available for the fine tuning of the algorithm
- Lane occupancy could be calculated mathematically
Five algorithms met the criteria for inclusion:

- California Algorithm #8
- Exponential Smoothing Algorithm
- McMaster Incident Detection Algorithm
- Shue Fuzzy Logic Algorithm
- Alabama Freeway Incident Detection System Algorithm

### 3.3.2.1 California Algorithm #8

The California Algorithm Family (Payne and Tignor, 1978) is a set of 10 algorithms that are founded in decision tree analysis. The original algorithm is a straightforward approach recognizing a potential incident has occurred when three tests on the measured occupancy from two adjacent stations surpass preset threshold values ($T_n$) associated with each test. Definitions associated with the general logic of the California Algorithm Family are presented in Table 3-2 followed by a graphical representation of the logic in decision tree form in Figure 3-1.

**Table 3-2. Definitions Associated with California Algorithm Family Logic**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>OCC(i,t)</td>
<td>Occupancy at detector station i at time t</td>
<td>OCC(i+1,t)</td>
</tr>
<tr>
<td>DOCC(i,t)</td>
<td>Downstream occupancy</td>
<td></td>
</tr>
<tr>
<td>OCCDF(i,t)</td>
<td>Spatial occupancy difference</td>
<td>OCC(i,t) - DOCC(i,t)</td>
</tr>
<tr>
<td>OCCRDF(i,t)</td>
<td>Relative spatial occupancy difference</td>
<td>OCCDF(i,t) / OCC(i,t)</td>
</tr>
<tr>
<td>DOCCTD(i,t)</td>
<td>Relative temporal downstream occupancy difference</td>
<td>(DOCC(i,t-2)-OCC(i,t))/OCC(i,t-2))</td>
</tr>
<tr>
<td>$T_n$</td>
<td>Predetermined threshold value</td>
<td></td>
</tr>
</tbody>
</table>
An incident state is terminated when threshold value $T_2$ is no longer exceeded. Threshold values are calibrated from empirical data.

The simplicity of the original algorithm resulted in an unacceptably high false alarm rate. Subsequent algorithms reduce the false alarm metric but are more complex.

The two that have demonstrated higher performance ratings are the #7 and #8. The California #7 replaces the use of relative temporal differences in downstream occupancy values with occupancy measurements (DOCCTD(i,t)). This reduces the false alarm rate through the recognition of recurring compression waves commonly found in heavy traffic. The #7 recognizes that simple downstream occupancy data dropping below a certain threshold, usually 20 percent is more indicative of an incident. This algorithm also incorporates a persistence check that requires traffic discontinuity persist for a specified period of time before a potential incident is recognized.

The California #8 is the most complex of the California family and it has been shown to be the best performer (Cohen and Ketselidou, 1993). The algorithm recognizes nine states and requires the calibration of five threshold values, two more than previous algorithms. This algorithm introduces a repetitive test for compression waves and a suppression of alarms related to these waves for up to five minutes. Through this approach, the #8 is less likely to give a false alarm in normal traffic congestion. The modified decision logic of the California #8 is presented in Figure 3-2 as suggested by Payne et al. (1976).

### 3.3.2.2 Exponential Smoothing Algorithm

The Exponential Smoothing Algorithm was developed by Cook (1974) using data from the John C. Lodge Freeway in Detroit. The method is an extension of the Standard Normal Deviate
Figure 3-1. Decision Tree for General Logic of California Algorithm Family
States:
0- Incident Free Condition
1- Compression wave this minute
2- Compression wave 2 minutes ago
3- Compression wave 3 minutes ago
4- Compression wave 4 minutes ago
5- Compression wave 5 minutes ago
6- Tentative incident
7- Incident confirmed
8- Incident continuing

Figure 3-2. California #8 Decision Tree Logic
Algorithm (Dubek, and Messer, 1974) but differs in the use of a more sophisticated forecasting method. The smoothing feature of the algorithm gives a heavier weight to recent traffic data than past records reducing false alarms related to traffic volumes. The algorithm uses a double smoothing approach indicated in Equations 3-1 and 3-2.

\[
S_1(k) = X(k) + (1 - S_1(k-1)) \\
S_2(k) = S_1(k) + S_2(k-1)
\]  

Where:

\(X\) = A smoothing constant determined from the weight of past data

\(S_1\) = The first set of smoothed data

\(S_2\) = The second set of smoothed data

\(k\) = Time step

The smoothed data set is then used to generate a tracking signal as the algebraic sum of all previous estimate errors to the present minute, divided by the current estimate of the standard deviation. An incident is indicated when the tracking signal deviates from zero beyond a pre-specified threshold. The threshold can be computed based on either the variability of the data or likelihood of a false alarm.

Cook used a set of 13 traffic variables resulting from the basic traffic variables of volume, occupancy, and speed to test the performance of the algorithm (Cook and Cleveland, 1974). The variables are indicated in Table 3-3.
Table 3-3. Exponential Smoothing Basic Traffic Variables

<table>
<thead>
<tr>
<th>Station volume</th>
<th>Subsystem volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Station occupancy</td>
<td>Subsystem occupancy</td>
</tr>
<tr>
<td>Station speed (volume/occupancy)</td>
<td>Subsystem speed</td>
</tr>
<tr>
<td>Station volume-occupancy</td>
<td>Subsystem kinetic energy</td>
</tr>
<tr>
<td>Station speed-occupancy</td>
<td>Volume-occupancy discontinuity</td>
</tr>
<tr>
<td>Station kinetic energy</td>
<td>Speed-occupancy discontinuity</td>
</tr>
<tr>
<td>Station discontinuity</td>
<td></td>
</tr>
</tbody>
</table>

3.3.2.3 McMaster Incident Detection Algorithm

The McMaster Incident Detection Algorithm is a catastrophe theory algorithm developed using data from Queen Elizabeth Way, Mississauga, Ontario. The algorithm is based on the belief that flow and occupancy, unlike speed, change smoothly when moving from a congested to an uncongested state. The algorithm starts by identifying congested states, and then, it attempts to determine if the congestion is the cause of a traffic incident or a permanent bottleneck. As suggested by Persaud et al. (1981) a volume-occupancy template (Figure 3-3) is derived from historical flow-occupancy data collected at times of change from congested to uncongested conditions. Traffic conditions are classified into one of four states, calibrated at each detector station:

State 1- Uncongested
State 2- Congestion
State 3- Congestion
State 4- Permanent bottleneck congestion
Once the volume-occupancy template is determined the following logic is applied:

1. If State 2 or 3 is indicated the algorithm examines the traffic condition at the downstream station.
2. An alarm is triggered if the downstream station is in State 1 or 2 on the belief that recurring and incident congestion result in different downstream traffic patterns.
3. If State 3 is detected the algorithm looks at the next downstream detector station using the same logic.
4. If State 4 is detected at the downstream detector station, the congestion is classified as recurring.
The initial McMaster algorithm was refined to include additional states intended to decrease the vulnerability of the algorithm to incident related traffic patterns resulting from non-incident conditions. This modified the original logic to include separate templates to discriminate between detector stations, depending on their location with respect to recurring bottlenecks. As suggested by Hall et al. (1993), Figure 3-4 indicates the templates, intended for normal and recurrent congestion stations.

Calibration of the algorithm involves distinguishing between the congested and un-congested regions. The minimum non-congested speed is estimated for the station. This is used to create the boundary between States 1 and 3. A quadratic equation is then 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 States 1 and 2.

3.3.2.4 Shue Fuzzy Logic Algorithm

The Shue algorithm (Shue, 2002) is a fuzzy clustering approach to freeway incident detection and characterization developed under simulation of traffic patterns through CORSIM. The method identifies lane blocking incidents from comparisons of time varying patterns of incident induced and incident free traffic states. Lane traffic counts and density, collected at successive traffic sensors, are the two primary types of input data.

The Shue algorithm is carried out in four steps:

1. Identification of traffic flow conditions
2. Determination of decision variable
Figure 3-4. Templates Intended for Normal and Recurrent Congestion
3. Determination of fuzzy set membership

4. Determination of a lane blocking incident

Step one is a pre-classification of traffic flow conditions as low, moderate, heavy, or over congestion. Each condition is assigned an occupancy based threshold determined through historical data. At a given time-step, the time varying occupancy based correlation associated with each type of traffic condition is calculated with lane occupancies collected at the upstream sensor along with the occupancy-based threshold. Comparisons of the time-varying occupancy based correlation values indicate the specific type of flow condition in accordance with the highest correlation value identified by the time varying occupancy values.

Incident occurrence is recognized through the execution of Steps 2 through 4. In Step 2, a decision variable is determined for the previously identified traffic condition. The decision variables for low, moderate, and heavy congestion are determined through equations 3-3, 3-4, and 3-5 respectively. No decision variable is determined for over congestion:

\[ v_i^5 (k) = \frac{[o_i^u(k) - o_i^d(k)]}{o_i^u(k)} \] (3-3)

\[ v_i^4 (k) = \left\{ \frac{[\sum_j f_j^d(k)]}{J} - f_i^d(k) \right\} \left\{ \frac{[\sum_j f_j^d(k)]}{J} \right\} \] (3-4)

\[ v_i^{10} (k) = \left\{ \sum_{\tau} f_i^d(k - \tau) \right\} - f_i^u(k - T) - \frac{\sum_j f_j^d(k)}{J} \] (3-5)

Where:

- \( f_i^u(k) \) and \( f_i^d(k) \) = the upstream and downstream traffic counts collected at target lane \( i \) and time step \( k \).
- \( o_i^u \) and \( o_i^d \) = collected occupancies,
$J = \text{total number of adjacent lanes},$

$T = \text{the maximum time lag predetermined for consideration of the travel time taken from the upstream detector station to the downstream detector station on the relationship between the upstream and downstream traffic data},$

$\tau = \text{time lag index}.$

Step 3 computes a time varying decision-variable correlation, Equation 3-6, for upstream, midstream, and downstream locations on a lane by lane basis. The decision variable measures the association between decision variables calculated in Step 2 to pattern clusters determined through historical data.

$$
\omega_{m,n}^{p,q}(k) = 1 - \frac{1}{\beta} \sqrt{\sum_{\tau=0}^{3} (v_{n}^{\tau}(k-\tau) - \mu_{m,n}^{p,q})^2}
$$

(3-6)

Where:
- $\beta = \text{a pre-determined value set for the boundaries of } \omega_{m,n}^{p,q}(k),$
- $m = \text{level of congestion},$
- $n = \text{lane code},$
- $p = \text{location parameter indicating the location being investigated},$
- $q = \text{a binary digit (} q_1 = \text{incident occurrence and } q_0 = \text{no incident}),$
- $\mu_{m,n}^{p,q} = \text{pattern of the decision variable pre clustered on the basis of historical traffic data associated with attributes } p, q, m, \text{and } n.$

An incident is recognized in Step 4 when the following condition is met:

\begin{align*}
\text{IF} & & \{\max[\omega_{m,n}^{1,1}(k), \omega_{m,n}^{2,1}(k), \omega_{m,n}^{3,1}(k)] - \omega_{m,n}^{p,0}(k)\} > \lambda_1 \\
\text{THEN} & & \text{A lane-blocking incident with the attributes } m \text{ and } n \text{ is recognized at time step } k
\end{align*}
Where:

\( m \) = low, moderate, or high level of congestion category;
\( n \) = lane code,
\( k \) = Specified time frame.

3.3.2.5 Alabama Freeway Incident Detection System (AFIDS) Algorithm

The Alabama Freeway Incident Detection System (AFIDS) is a three module approach to incident detection, characterization, and re-routing in emergency evacuation situations. Incident detection is through a single module, Alabama Freeway Incident Detection System- Incident Detection Module (AFIDS-IDM). AFIDS-IDM incorporates a fuzzy cluster approach to incident detection is an extension of the Shue algorithm. The primacy differences between the two algorithms lies in the environments in which they were developed and the intended application. The Shue algorithm was developed through a simulated environment using Corridor Simulation (CORSIM) software for use in normal freeway incident detection. AFIDS, on the other hand, was developed from freeway data from the South Carolina Department of Transportation (SCDOT) for use in emergency evacuation situations. This difference is compounded in that AFIDS centers on real world traffic patterns and states while the Shue was developed on traffic patterns and states defined through simulation. The patterns and states defining AFIDS are identified through the Transportation Research Record.

AFIDS-IDM logic, Table 3-4, is carried out in seven steps. Like most fuzzy set algorithms, AIDS does not give a clear incident or no-incident signal but rather the likelihood that an incident has occurred. The fuzzy logic incorporated into the algorithm is designed to approximate human thinking in situations of imperfect knowledge.
### Table 3-4. AFID-IDM Incident Detection Process

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Input data</td>
</tr>
<tr>
<td>2</td>
<td>The determination of a Level of Congestion Index (LOC&lt;sub&gt;Index&lt;/sub&gt;)</td>
</tr>
<tr>
<td>3</td>
<td>The determination of the Level of Congestion (LOC) from the index</td>
</tr>
<tr>
<td>4</td>
<td>The determination of the decision variable v′ associated with the specified LOC</td>
</tr>
<tr>
<td>5</td>
<td>The determination of the comparison variable lambda (λ) associated with the input data and posted speed limit</td>
</tr>
<tr>
<td>6</td>
<td>The determination of the fuzzy set membership, ω&lt;sub&gt;m&lt;/sub&gt;, associated with the specified v′</td>
</tr>
<tr>
<td>7</td>
<td>A lane blocking incident exists when ω&lt;sub&gt;m&lt;/sub&gt; &gt; λ.</td>
</tr>
</tbody>
</table>

Step 1 is data input. From the data, the LOC<sub>Index</sub> is determined in Step 2, from Equation 3-7.

\[
LOC_{ijk} = \left( \frac{SF_{ik}}{c_j} \right) \times \left( 1/f_p \right)
\]  

(3-7)

Where:

\(LOC_{ijk}\) = Level of congestion for \(i\) lane of traffic in evacuation route \(j\) at time period \(k\),

\(SF\) = Service flow rate for LOC \(i\) under prevailing roadway and traffic conditions for \(I\), lanes in one direction, in vehicles per hour. This value is obtained from the input data, and it is the total number of actual vehicles across all bin numbers for that ATR for that hourly update,

\(c_j\) = Capacity for the road section under study. This value is obtained from the Capacity field in the ATR data,

\(\left( SF_{ik} / c_j \right)\) = Utilization at time factor \(k\),

\(f_p\) = factor for further adjustments due to time of day determined from a look-up table.
The LOC Index is applied to a look-up table to determine the Level of Congestion (LOC). Posted speed limit and LOC Index are the two variables in determining the LOC. Congestion categories are rated as: a) low, b) moderate, c) heavy, and d) over congested.

LOC Categories are derived from Level of Service Categories (LOS) A through F, described in the Transportation Research Board’s publication Highway Capacity Manual, where:

LOC Category Low = LOS Categories A and B
LOC Category Moderate = LOS Categories C and D
LOC Category High = LOS Category E
LOC Category Over Congestion = LOS Category F.

Decision variable \( v^i \) is determined through the application algorithms \( v^1 \), \( v^2 \), and \( v^3 \), each representing the LOC’s low, moderate, and high, respectively.

\[
v^1_i (k) = \frac{o^u_i (k-n) - o^d_i (k)}{o^u_i (k-n)}
\]

\[
v^2_i (k) = \left\{ \left[ \frac{f^d_i (k)}{j} \right] - f^d_i (k) \right\} - \{ f^d_i (k)/I \}
\]

\[
v^3_i (k) = \{ f^d_i (k) \ast Min(1.0, F_p) \} - \{ f^u_i (k-n) \ast (C_{fs}) \} - \{ f^d_i (k)/I \}
\]

Where:

\( f^u_i (k) \) and \( f^d_i (k) \) = the upstream and downstream traffic counts collected at target lane \( i \) and time step \( k \),

\( o^u_i (k) \) and \( o^d_i (k) \) = collected occupancies,

\( I \) = total number of adjacent lanes,
\( T \) = the maximum time lag predetermined for consideration of the travel time taken from the upstream detector station to the downstream detector station on the relationship between the upstream and downstream traffic data,

\( F_p \) = time lag index defined as the posted speed limit / distance between \( f_i^u(k) \) and \( f_i^d(k) \).

Comparison variable \( \lambda \) is determined by offsetting the traffic count at the upstream ATR by a correction factor adjusting for the minimum speed expected to navigate each detection zone based on the appropriate LOC.

The comparison value, \( \lambda \), is arrived through the following equation:

\[
\lambda = \text{(Upstream traffic count at ATR}_i) \times (C_{fs})
\]

(3-11)

Where:

Upstream traffic count at ATR\(_i\) is the vehicle count at time period \( k \) determined from the upstream ATR;

\( C_{fs} \) is a correction factor derived from dividing the minimum expected speed for a detection zone at a specified LOC by the posted speed for the detection zone.

Fuzzy set membership is determined by applying Equation 3-12:

\[
\omega_m(k) = 1 - (v^s (k - f_p) - \mu_m)
\]

(3-12)

Where:

\( \omega_m = \) Fuzzy set membership value,
\( \mu_m = \) pattern of the decision variable pre clustered on the basis of historical traffic data associated with attribute \( m \).

AFIDS-IDM recognizes a lane blocking incident when the following fuzzy rule is fired:

\[
\text{IF } \omega_m(k) > \lambda \\
\text{THEN a lane blocking incident with attribute } m \text{ is recognized at time step } k \\
\text{ELSE } k = k + 1 \text{ and go back to previous procedure}
\]

3.3.3. Comparison of Short-Listed Algorithms

Twenty-two incident detection algorithms were identified through an extensive literature review. The algorithms were evaluated against a set of criteria to determine a short-list of algorithms applicable to field application. This list included the California Algorithm #8, Exponential Smoothing Algorithm, McMaster Incident Detection Algorithm, Shue Fuzzy Logic Algorithm, and Alabama Freeway Incident Detection System Algorithm. The effectiveness of the five algorithms was compared against a set of metrics accepted in the evaluation of incident detection algorithms.

3.3.3.1 Data

Data from 269 sensors across South Carolina was made available for the study. Out of these, 12 detection zones, representing continuous sections of the highway, were selected. Data were obtained in terms of vehicle speed and traffic counts from upstream and downstream sensors. Two sensors, or Automatic Traffic Recorders (ATR), in succession define a detection zone. Occupancy values are mathematically calculated from the data. The format in which the collected data was made available for the study is presented in Table 3-5.
ID is the road identification number. Hour refers to the hour of the day the data was reported number sequentially. Lanes indicates the specific lane under consideration and the number lanes in the specific section of road. Bin numbers indicate the number of vehicles traveling at a given speed. Total Volume is the summation of vehicles across all Bins.

Road sections under study, Figure 3-5, were primarily north and south of Greenville, S.C., along Interstate Highway 185, north and south of Spartanburg, S.C., along Interstate Highway 85, and north and south of Laurens County, S.C., along Interstate 385. Data was collected over a period of two and a half months by SCDOT.

### Table 3-5. Sample of Collected Traffic Data

<table>
<thead>
<tr>
<th>ID</th>
<th>ATR_ID</th>
<th>HOUR</th>
<th>LANE</th>
<th>Bin_0_5</th>
<th>Bin_11_5</th>
<th>Total Volume</th>
<th>ID1</th>
</tr>
</thead>
<tbody>
<tr>
<td>137085</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>237</td>
<td>1</td>
</tr>
<tr>
<td>137086</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>150</td>
<td>2</td>
</tr>
<tr>
<td>137087</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>31</td>
<td>3</td>
</tr>
<tr>
<td>137088</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>137089</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>87</td>
<td>5</td>
</tr>
</tbody>
</table>

#### 3.3.3.2 Comparative Evaluation

Each of the short-listed algorithms was evaluated to determine the number of incidents each identified across four road sections taken from the data set. Each road section formed a detection zone and was bounded by upstream and downstream ATR’s. The road sections and ATR’s forming the detection zones are presented in Table 3-6. Incident detection results are presented in Tables 3-7 through 3-11.
Figure 3-5. Road Sections Considered
### Table 3-6. Road Sections by ATR’s

<table>
<thead>
<tr>
<th>Road Section #</th>
<th>Upstream ATR</th>
<th>Downstream ATR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>194</td>
<td>196</td>
</tr>
<tr>
<td>2</td>
<td>196</td>
<td>197</td>
</tr>
<tr>
<td>3</td>
<td>242</td>
<td>243</td>
</tr>
<tr>
<td>4</td>
<td>243</td>
<td>244</td>
</tr>
</tbody>
</table>

### Table 3-7. Performance Results for California #8 Algorithm

<table>
<thead>
<tr>
<th>Road Section</th>
<th>Total Number of Incidents</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATR 194-196</td>
<td>6</td>
</tr>
<tr>
<td>ATR 196-197</td>
<td>26</td>
</tr>
<tr>
<td>ATR 242-243</td>
<td>2</td>
</tr>
<tr>
<td>ATR 243-244</td>
<td>2</td>
</tr>
</tbody>
</table>

### Table 3-8. Performance Results for Exponential Smoothing Algorithm

<table>
<thead>
<tr>
<th>Road Section</th>
<th>Total Number of Incidents</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATR 194-196</td>
<td>5</td>
</tr>
<tr>
<td>ATR 196-197</td>
<td>38</td>
</tr>
<tr>
<td>ATR 242-243</td>
<td>2</td>
</tr>
<tr>
<td>ATR 243-244</td>
<td>2</td>
</tr>
</tbody>
</table>

### Table 3-9. Performance Results for McMasters Algorithm

<table>
<thead>
<tr>
<th>Road Section</th>
<th>Total Number of Incidents</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATR 194-196</td>
<td>4</td>
</tr>
<tr>
<td>ATR 196-197</td>
<td>16</td>
</tr>
<tr>
<td>ATR 242-243</td>
<td>1</td>
</tr>
<tr>
<td>ATR 243-244</td>
<td>2</td>
</tr>
</tbody>
</table>
Table 3-10. Performance Results for Shue Algorithm

<table>
<thead>
<tr>
<th>Road Section</th>
<th>Total Number of Incidents</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATR 194-196</td>
<td>5</td>
</tr>
<tr>
<td>ATR 196-197</td>
<td>36</td>
</tr>
<tr>
<td>ATR 242-243</td>
<td>2</td>
</tr>
<tr>
<td>ATR 243-244</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 3-11. Performance Results for AFIDS-IDM

<table>
<thead>
<tr>
<th>Road Section</th>
<th>Total Number of Incidents</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATR 194-196</td>
<td>5</td>
</tr>
<tr>
<td>ATR 196-197</td>
<td>39</td>
</tr>
<tr>
<td>ATR 242-243</td>
<td>3</td>
</tr>
<tr>
<td>ATR 243-244</td>
<td>2</td>
</tr>
</tbody>
</table>

Performance results indicate that the Exponential Smoothing, Shue, and AFIDS-IDM algorithms report similar results. This indicates that the sensitivity of the three algorithms is tuned to pick up similar categories of incidents across a range of severities. The California #8 and McMasters algorithms, on the other hand, indicate that they are tuned to detect only more severe incidents.

Results indicate that the rankings of incident occurrence for the five algorithms are identical, with ATR’s 196-197 reporting the most incidents followed by ATR’s 194-196. ATR’s 243-244 reported the least number of incidents in the AFIDS-IDM algorithm, while the McMasters reported the least number of incidents through ATR’s 242-243. The remaining three algorithms reported equal incidents from ATR’s 242-243 and ATR’s 243-244.
3.4 Conclusion and Recommendations

This research surveyed current literature related to AID, to list present methods in this field of study. These methodologies were then compared to a set of criteria to determine a short-list of algorithms relevant to field practice. Each of the five algorithms represented a different methodology in automatic incident detection. The five algorithms identified were then implemented with data made available from the South Carolina Department of Transportation (SCDOT) to determine the number of incidents detected by each algorithm.

Of the short-listed algorithms, the Exponential Smoothing (ES), Shue, and AFIDS-IDM algorithms performed at similar sensitivities. The California #8 and McMasters algorithms were noticeably less sensitive than other algorithms.

A limitation of this research lies in its reliance on a single data set. More research is needed with the short-listed algorithms using more diverse data sets demonstrating more varied traffic patterns across significantly different weather patterns.
REFERENCES


CONCLUSIONS AND RECOMMENDATIONS

Introduction

This study, written in journal article form, presents three papers centered on automatic incident detection. Working in building block fashion, each article addresses the subject from a different perspective. As a whole the three papers form a coherent body of knowledge that introduce a new methodology, define a method for its implementation, and compare the method to others in the field.

The Three Journal Articles

Article One- Traffic Incident Detection Algorithm for Emergency Evacuation Using Real Data

This article introduces the Alabama Freeway Incident Detection System-Incident Detection Module (AFIDS-IDM) as a methodology for the detection of freeway incidents. AFIDS-IDM incorporates fuzzy cluster analysis with traffic research reported in the 2008 Highway Capacity Manual in the identification of lane blocking incidents from comparisons of time varying patterns of incident induced and incident free traffic states. Lane traffic counts and density, collected at successive traffic sensors, are the two primary types of input data. State variables are defined from the spatial and temporal relationships of the raw data, and then evaluated quantitatively and qualitatively to determine the decision variables necessary for the determination of lane blocking
incidents. The specified decision variable is then compared to a fuzzy cluster analysis algorithm to determine the existence of a lane blocking incident.

AFIDS-IDM was evaluated using data supplied through the South Carolina Department of Transportation (SCDOT). Performance results indicate that AFIDS-IDM was able to identify traffic incidents across a range of road sections.

**Article Two- Incident Characterization and Re-routing After Automatic Incident Detection**

Article Two defines the Alabama Freeway Incident Detection System- Incident Characterization Module (AFIDS-ICM) as a methodology for the characterization of traffic incidents identified by the AFIDS-ID. The method characterizes incidents through the firing of a series of fuzzy based rules that prioritize traffic zones as “green”, “yellow”, or “red” to indicate severity of traffic conditions, with red conditions consider the highest priority. The Alabama Freeway Incident Detection System-Rerouting Module (AFIDS-RM) is employed when "red" incidents are recognized. This module selects alternate routes using Geo-Mapping. Users are presented with a decision support system with computer based interface as a means of implementing AFIDS-ICM and AFIDS-RM.

**Article Three- Comparison of Five Algorithms for Automatic Freeway Incident Detection**

It is the purpose of Article Three to survey current literature related to Automatic Incident Detection (AID) and to list present methods in this field of study. A short list of algorithms is determined from a set of criteria designed to identify algorithms capable of implementation to real-world traffic incident detection. The algorithms are then implemented using real data collected by the South Carolina Department of Transportation (SCDOT) to determine the
number and location of traffic incidents identified by each algorithm. The five algorithms selected for comparison are the California Algorithm #8, the Exponential Smoothing Algorithm, the McMaster Incident Detection Algorithm, the Shue Algorithm, and the Alabama Freeway Incident Detection System- Incident Detection Module Algorithm.

**Further Development**

Further development of the study presented through this dissertation lies in its boundaries. As such, a number of limitations become apparent. Chief among these is the use of the single South Carolina Department of Transportation (SCDOT) data set, and the limited resources made available to Department of Transportation (DOT) users.

The chief limitation of the study lies in the South Carolina Department of Transportation (SCDOT) data set, which was somewhat incomplete in that it did not provide the actual traffic incident data necessary for the determination of real-time false alarm rates (FAR), detection rates (DR), and mean time to detect incident (MTTD), nor did it provide data in any means other than at hourly intervals. While this data is seldom maintained by Department of Transportations (DOTs), simulation offers the prospect of making reasonable determinations from combinations of computer-generated traffic conditions and actual DOT data sets that allow the determination of these metrics. It would be expected then, that this work would be extended using this methodology.

A second limitation of the study lies in the use of a single data set. This restricts the testing of the proposed methodology by presenting a limited exposure to climatic and seasonal changes that impact traffic patterns. Additional research is needed in testing the methodology with data sets that exhibit extreme conditions to test the limits of the methodology.
While the methodology presented is in a plain and uncomplicated form, it is the result of the infant nature of the proposed system. This is obvious from the limited support provided to end users. Additional development is needed in the identification and incorporation of supporting information such as weather conditions surrounding occurred incidents, congestion of adjoining traffic arteries, and location of first responders. This information can be invaluable in the routing of first responders to incident areas.

**Potential Use in Education**

The proposed methodology has a number of uses within the educational community. Chief among these are the disproportional number of evacuations that plague the educational community and the vulnerability of school age students to real or perceived danger.

Because the majority of school age students are congregated in relatively close spaces without immediate transportation, issues related to inclement weather and other issues often necessitate their evacuation to safer locations. This creates a need to insure that any resulting traffic incidents be recognized as quickly as possible to facilitate their clean up and return of traffic to normal conditions.

Failure to insure the safe evacuation of school age students can result in an increased perception of the immediate situation that can grow into hysteria, adding to the value of the propose system to the school system. The immediate recognition and characterization of incidents can lead to an increased sense of security for those being evacuated.


j=1;

for i=1:3:4103

occa(j)=a(i)/(a(i)+a(i+1)+a(i+2));

occa(j+1)=a(i+1)/(a(i)+a(i+1)+a(i+2));

occa(j+2)=a(i+2)/(a(i)+a(i+1)+a(i+2));

j=j+3;
end

j=1;

for i=1:3:4103

occb(j)=b(i)/(b(i)+b(i+1)+b(i+2));

occb(j+1)=b(i+1)/(b(i)+b(i+1)+b(i+2));

occb(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));

j=j+3;
end
\begin{verbatim}
 j=1;

 for i=1:3:4103

   lanea1(j)=a(i);

   lanea2(j)=a(i+1);

   lanea3(j)=a(i+2);

   j=j+1;

 end

 j=1;

 for i=1:3:4103

   laneb1(j)=b(i);

   laneb2(j)=b(i+1);

   laneb3(j)=b(i+2);

   j=j+1;

 end

 k=1;

 j=1;

 l=1;
\end{verbatim}
for i=1:24:660
    for k=1:24
        olaneaa1(l,k)=occa(i);
        olaneaa2(l,k)=occa(i);
        olaneaa3(l,k)=occa(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end

k=1;
j=1;
l=1;

for i=1:24:660
    for k=1:24
        olanebb1(l,k)=occb(i);
        olanebb2(l,k)=occb(i);
    end
    l=l+1;
end
olanebb3(l,k)=occb(i);

j=j+1;

k=k+1;

i=i+1;

end

l=l+1;

end

k=1;

j=1;

l=1;

for i=1:24:660

    for k=1:24

        lanea1(l,k)=lanea1(i);

        lanea2(l,k)=lanea2(i);

        lanea3(l,k)=lanea3(i);

        k=k+1;

        i=i+1;

    end

end
end

l=l+1;

end

k=1;

j=1;

l=1;

for i=1:24:660

    for k=1:24

        lanebb1(l,k)=laneb1(i);

        lanebb2(l,k)=laneb2(i);

        lanebb3(l,k)=laneb3(i);

        j=j+1;

        k=k+1;

        i=i+1;

    end

end

l=l+1;

end
% THRESHOLD VALUES

T1 = 0;
count = 0;
k = 1;
l = 1;
pt1 = 0
pt2 = 0
for i = 1:28
    for j = 3:24
        OCCDF(i,j) = lanebb1(i,j) - laneaa1(i,j);
        if OCCDF(i,j) > 398
            OCCRDF(i,j) = OCCDF(i,j) / laneaa1(i,j);
            if OCCRDF(i,j) > 5
                DOCCTD(i,j) = (lanebb1(i,j-2) - lanebb1(i,j)) / lanebb1(i,j-2);
                if DOCCTD(i,j) > 0.1540

%
count = count + 1;

i;

j;

pt1(l) = olanebb1(i, j);

pt2(l) = lanebb1(i, j);

l = l + 1

% plot(olanebb1(i,j),lanebb1(i,j),'-o')

% hold on

end

end

end

end

end

count

pt1

pt2

% a = [0.4124, 0.4097, 0.4066]
% b=[554,496,456]
%
% % FOR SECTION OF ROAD FROM ATR_ID_196 TO ID_197 %
%
% j=1;
%
% for i=1:3:5399
%
%    occa(j)=a(i)/(a(i)+a(i+1)+a(i+2));
%
%    occa(j+1)=a(i+1)/(a(i)+a(i+1)+a(i+2));
%
%    occa(j+2)=a(i+2)/(a(i)+a(i+1)+a(i+2));
%
%    j=j+3;
%
% end
%
% j=1;
%
% for i=1:3:4103
%
%    occb(j)=b(i)/(b(i)+b(i+1)+b(i+2));
%
%    occb(j+1)=b(i+1)/(b(i)+b(i+1)+b(i+2));
%
%    occb(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));
%
%    j=j+3;
%
% end
% j=1

% for i=1:3:5399

%    lanea1(j)=a(i);
%    lanea2(j)=a(i+1);
%    lanea3(j)=a(i+2);
%    j=j+1;

% end

% j=1;

% for i=1:3:4103

%    laneb1(j)=b(i);
%    laneb2(j)=b(i+1);
%    laneb3(j)=b(i+2);
%    j=j+1;

% end

% % j

%    k=1;
%    j=1;
% l = 1;

% for i = 1:24:1368
  for k = 1:24
    olaneaa1(l, k) = occa(i);
    olaneaa2(l, k) = occa(i);
    olaneaa3(l, k) = occa(i);
    k = k + 1;
    i = i + 1;
  end
  l = l + 1;
end

% k = 1;
% j = 1;
% l = 1;
% for i = 1:24:1368
%   for k = 1:24
%     olanebb1(l, k) = occb(i);
%   end
% end
\% % \% olannebb(2,l,k)=occb(i);
\% \% olannebb3(l,k)=occb(i);
\% \% j=j+1;
\% \% k=k+1;
\% \% i=i+1;
\% \% end
\% \% l=l+1;
\% \% end
\% \% k=1;
\% \% j=1;
\% \% l=1;
\% \% for i=1:24:1368
\% \% for k=1:24
\% \% laneaa1(1,l,k)=lanea1(i);
\% \% laneaa2(l,k)=lanea2(i);
\% \% laneaa3(l,k)=lanea3(i);
\% \% k=k+1;
% i=i+1;
%
% end
%
% l=l+1;
%
% end
%
% k=1;
%
% j=1;
%
% l=1;
%
% for i=1:24:1368
%
% for k=1:24
%
%   lanebb1(l,k)=laneb1(i);
%
%   lanebb2(l,k)=laneb2(i);
%
%   lanebb3(l,k)=laneb3(i);
%
%   j=j+1;
%
%   k=k+1;
%
%   i=i+1;
%
% end
%
% l=l+1;
% end
%
%
%
%
%
%
%
%
%
T1=0;
%
%
%
%
%
%
%
%

count=0;
%
k=1;
%
for i=1:57
%
for j=3:24
%
OCCDF(i,j)=lanebb1(i,j)-laneaa1(i,j);
%
if OCCDF(i,j)>268
%
OCCRDF(i,j)=OCCDF(i,j)/laneaa1(i,j);
%
if OCCRDF(i,j)>3.92
%
DOCCTD(i,j)=(lanebb1(i,j-2)-lanebb1(i,j))/lanebb1(i,j-2);
%
if DOCCTD(i,j)>0.1358
%
count=count+1;


% i;
%
% j;
%
% end
%
% end
%
% end
%
% end
%
% count
%
% % T1
%
%
% % FOR SECTION OF ROAD FROM ATR_ID_242 TO ID_243 %
%
%
% j=1;
%
% for i=1:3:4127
%
% occa(j)=a(i)/(a(i)+a(i+1)+a(i+2));
%
% occa(j+1)=a(i+1)/(a(i)+a(i+1)+a(i+2));
occa(j+2)=a(i+2)/(a(i)+a(i+1)+a(i+2));

j=j+3;

end

j=1;

for i=1:3:4127
    occb(j)=b(i)/(b(i)+b(i+1)+b(i+2));
    occb(j+1)=b(i+1)/(b(i)+b(i+1)+b(i+2));
    occb(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));
    j=j+3;
end

j=1;

for i=1:3:4127
    lanea1(j)=a(i);
    lanea2(j)=a(i+1);
    lanea3(j)=a(i+2);
    j=j+1;
end
% j=1;

% for i=1:3:4127

% laneb1(j)=b(i);
% laneb2(j)=b(i+1);
% laneb3(j)=b(i+2);
% j=j+1;

% end

% % j

% k=1;
% j=1;
% l=1;

% for i=1:24:1377

% for k=1:24

% olaneaa1(l,k)=occa(i);
% olaneaa2(l,k)=occa(i);
% olaneaa3(l,k)=occa(i);
% k=k+1;
i=i+1;
end
l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        olanebb1(l,k)=occb(i);
        olanebb2(l,k)=occb(i);
        olanebb3(l,k)=occb(i);
        k=k+1;
    i=i+1;
end
l=l+1;
end
%        k=1;
%
%        j=1;
%
%        l=1;
%
%        for i=1:24:1377
%
%            for k=1:24
%
%                laneaa1(l,k)=lanea1(i);
%
%                laneaa2(l,k)=lanea2(i);
%
%                laneaa3(l,k)=lanea3(i);
%
%                k=k+1;
%
%                i=i+1;
%
%            end
%
%        l=l+1;
%
%    end
%
%        k=1;
%
%        j=1;
%
%        l=1;
%
%        for i=1:24:1368
for k=1:24
    lanebb1(l,k)=laneb1(i);
    lanebb2(l,k)=laneb2(i);
    lanebb3(l,k)=laneb3(i);
    k=k+1;
    i=i+1;
end

l=l+1;
end

T1=0;
count=0;
k=1;
for i=1:57

for j=3:24

    OCCDF(i,j)=lanebb1(i,j)-laneaa1(i,j);

    if OCCDF(i,j)> 229

        T1=OCCDF(i,j)

    end

if OCCDF(i,j)> 229

    T1=OCCDF(i,j)

end

OCCRDF(i,j)=OCCDF(i,j)/laneaa1(i,j);

if OCCRDF(i,j)> 3.6

    T1=OCCRDF(i,j)

end

DOCCTD(i,j)=(lanebb1(i,j-2)-lanebb1(i,j))/lanebb1(i,j-2);

if DOCCTD(i,j)> 0.2578

    count=count+1;

end

end

end

end
% end

% count

% %T1

%

%

% % FOR SECTION OF ROAD FROM ATR_ID_243 TO ID_244 %

% j=1;

% for i=1:3:5831

% occa(j)=a(i)/(a(i)+a(i+1)+a(i+2));

% occa(j+1)=a(i+1)/(a(i)+a(i+1)+a(i+2));

% occa(j+2)=a(i+2)/(a(i)+a(i+1)+a(i+2));

% j=j+3;

% end

% j=1;

% for i=1:3:5831

% occb(j)=b(i)/(b(i)+b(i+1)+b(i+2));

% occb(j+1)=b(i+1)/(b(i)+b(i+1)+b(i+2));

% occb(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));
% \quad occe(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));

% \quad j=j+3;

% end

% j=1;

% for i=1:3:5831

% \quad lanea1(j)=a(i);

% \quad lanea2(j)=a(i+1);

% \quad lanea3(j)=a(i+2);

% \quad j=j+1;

% end

% j=1;

% for i=1:3:5831

% \quad laneb1(j)=b(i);

% \quad laneb2(j)=b(i+1);

% \quad laneb3(j)=b(i+2);

% \quad j=j+1;

% end
%% j

%% k=1;

%% j=1;

%% l=1;

%% for i=1:24:1944

%% for k=1:24

%% olanea1(l,k)=occa(i);

%% olanea2(l,k)=occa(i);

%% olanea3(l,k)=occa(i);

%% k=k+1;

%% i=i+1;

%% end

%% l=l+1;

%% end

%% k=1;

%% j=1;

%% l=1;
for i=1:24:1944
% for k=1:24
%        olanebb1(l,k)=occb(i);
%        olanebb2(l,k)=occb(i);
%        olanebb3(l,k)=occb(i);
%        j=j+1;
%        k=k+1;
%        i=i+1;
end
l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1944
% for k=1:24
%        laneaa1(l,k)=lanea1(i);
laneaa2(l,k)=lanea2(i);

laneaa3(l,k)=lanea3(i);

k=k+1;

i=i+1;

end

l=l+1;

end

k=1;

j=1;

l=1;

for i=1:24:1944

for k=1:24

lanebb1(l,k)=laneb1(i);

lanebb2(l,k)=laneb2(i);

lanebb3(l,k)=laneb3(i);

j=j+1;

k=k+1;

end

end


\% i=i+1;
\%
\% end
\%
\% l=l+1;
\%
\% end
\%
\% %
\%
\% % THRESHOLD VALUES
\%
\% %
\%
\%
\%
\%
\%
\% T1=0;
\%
\% count=0;
\%
DOCCRDF
\%
\% k=1;
\%
\% for i=1:81
\%
\% for j=3:24
\%
\% OCCDF(i,j)=lanebb1(i,j)-laneaa1(i,j);
\%
\% if OCCDF(i,j)> 217 %T1
T1 = OCCDF(i,j)

OCCRDF(i,j) = OCCDF(i,j) / laneaa1(i,j);

if OCCRDF(i,j) > 0.3036

T1 = OCCRDF(i,j)

DOCCTD(i,j) = (lanebb1(i,j-2) - lanebb1(i,j)) / lanebb1(i,j-2);

if DOCCTD(i,j) > 0.21235

T1 = DOCCTD(i,j)

count = count + 1;

i;

j;

end

end

end

end
% end

% % T1

% count
% SMOOTHENING ALGORITHM

function f1=smotheningalgorithm()

fid=fopen('thesis1.xls');

% ALGORITHM FOR FINDING THE INCIDENTS ON THE LANE

% KEEPS TRACK OF NUMBER OF INCIDENTS

% FOR SECTION OF ROAD FROM ATR_ID_194 TO ID_195

j=1;
for i=1:3:4103
    lanea1(j)=a(i);
    lanea2(j)=a(i+1);
    lanea3(j)=a(i+2);
    j=j+1;
end
j=1;
for i=1:3:4103
    laneb1(j)=b(i);
    laneb2(j)=b(i+1);
    laneb3(j)=b(i+2);
    j=j+1;
end
k=1;
j=1;
l=1;
for i=1:24:660
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end

k=1;
j=1;
l=1;
for i=1:24:660
    for k=1:24
        lanebb1(l,k)=laneb1(i);
        lanebb2(l,k)=laneb2(i);
        lanebb3(l,k)=laneb3(i);
    end
end
j=j+1;
k=k+1;
i=i+1;
end
l=l+1;
end

T1=0;
T2=0;
count=0;
k=1;
for i=1:28
   for j=1:24
      OCCDFA(i,j)=laneaa2(i,j)-laneaa1(i,j);
      OCCDFB(i,j)=lanebb2(i,j)-lanebb1(i,j);
      if OCCDFA(i,j)> 50
         if OCCDFB(i,j)> 100
            count=count+1;
            i
            j
         end
      end
   end
end
end
% T1=0
count
count=0;
for i=1:28
    for j=1:24
        OCCDFA(i,j)=laneaa3(i,j)-laneaa2(i,j);
        OCCDFB(i,j)=lanebb3(i,j)-lanebb2(i,j);
        if OCCDFB(i,j)> 85
            %            T1=OCCDFB(i,j)
            if OCCDFB(i,j) > 69
                count=count+1;
                i
                j
            end
        end
    end
end
% T1
count

% FOR SECTION OF ROAD FROM ATR_ID_196 TO ID_197  %

j=1;
for i=1:3:5399
    lanea1(j)=a(i);
    lanea2(j)=a(i+1);
    lanea3(j)=a(i+2);
j=j+1;
end
j=1;
for i=1:3:5399
    laneb1(j)=b(i);
    laneb2(j)=b(i+1);
    laneb3(j)=b(i+2);
    j=j+1;
end

k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end

for k=1:24
    lanebb1(l,k)=laneb1(i);
    lanebb2(l,k)=laneb2(i);
    lanebb3(l,k)=laneb3(i);
    j=j+1;
    k=k+1;
    i=i+1;
    end
l=l+1;
end
% l
% % % THRESHOLD VALUES
% %

% T1=0;
count=0;
k=1;
for i=1:57
    for j=1:24
        OCCDFA(i,j)=laneaa2(i,j)-laneaa1(i,j);
        OCCDFB(i,j)=lanebb2(i,j)-lanebb1(i,j);
        if OCCDFA(i,j)> 166
            T1=OCCDFB(i,j);
            if OCCDFB(i,j)> 151
                count=count+1;
                i
                j
        end
    end
end
end
end
end
end
count
count=0;
for i=1:57
  for j=1:24
    OCCDFA(i,j)=laneaa3(i,j)-laneaa2(i,j);
    OCCDFB(i,j)=lanebb3(i,j)-lanebb2(i,j);
    if OCCDFA(i,j)> 61
      T1=OCCDFB(i,j);
    end
    if OCCDFB(i,j)> 151
      count=count+1;
      i
      j
    end
  end
end
count
% T1

% FOR SECTION OF ROAD FROM ATR_ID_242 TO ID_243  
% a=xlsread('thesis1.xls','Z21668:Z25795');
% b=xlsread('thesis1.xls','Z25796:Z29923');
% j=1;
for i=1:3:4127
    lanea1(j)=a(i);
    lanea2(j)=a(i+1);
    lanea3(j)=a(i+2);
    j=j+1;
end

j=1;
for i=1:3:4127
    laneb1(j)=b(i);
    laneb2(j)=b(i+1);
    laneb3(j)=b(i+2);
    j=j+1;
end

%  j

k=1;

j=1;
l=1;

for i=1:24:1377
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1377
    for k=1:24
        lanebb1(l,k)=laneb1(i);
        lanebb2(l,k)=laneb2(i);
        lanebb3(l,k)=laneb3(i);
        j=j+1;
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
% I
% %
% % THRESHOLD VALUES
% %
T1=0;
count=0;
% k=1;
for i=1:57
    for j=1:24
        OCCDFA(i,j)=laneaa2(i,j)-laneaa1(i,j);
        OCCDFB(i,j)=lanebb2(i,j)-lanebb1(i,j);
    end
if OCCDFA(i,j) > 129
    T1 = OCCDFB(i,j);
    if OCCDFB(i,j) > 149
        count = count + 1;
        i
        j
    end
end
end
end

% T1
count

count = 0;
T1 = 0;
for i = 1:57
    for j = 1:24
        OCCDFA(i,j) = laneaa3(i,j) - laneaa2(i,j);
        OCCDFB(i,j) = lanebb3(i,j) - lanebb2(i,j);
        if OCCDFB(i,j) > 217
            T1 = OCCDFB(i,j);
            if OCCDFB(i,j) > 150
                count = count + 1;
                i
                j
            end
        end
    end
end
end
count
% T1
%
%

% % FOR SECTION OF ROAD FROM ATR_ID_243 TO ID_244 %
j=1;
for i=1:3:5831
    lanea1(j)=a(i);
    lanea2(j)=a(i+1);
    lanea3(j)=a(i+2);
    j=j+1;
end
j=1;
for i=1:3:5831
    laneb1(j)=b(i);
    laneb2(j)=b(i+1);
    laneb3(j)=b(i+2);
    j=j+1;
end
j=1;
for i=1:3:5831
    laneaa1(l,k)=lanea1(i);
    laneaa2(l,k)=lanea2(i);
    laneaa3(l,k)=lanea3(i);
end

% %FOR SECTION OF ROAD FROM ID_244 TO ATR_ID_243%

end
k=1;
j=1;
l=1;
for i=1:24:1944
    for k=1:24
        laneaa1(l,k)=lanea1(i);
    end
end

% % FOR SECTION OF ROAD FROM ID_244 TO ATR_ID_243 %
lanea2(l,k)=lanea2(i);
lanea3(l,k)=lanea3(i);
k=k+1;
i=i+1;
end
l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1944
    for k=1:24
        lanebb1(l,k)=laneb1(i);
        lanebb2(l,k)=laneb2(i);
        lanebb3(l,k)=laneb3(i);
        j=j+1;
        k=k+1;
        i=i+1;
    end
    l=l+1;
end

T1=0;
count=0;
% k=1;
for i=1:81
    for j=3:24
        OCCDFA(i,j)=laneaa2(i,j)-laneaa1(i,j);
        OCCDFB(i,j)=lanebb2(i,j)-lanebb1(i,j);
        if OCCDFA(i,j)> 100
            T1=OCCDFB(i,j);
            if OCCDFB(i,j)> 140
                count=count+1;
                i
                j
            end
        end
    end
end
% T1
% T1=0;
count
count=0
for i=1:81
    for j=3:24
        OCCDFA(i,j)=laneaa3(i,j)-laneaa2(i,j);
        OCCDFB(i,j)=lanebb3(i,j)-lanebb2(i,j);
        if OCCDFA(i,j)> 12
            T1=OCCDFB(i,j);
            if OCCDFB(i,j)> 35

count = count + 1;
    i
    j
    end
    end
    end
    end
% T1
  Count
APPENDIX C
CODE FOR MCMASTER ALGORITHM

% McMaster ALGORITHM

function f1=mcmaster()

% %
% %
% ALGORITHM FOR FINDING THE INCIDENTS ON THE LANE %
% %

% KEEPS TRACK OF NUMBER OF INCIDENTS

% FOR SECTION OF ROAD FROM ATR_ID_194 TO ID_195 %

a=xlsread('thesis1.xls','Z2660:Z6763');
b=xlsread('thesis1.xls','Z6764:Z10867');
j=1;
for i=1:3:4103
    occa(j)=a(i)/(a(i)+a(i+1)+a(i+2));
    occa(j+1)=a(i+1)/(a(i)+a(i+1)+a(i+2));
\[ \text{occa}(j+2) = \frac{a(i+2)}{a(i)+a(i+1)+a(i+2)}; \]

\[ j = j + 3; \]

end

\[ j = 1; \]

for \( i = 1:3:4103 \)

\[ \text{occb}(j) = \frac{b(i)}{b(i)+b(i+1)+b(i+2)}; \]

\[ \text{occb}(j+1) = \frac{b(i+1)}{b(i)+b(i+1)+b(i+2)}; \]

\[ \text{occb}(j+2) = \frac{b(i+2)}{b(i)+b(i+1)+b(i+2)}; \]

\[ j = j + 3; \]

end

\[ j = 1; \]

for \( i = 1:3:4103 \)

\[ \text{lanea1}(j) = a(i); \]

\[ \text{lanea2}(j) = a(i+1); \]

\[ \text{lanea3}(j) = a(i+2); \]

\[ j = j + 1; \]

end

\[ j = 1; \]

for \( i = 1:3:4103 \)

\[ \text{laneb1}(j) = b(i); \]

\[ \text{laneb2}(j) = b(i+1); \]

\[ \text{laneb3}(j) = b(i+2); \]

\[ j = j + 1; \]

end

\[ k = 1; \]

\[ j = 1; \]

\[ l = 1; \]
for i=1:24:660
    for k=1:24
        olaneaa1(l,k)=occa(i);
        olaneaa2(l,k)=occa(i);
        olaneaa3(l,k)=occa(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:660
    for k=1:24
        olanebb1(l,k)=occb(i);
        olanebb2(l,k)=occb(i);
        olanebb3(l,k)=occb(i);
        j=j+1;
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:660
    for k=1:24
        laneaa1(l,k)=lanea1(i);
        laneaa2(l,k)=lanea2(i);
        laneaa3(l,k)=lanea3(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:660
    for k=1:24
        lanebb1(l,k)=laneb1(i);
        lanebb2(l,k)=laneb2(i);
        lanebb3(l,k)=laneb3(i);
        j=j+1;
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
%  
%  THRESHOLD VALUES
% T1=0;
count=0;
% THE NO. OF ACCIDENTS TAKEN THESE THRESHOLD VALUES IS 6
k=1;
l=1;
pt1=0
pt2=0
for i=1:28
    for j=3:24
        OCCDF(i,j)=lanebb1(i,j)-laneaa1(i,j);
        if OCCDF(i,j)>398
            OCCRDF(i,j)=OCCDF(i,j)/laneaa1(i,j);
            if OCCRDF(i,j)>5
                DOCCTD(i,j)=(lanebb1(i,j-2)-lanebb1(i,j))/lanebb1(i,j-2);
                if DOCCTD(i,j)>0.1540
                    count=count+1;
                    i;
                    j;
                    pt1(l)=olanebb1(i,j);
                    pt2(l)=lanebb1(i,j);
                    l=l+1
                    plot(olanebb1(i,j),lanebb1(i,j),'-o')
                    hold on
                end
            end
        end
    end
end
end
end
count
pt1
pt2
% a=[0.4124,0.4097,0.4066]
% b=[554,496,456]
% plot(a,b,'o')
plot(pt1,pt2,'o')

% % % FOR SECTION OF ROAD FROM ATR_ID_196 TO ID_197 %
% %
% j=1;
% for i=1:3:5399
%    occa(j)=a(i)/(a(i)+a(i+1)+a(i+2));
%    occa(j+1)=a(i+1)/(a(i)+a(i+1)+a(i+2));
%    occa(j+2)=a(i+2)/(a(i)+a(i+1)+a(i+2));
%    j=j+3;
% end
% j=1;
% for i=1:3:4103
%    occb(j)=b(i)/(b(i)+b(i+1)+b(i+2));
%    occb(j+1)=b(i+1)/(b(i)+b(i+1)+b(i+2));
%    occb(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));
%    j=j+3;
% end
% j=1
% for i=1:3:5399
%     lanea1(j)=a(i);
%     lanea2(j)=a(i+1);
%     lanea3(j)=a(i+2);
%     j=j+1;
% end
% j=1;
% for i=1:3:4103
%     laneb1(j)=b(i);
%     laneb2(j)=b(i+1);
%     laneb3(j)=b(i+2);
%     j=j+1;
% end
% % j
% k=1;
% j=1;
% l=1;
% for i=1:24:1368
%     for k=1:24
%         olaneaa1(l,k)=occa(i);
%         olaneaa2(l,k)=occa(i);
%         olaneaa3(l,k)=occa(i);
%         k=k+1;
%         i=i+1;
%     end
% l=l+1;
% end
% k=1;
% j=1;
% l=1;
% for i=1:24:1368
  % for k=1:24
    % olanebb1(l,k)=occb(i);
    % olanebb2(l,k)=occb(i);
    % olanebb3(l,k)=occb(i);
    % j=j+1;
    % k=k+1;
    % i=i+1;
  % end
% l=l+1;
% end
% k=1;
% j=1;
% l=1;
% for i=1:24:1368
  % for k=1:24
    % laneaa1(l,k)=lanea1(i);
    % laneaa2(l,k)=lanea2(i);
    % laneaa3(l,k)=lanea3(i);
    % k=k+1;
    % i=i+1;
  % end
l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        lanebb1(l,k)=laneb1(i);
        lanebb2(l,k)=laneb2(i);
        lanebb3(l,k)=laneb3(i);
        j=j+1;
        k=k+1;
        i=i+1;
    end
    l=l+1;
end

% % l
% % %
% % % THRESHOLD VALUES
% % %
% %
% % T1=0;
% count=0;
% k=1;
for i=1:57
    for j=3:24
        OCCDF(i,j)=lanebb1(i,j)-laneaa1(i,j);
    end
end
if OCCDF(i,j) > 268
    OCCRDF(i,j) = OCCDF(i,j) / lanea1(i,j);
if OCCRDF(i,j) > 3.92
    DOCCTD(i,j) = (lanebb1(i,j-2) - lanebb1(i,j)) / lanebb1(i,j-2);
if DOCCTD(i,j) > 0.1358
    count = count + 1;
j = i;
j = j;
end
end
end
count

% FOR SECTION OF ROAD FROM ATR_ID_242 TO ID_243

% a = xlsread('Book1.xlsx', 'Z21668:Z25795');
% b = xlsread('Book1.xlsx', 'Z25796:Z29923');
j = 1;
for i = 1:3:4127
    occa(j) = a(i) / (a(i) + a(i+1) + a(i+2));
    occa(j+1) = a(i+1) / (a(i) + a(i+1) + a(i+2));
    occa(j+2) = a(i+2) / (a(i) + a(i+1) + a(i+2));
j = j + 3;
% end
% j=1;
% for i=1:3:4127
%   occb(j)=b(i)/(b(i)+b(i+1)+b(i+2));
%   occb(j+1)=b(i+1)/(b(i)+b(i+1)+b(i+2));
%   occb(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));
%   j=j+3;
% end
% j=1;
% for i=1:3:4127
%   lanea1(j)=a(i);
%   lanea2(j)=a(i+1);
%   lanea3(j)=a(i+2);
%   j=j+1;
% end
% j=1;
% for i=1:3:4127
%   laneb1(j)=b(i);
%   laneb2(j)=b(i+1);
%   laneb3(j)=b(i+2);
%   j=j+1;
% end
% % j
% k=1;
% j=1;
% l=1;
% for i=1:24:1377
for k=1:24
    olaneaa1(l,k)=occa(i);
    olaneaa2(l,k)=occa(i);
    olaneaa3(l,k)=occa(i);
    k=k+1;
    i=i+1;
end
l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1368
    for k=1:24
        olanebb1(l,k)=occb(i);
        olanebb2(l,k)=occb(i);
        olanebb3(l,k)=occb(i);
        k=k+1;
        i=i+1;
    end
    l=l+1;
end
k=1;
j=1;
l=1;
for i=1:24:1377
    for k=1:24
        "
```matlab
% laneaa1(l,k)=lanea1(i);
% laneaa2(l,k)=lanea2(i);
% laneaa3(l,k)=lanea3(i);
% k=k+1;
% i=i+1;
% end
% l=l+1;
% end
% k=1;
% j=1;
% l=1;
% for i=1:24:1368
%     for k=1:24
%         lanebb1(l,k)=laneb1(i);
%         lanebb2(l,k)=laneb2(i);
%         lanebb3(l,k)=laneb3(i);
%         k=k+1;
%         i=i+1;
%     end
%     l=l+1;
% end
% % l
% % % % %
% % % % % THRESHOLD VALUES
% % % % %
% %
% % T1=0;
```
% count=0;
% k=1;
% for i=1:57
% for j=3:24
% OCCDF(i,j)=lanebb1(i,j)-laneaa1(i,j);
% if OCCDF(i,j)> 229    %T1
%     T1=OCCDF(i,j)
%     OCCRDF(i,j)=OCCDF(i,j)/laneaa1(i,j);
%     if OCCRDF(i,j)> 3.6
%         T1=OCCRDF(i,j)
%     DOCCTD(i,j)=(lanebb1(i,j-2)-lanebb1(i,j))/lanebb1(i,j-2);
%     if DOCCTD(i,j)> 0.2578
%         count=count+1;
%             i;
%             j;
%         end
%     end
% end
% end
% end
% end
% count
% %T1
%
%
% %    FOR SECTION OF ROAD FROM ATR_ID_243 TO ID_244  %
%
% j=1;
% for i=1:3:5831
%    occa(j)=a(i)/(a(i)+a(i+1)+a(i+2));
%    occa(j+1)=a(i+1)/(a(i)+a(i+1)+a(i+2));
%    occa(j+2)=a(i+2)/(a(i)+a(i+1)+a(i+2));
%    j=j+3;
% end
% j=1;
% for i=1:3:5831
%    occb(j)=b(i)/(b(i)+b(i+1)+b(i+2));
%    occb(j+1)=b(i+1)/(b(i)+b(i+1)+b(i+2));
%    occb(j+2)=b(i+2)/(b(i)+b(i+1)+b(i+2));
%    j=j+3;
% end
% j=1;
% for i=1:3:5831
%    lanea1(j)=a(i);
%    lanea2(j)=a(i+1);
%    lanea3(j)=a(i+2);
%    j=j+1;
% end
% j=1;
% for i=1:3:5831
%    laneb1(j)=b(i);
%    laneb2(j)=b(i+1);
%    laneb3(j)=b(i+2);
%    j=j+1;
% end
% % j
% k=1;
% j=1;
% l=1;
% for i=1:24:1944
%     for k=1:24
%         olaneaa1(l,k)=occa(i);
%         olaneaa2(l,k)=occa(i);
%         olaneaa3(l,k)=occa(i);
%         k=k+1;
%         i=i+1;
%     end
%     l=l+1;
% end
% k=1;
% j=1;
% l=1;
% for i=1:24:1944
%     for k=1:24
%         olanebb1(l,k)=occb(i);
%         olanebb2(l,k)=occb(i);
%         olanebb3(l,k)=occb(i);
%         j=j+1;
%         k=k+1;
%         i=i+1;
%     end
%     l=l+1;
% end
% k=1;
% j=1;
% l=1;
% for i=1:24:1944
%   for k=1:24
%       laneaa1(l,k)=lanea1(i);
%       laneaa2(l,k)=lanea2(i);
%       laneaa3(l,k)=lanea3(i);
%       k=k+1;
%       i=i+1;
%   end
%   l=l+1;
% end
% k=1;
% j=1;
% l=1;
% for i=1:24:1944
%   for k=1:24
%       lanebb1(l,k)=laneb1(i);
%       lanebb2(l,k)=laneb2(i);
%       lanebb3(l,k)=laneb3(i);
%       j=j+1;
%       k=k+1;
%       i=i+1;
%   end
%   l=l+1;
T1=0;
count=0;
DOCCRDF

% THE NO. OF ACCIDENTS TAKING THESE THRESHOLD VALUES IS 2
% k=1;
% for i=1:81
% for j=3:24
% OCCDF(i,j)=lanebb1(i,j)-laneaa1(i,j);
% if OCCDF(i,j)> 217 %T1
% T1=OCCDF(i,j)
% OCCRDF(i,j)=OCCDF(i,j)/laneaa1(i,j);
% if OCCRDF(i,j)> 0.3036
% T1=OCCRDF(i,j)
% DOCCTD(i,j)=(lanebb1(i,j-2)-lanebb1(i,j))/lanebb1(i,j-2);
% if DOCCTD(i,j)> 0.21235
% T1 = DOCCTD(i,j)
% count=count+1;
% i;
% j;
% end
end
end
end
end
% % T1
% count
% Shue Fuzzy Logic Algorithm

CONGESTION = 0;
Low = 1;
Medium = 2;
High = 3;

% Assign threshold level to Congestion based on historical data
% Congestion = f(lane occupancy, occupancy threshold)

% Using congestion level, determine Incident occurrence
% Each congestion level has a unique equation
% Used to compute a decision variable at time step k

Decision(k) = 0;

% U(i,k) and D(i,k) represent upstream and downstream counts
% at lane i and time k
% Ou(i,k) & Od(i,k) = collected occupancies of up and downstream
% at lane i and time k

% J = total number of adjacent lanes
% T = maximum time lag
% Lag = time lag index

if Congestion == Low
    Decision(k) = ((Ou(k) - Od(k)) / Ou(k));
end

if Congestion == Medium
    Sum = 0;
    for j=1:J
        Sum = Sum + D(j,k);
    end
    Decision(k) = {((Sum / J) - D(i,k)) * (Sum / J)};
end

if Congestion == High
    Sum = 0;
    for j=Lag:T
        Sum = Sum + D(i,k-Lag);
end
end

Sum1 = 0;
for j=1:J
    Sum1 = Sum1 + D(j,k);
end
Decision(k) = Sum - U(i,k-T) - (Sum1 / J);
end

% Now compute a time varying decision-variable correlation

% B = predetermined value set for the boundaries of w(p,q,m,n,k)
% m = level of congestion
% n = lane code
% p = location parameter
% q = binary digit representing incident or no incident (1 or 0)
% k still represents current time step

% u(p,q,m,n,k) = pattern of the decision variable
% on basis of historical data

Sum2 = 0;
for Lag=0:3
    Sum2 = Sum2 + ((Decision(n)*(k-Lag)-u(p,q,m,n,k))^2;
\[ \text{Incident\_Decision}(k) = 1 - \frac{1}{B} \sqrt{\text{Sum2}}; \]

% Recognize an Incident if the following condition is met
% Judgement is made against a threshold value
% We will use 0.5 for Demonstrative Purpose

Threshold = 0.5;

if (Max(w(1.1,m,n,k),w(2.1,m,n,k),w(3.1,m,n,k)) - w(0,m.n,k) > Threshold)
    disp('A lane blocking incident with the attributes m and n is recognized at time step k')
end.
APPENDIX E

CODE FOR AFIDS-IDM ALGORITHM

% AFIDS ALGORITHM

% j=evacuation route

% SF(i,k)=service flow rate
% c(j)=capacity for the road section under study
% f(p)=further adjustment
% LOC(i,j,k)=level of congestion index
% LOC = level of congestion

\[ LOC(i,j,k) = \frac{SF(i,k)}{c(j)} \times \frac{1}{f(p)} \]

\[ LOC = \text{table}(LOC(i,j,k),sl) \]

% U(i,k) and D(i,k) represent upstream and downstream counts
% at lane i and time k

% Ou(i,k) & Od(i,k) = collected occupancies of up and downstream
% at lane i and time k

% I=total number of adjacent lanes
%T = time lag

%F(p) = speed limit

if LOC == LOW
    Vs(k) = (Ou(k-n) - Od(k))/Ou(k-n)
end

if LOC == MEDIUM
    Vs(k) = ((D(k)/J) - D(k)) - (D(k)/I)
end

if LOC == HIGH
    Vs(k) = (D(k) * min(1.0, F(p)) - (U(k(k-n))*(Cfs))) - (D(k)/I)
end

%delta = comparison value

%Cfs = correction factor

delta = (U(ATRi))*(Cfs)
$W_m(k) = 1 - (V_s(k-fp) - U_m)$

$W_m = \text{fuzzy set membership value}$

$U_m = \text{pattern of decision variable}$