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

Terry Brumback*, Daniel J. Fonseca**,# and Gary P. Moynihan***

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.

Keywords: Freeway Incident Detection, Fuzzy Clustering, Traffic Management, Decision Support Systems (DSS).

1. INTRODUCTION

Although most highway and road networks around the world are designed to accommodate normal traffic movements, congestion and gridlock can occur as the design capacity of a road system is overwhelmed by an “abnormal” magnitude of vehicles moving through a particular section of the transit network. The resulting traffic patterns affect the safety and mobility of subjects moving through the roadways. 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.

* Industrial Engineering Program, The University of Alabama, Tuscaloosa, AL 35487. E-mail: terry.brumback@ua.edu
** Department of Mechanical Engineering, The University of Alabama, Tuscaloosa, AL 35487-0276. Fax: 205-348-6419, Voice mail: 205-348-3337.
*** Department of Civil, Construction and Environmental Engineering, The University of Alabama, Tuscaloosa, AL 35487. E-mail: gmoynihan@eng.ua.edu
# Corresponding Author: dfonseca@eng.ua.edu
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.

This paper describes the Alabama Freeway 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 traffic management operations. The developed methodology, which is based on fuzzy set theory, outperforms previously formulated traffic-management algorithms in that it decreases the complexity of necessary calculations, eliminating the need for elaborate calibration, and reducing the number of false alarms associated with most mathematical methods currently in use. Since the developed platform has been automated via a decision support system, it is expected to reduce the trigger time associated with the deployment of first responders to traffic incidents.

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 circulating through a network of roads. 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.

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 (Singlier 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).

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 Cleveland, 1974).
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; Kurkjian et al., 1977).

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.

3. AFIDS-IDM

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. AFIDS-IDM incorporates a fuzzy cluster approach to incident detection that is an extension of Shue’s (2002) algorithm. The primary differences between the two algorithms lies in the environments in which they were developed and their intended application. Shue’s algorithm was developed through a simulated environment using the Corridor Simulation (CORSIM) software for use in normal freeway incident detection. AFIDS-IDM, 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-IDM centers on real world traffic patterns and states while Shue’s was developed on traffic patterns and states defined through simulation. The traffic patterns and states incorporated into AFIDS-IDM are clearly identified in the Transportation Research Record (TRB, 2008).

The AFID-IDM logic is a continuous loop process carried out in seven steps. These steps are indicated in Table 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.

### 3.1 Determination of Level of Congestion Index

The determination of the Level of Congestion Index (LOC Index), Equation 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 Index at the upstream and downstream sensors:

\[
\text{LOC}_{\text{Index},ijk} = \left( \frac{SF_{ik}}{c_j} \right) \times \left( \frac{1}{f_p} \right)
\]

where:

- \( \text{LOC}_{\text{Index},ijk} \) = Level of congestion for \( i \) lane of traffic in evacuation route \( j \) at time period \( k \);
- \( SF \) = Service flow rate for \( \text{LOC}_i \) 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 specific automatic traffic recorder (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 (Table 2).

### 3.2 Determination of Level of Congestion (LOC)

The LOC Index is applied to Table 3 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 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&lt;sub&gt;Index&lt;/sub&gt;)</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 $v^s$ associated with the specified LOC</td>
</tr>
</tbody>
</table>

*Contd…*
Determination of the comparison variable lambda ($\lambda$) associated with the input data and posted speed limit

Determination of the fuzzy set membership, $\omega_{m}$, associated with the specified $v^e$

A lane blocking incident exists when $\omega_{m} > \lambda$.

**Table 2**
Calculation of $f_p$: Adjustment Due to Time of Day

<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</td>
</tr>
</tbody>
</table>

*a* Engineering judgment and local data must be used in selecting the exact value.


**Table 3**
Level of Congestion from LOC Index

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

* Highly variable, unstable

**3.3 Determination of Decision Variable $v^e$**

Decision variable $v^e$ is determined through the application algorithms $v_1$, $v_2$ and $v_3$, each representing the LOC’s low, moderate, and high, respectively.

$$
\begin{align*}
  v_1^i(k) & = \frac{o^u(k) - o^d(k)}{o^e(k)} \\
  v_2^2(k) & = \left\lfloor \frac{f^d(k)}{I} \right\rfloor - f^d(k) - \{f^d(k)/I\} \\
  v_3^3(k) & = \{f^d(k) * \text{Min}(1.0, F_p)\} - \{f^u(k_i)\} - (f^d(k))/I
\end{align*}
$$

where:

$f^u_i(k)$ and $f^d_i(k)$ = the upstream and downstream traffic counts collected at target lane $i$ and time step $k$;
\( o_u^v(k) \) and \( o_d^v(k) \) = collected occupancies;
\( I \) = total number of adjacent lanes;
\( F_p \) = time lag index defined as the posted speed limit/distance between
\( f_u^v(k) \) and \( f_d^v(k) \).

### 3.4 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 4.

#### Table 4

<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>Low</td>
<td>Moderate</td>
<td>High</td>
<td>Over Congestion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum Expected Speed</td>
<td>26</td>
<td>25</td>
<td>23</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>32</td>
<td>25</td>
<td>*</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td>38</td>
<td>37</td>
<td>26</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>42</td>
<td>38</td>
<td>27</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>45</td>
<td>40</td>
<td>28</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>48</td>
<td>41</td>
<td>30</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>51</td>
<td>43</td>
<td>30</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>54</td>
<td>44</td>
<td>30</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>57</td>
<td>46</td>
<td>30</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:

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

where:

Upstream traffic count at ATR = 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.

### 3.5 Determining Fuzzy Set Membership

Fuzzy set membership is determined by applying Equation 6:

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

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

3.6 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.

4. VALIDATION

4.1 AFIDS-IDM Comparison To Accepted Incident Detection Algorithms
Twenty-two incident detection algorithms were identified through an extensive literature review to be used as benchmarks in the validation phase of the research. The algorithms were evaluated against a set of criteria (e.g., minimum data collection time intervals, occupancy data requirements, ease of calibration, etc.) to determine a short-list of algorithms applicable to field application. These final chosen algorithms included the California Algorithm #8, the Exponential Smoothing Algorithm, the McMaster Incident Detection Algorithm, and Shue’s Fuzzy Logic Algorithm. These were selected as benchmarks to assess the effectiveness of the developed Alabama Freeway Incident Detection System Algorithm. The performance of the five algorithms was compared against a set of metrics widely accepted in the evaluation of incident detection algorithms.

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 ($T_{th}$) associated with each test. 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 #8 replaces the use of relative temporal differences in downstream occupancy values with occupancy measurements. This reduces the false alarm rate through the recognition of recurring compression waves commonly found in heavy traffic.

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 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 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.

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 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, i.e., uncongested, congested, saturated, and over-saturated. 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. Calibration of the algorithm then 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. A quadratic equation is then estimated to obtain flow as a function of occupancy at each station, and a constant flow value is estimated.

Shue’s incident detection 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. Shue’s algorithm is carried out in four steps: (a) identification of traffic flow conditions, (b) determination of decision variables, (c) determination of fuzzy set memberships, and (e) 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.
4.2 Traffic Data Set

Pertinent traffic data for this study was made available by the South Carolina Department of Transportation (SCDOT). Vehicle speed and traffic counts from successive upstream and downstream sensors, or Automatic Traffic Recorders (ATR), collected at hourly intervals were the primary inputs. Together, two adjacent 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 5 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 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.

Figure 2: Road Sections Considered
Table 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>
</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>
</tr>
<tr>
<td>137086</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>150</td>
</tr>
<tr>
<td>137087</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>31</td>
</tr>
<tr>
<td>137088</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>137089</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>87</td>
</tr>
</tbody>
</table>

4.3 Comparative Evaluation

Each of the 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 6. Incident detection results are presented in tables 7 through 11.

Table 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 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 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>
</tbody>
</table>

Contd…
Table 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 10
Performance Results for Shue's 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 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’s, 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.
5. CONCLUSION & REMARKS

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 introduced 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.

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REFERENCES


