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The Role of Non-Recurring Congestion in Massive Hurricane Evacuation Events

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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 pre-planned 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 of crashes by incidents involving personnel responding to traffic incidents
- Negative public image of first responders involved in incident management activities.

This paper discusses the dynamics involved in non-recurrent congestion and its potential impact on massive evacuation events, as in the case of a hurricane evacuation. It also presents a comprehensive literature review of the most widely used incident detection algorithms (AID's) developed throughout the years to identify non-recurring congestion conditions.

2. Non-recurring congestion

Roadway incidents refer to non-recurring events resulting in traffic congestion or disruptions. During an incident, the normal capacity of the roadway is restricted, leading to queues and delays. Incidents have far-reaching consequences for safety, congestion, pollution, and the cost of travel.

Previous studies indicated that incidents are one of the major causes of loss of time and increases in avoidable costs in transportation networks in the U.S. For example, in 2003, it was determined that more than 60% of urban freeway congestion was caused by incidents, and that indicator was estimated to be 70% by 2005 (Schrank & Lomax, 2003). Prompt and reliable incident detection is vital in reducing incident congestion, post-incident delay, and the potential for additional incidents.

Incident management is a crucial function in the design and deployment of Advanced Transport Management Systems (ATMS) and Advanced Traveller Information Services (ATIS). It primarily includes incident detection, verification, validation, response, and clearance. Incident detection is a critical step in incident management. It affects consequent actions and determines the reliability and efficiency of the whole system. The procurement of real-time incident detection information is an integral element of and supports the realization of many other functions in traffic management (Presley & Wyrosdick, 1998). Nevertheless, incident detection is one of the weakest links in implementing advanced traffic controls.

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 traffic management techniques oriented to reporting and identification of changes in traffic flow patterns would have dramatic effects on the reduction of the impact of traffic incidents in emergency evacuations, such as in the case of a massive evacuation prompted by a hurricane event. Among such techniques incident detection paradigms have been the most widely sought by practitioners in the field.

3. Incident detection

3.1 Traffic data collection

Despite substantial research, the implementation of effective incident detection algorithms has been hampered by limited performance reliability, substantial implementation needs, and strong data requirements (Takaba & Matsuno, 1985).

Traffic information is typically collected from loop detectors and includes occupancy and volume data gathered over a 20- to 60-second interval. Inductive loop detectors (ILD) consist of one or more loops of wire embedded in the pavement and connected to a control box, excited by a signal ranging in frequency from 10 KHz to 200 KHz. When a vehicle passes over or rests on the loop, the inductance of the loop is reduced, showing the presence

of a vehicle. The data supplied by inductive loop detectors are vehicle passage, presence, count, and occupancy.

The benefits of inductive loop detectors come from the fact that they are an established technology in the United States and in most parts of the world, they have a well defined zone of detection, and they are generally reliable. ILDs are an established technology in the United States and in most parts of the world. They have a well defined zone of detection, and they are considered reliable. ILDs are generally used for the following reasons (Hualiang & Qi, 2003):

- When properly installed and maintained, ILDs continue to be the best in all weather applications.
- They are the most consistently accurate detectors in terms of vehicle counts.
- ILDs perform well in both high and low volume traffic and in different weather conditions.
- Even with crosstalk problems and a high proportion of lane changes, ILDs have over counts of only around 0.6 percent.
- ILDs meet even the most stringent vehicle flow error specifications required by some ITS applications.

Some reported ILD disadvantages are (Hualiang & Qi, 2003):

- The loop detector system may suffer from poor reliability, primarily from improper connections made in the pull boxes and in the application of sealants over the saw cut. These problems are accentuated when loops are installed in poor pavement or in areas where utilities frequently dig up the roadbed.
- Sources of loop malfunction, such as stuck sensors, can produce erroneous data and may lead to inaccurate detection.
- Another disadvantage of loops is their inability to directly measure speed. If speed is required, then a two-loop speed trap is employed, or an algorithm involving loop length, average vehicle length, time over the detector, and number of vehicles counted is used with a single loop detector.

3.2 Performance measures of incident detection algorithms

Different algorithms may be suitable on different stretches of a road. A gauging factor to be considered is the detection rate and the false alarm rate. The detection rate (DR) is the number of incidents detected as a percentage of the number of incidents occurred. The false alarm rate (FAR) is the number of false alarm signals as a percentage of tests performed by the algorithm. The DR and the FAR are defined as follows:

$$\text{Detection rate} = \frac{\text{number of detected incidents}}{\text{total number of incidents detected}} \times 100\% \quad (1)$$

$$\text{False Alarm Rate (FAR)} = \frac{\text{Number of False Alarms}}{\text{Total Number of Applications of the Algorithm}} \times 100 \quad (2)$$

Most algorithms use thresholds for incident detection. Thresholds for the algorithms are generally calculated by trial and error and from empirical experimentation on historical data and performance curves. These curves are obtained from multiple runs of the respective algorithm on data with incrementally changing thresholds. Several factors affect the

performance of all types of incident detection algorithms. The key factors are shown in Table 1 (Busch, 1987).

3.3 Classification of incident detection algorithms

The concept of incident detection algorithms is not new. Algorithms have been developed as early as the 1970’s and new algorithms are being developed even now. Depending on how an algorithm analyzes the traffic data in order to detect incidents, it is usually classified into one of five major categories: comparative algorithms, statistical algorithms, time-series and filtering-based algorithms, traffic theory based-algorithms, and advanced algorithms (Dudek, Messer, & Nuckles, 1974).

3.3.1 Comparative algorithms

Comparative algorithms evaluate the tracking variables against certain thresholds or against one another in order to identify anomalies. The tracking variable is usually one of the traffic parameters or a variable derived from the traffic parameters. Occupancy is the most common tracking variable (Chow et al., 1977). The comparative algorithms are also sometimes referred to as the pattern recognition algorithms, as the process is analogous to identification of patterns of behavior of the variables under incident conditions. The California Algorithm is a classic example of this category (Courage & Levin, 1968).

3.3.2 Statistical algorithms

Statistical algorithms use standard statistical techniques to identify sudden changes and other unusual behavior in the variable. Incidents generally result in unusual behavior of the traffic variables. These algorithms are based on the premise that the reverse is also true under most circumstances and that such behavior indicates incidents. The standard traffic variables – flow, average speed, and lane occupancy – as well as variables derived from these primary variables have been used as tracking variables. Examples of the statistical approach include the Standard Normal Deviate and the Bayesian Algorithm (Payne & Tignor, 1978).

Operating conditions of the highway, e.g. at full capacity
Duration of the Incident
Geometric Factors: <ul style="list-style-type: none">• Grade• Lane Drops• Ramps
Environmental Factors: <ul style="list-style-type: none">• Snow, Ice or Fog• Road Surface – Dry or Wet
Severity of the Incident
Detector Spacing
Location of the Incident Relative to the Detector Station
Heterogeneity of the Vehicle Fleet

Table 1. Factors Affecting Incident Detection

3.3.3 Time series and filtering algorithms

Time series and filtering algorithms treat the tracking variable as a time-series variable. Deviation of the variable from the modeled time-series behavior is used to indicate incidents. The challenge is to differentiate random variations from variations due to incidents. These models include the Auto-Regressive Integrated Moving Average (ARIMA)-based algorithm, the Exponential Smoothing-based Algorithm, and the Kalman Filtering-based Algorithm (Chow et al., 1977).

3.3.4 Traffic theory-based algorithms

The traffic theory-based algorithms depend on the relationship between the traffic variables for their analysis. For example, the McMaster Algorithm, which is based on catastrophe theory, determines the state of traffic based on its position in the flow-density plot. It detects incidents based on the transition from one state to another. The GLR algorithm and the McMaster algorithm are examples of traffic theory-based algorithms (Chow et al., 1977).

3.3.5 Advanced algorithms

In some cases, algorithms with advanced mathematical formulation-based techniques, as well as algorithms that incorporate inexact reasoning and uncertainty into the detection logic, have been developed. These algorithms are based on Artificial Intelligence techniques such as Fuzzy Adaptive Resonance Theory and Probabilistic Neural Networks. For example, in Neural Network-based algorithms, the traffic data is input into a black box of learning layers and a binary decision is generated (Isaksen & Payne, 1973).

3.4 Evolution of incident detection algorithms

Review of the literature has noted considerable work on the development of mathematical models which focus on evacuation route planning. Network representations of evacuation problems are extensions of the classical operations research assignment problem. For these problems, the basic form of the network is that of the more general minimal cost transshipment (or flow) network (Hillier & Lieberman, 2005). In the network, the arcs represent the flow of people, the source nodes represent initial source inventories (points of entrance into the evacuation network), and the sink nodes represent the final inventories (in this case, destinations). Optimization models (e.g. linear programming, goal programming or dynamic programming) are another category of mathematical models. The model is formulated to either maximize (or minimize) the objective function (depending upon the purpose of the model) within the context of available resources and constraints (Hillier & Lieberman, 2005).

The most commonly reported incident detection algorithms in the literature that have been developed to identify non-recurring congestion conditions in transit networks are discussed next. They are presented in the temporal chronology of their associated creations. The emphasis is on providing the outline of algorithms that are significantly methodologically different rather than describing all the available algorithms in meticulous detail.

3.4.1 Standard Normal Deviate algorithm

The Standard Normal Deviate (SND)-based incident detection algorithm (Dudek et al., 1974) was developed at the Texas Transportation Institute (TTI). The SND of a variable is computed as the difference of the given variable from its mean, divided by the standard

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

3.4.2 Exponential Smoothing Algorithm

The Exponential Smoothing Algorithm (Cook & Cleveland, 1974) was developed using data from the John C. Lodge Freeway in Detroit. This method uses double exponential smoothing for generating a forecast variable. A tracking signal is generated as the algebraic sum of all the previous estimate errors to the present minute, divided by the current estimate of the standard deviation. When the tracking signal deviates from zero, beyond a pre-specified threshold, detection is indicated. A set of 13 traffic variables, which were derived from the basic traffic variables of volume, occupancy, and speed, were used to test algorithm performance. The thirteen variables are: station volume; station occupancy; station speed (volume/occupancy); station volume-occupancy (root of squared sum of errors for both was used for the error values); station speed-occupancy (analogous to volume-occupancy); station kinetic energy; station discontinuity; subsystem volume; subsystem occupancy; subsystem speed; subsystem kinetic energy; subsystem volume-occupancy discontinuity; and subsystem speed-occupancy discontinuity. Station discontinuity is computed in the same manner as in Courage and Levin (1968). Kinetic energy computations use the surrogate for speed. Station occupancy, volume, and discontinuity were found to give better performance in terms of detection levels at different levels of false alarms.

3.4.3 Low Volume-Based algorithm

An algorithm (Dudek et al., 1974) was specifically developed at the TTI for detecting vehicles under low volume conditions. This algorithm tracks individual vehicle input-output. The time of exit of a vehicle from the control section, the edges of which are defined by detectors, is projected as the summation of the time of entry, with the ratio of distance between detectors to speed of vehicle at the time of entry. The TTI researchers made a preliminary assumption of the constant speed of the vehicle over the section. Two different approaches are defined here: a time-scan operation system and an event-scan operation system. In the time scan operation, fixed sized account intervals are considered and the

numbers of vehicles entering and exiting during these intervals are balanced. Projected times of exit are computed for each vehicle entering the control section within an accounting interval, and if the projected time falls within the interval, the vehicle is expected to exit within that interval. If the vehicle fails to do so, an alarm is raised. If nothing had happened to the vehicles and it was just a reduction of speed that delayed the exit, the alarm would then be a false one. Waiting for one more accounting period does not alleviate the problem, because a similar situation may arise in the next interval, and the accounting will still show one less vehicle exiting than expected. This problem is addressed in the event scan approach. It uses a variable time interval for vehicle accounting. For each vehicle, a set of three computations are executed: the shortest possible time the vehicle can take to arrive based on an upper speed limit of 100 miles per hour (mph), the expected arrival time of the vehicle based on the constant speed assumption, and a late expected exit time based on a speed with a 10% factor of safety. If a second vehicle does not arrive at the beginning of the section before the late expected exit time, the accounting interval is closed. If a vehicle does arrive, the process is repeated until such a situation arises in which no vehicle arrives at the upstream detector before the late expected exit time at the downstream detector. If a vehicle is not accounted for at the close of the accounting period, an alarm is raised. Some results pertaining to detector spacing requirements for event scan operations were obtained from simulation runs. Actual data was used to validate the claim that pattern recognition of headway, occupancy, and speed has to supplement volume counts, for the algorithm to work satisfactorily. An average of one false alarm per 10 minutes at 200 vehicles per hour (vph) on a three lane directional freeway was observed during the use of this algorithm (Chow, Willsky, Gershwin, & Houpt, 1977).

3.4.4 Dynamic Model based algorithms (MM and GLR)

Chow et al. (1977) proposed an incident detection approach based on a dynamic model that would make use of all information about the dynamic and stochastic evolution of traffic variables in time and space. Two algorithms resulted from this approach: the Multiple Model (MM) algorithm and the Generalized Likelihood Ratio (GLR) algorithm. The dynamic model uses the Payne equations (Isaksen & Payne, 1973). The MM algorithm models different scenarios, one of them being the occurrence of an incident. Constant-gain Kalman filters are used on the output of the model for the different scenarios to compare against the observations. The residuals from these filters are fed into a probability calculator that is subsequently used in a set of detection rules to isolate incidents. In the GLR algorithms, only one extended Kalman filter is used, corresponding to the normal operations scenario. Using Incident Innovations Signatures (IIS) that are pre-determined from simulations, a correlation is drawn between the residuals of the filter and the corresponding IIS in order to obtain the likelihood of different events. Unlike other algorithms that perform well only in heavy traffic, these algorithms were found to perform well under light and moderate traffic conditions.

3.4.5 The California Algorithms

The California Algorithms (Payne & Tignor, 1978) are a set of 10 algorithms that are based on the same principle. They use a decision tree based on traffic states for incident detection. In this set, Algorithm #8 and Algorithm #7 are the most popular ones. The California Algorithms, developed using data from the Los Angeles roadway system, are one of the first

full-scale incident detection algorithms developed. They are normally used as benchmarks for evaluating the performance of other algorithms. At present, several modified forms of the original California algorithms exist and are implemented in several TMCs. The algorithms use 20- and 30-second occupancies and volumes averaged over all lanes at a particular station. Several variables are derived based on the occupancy values at the concerned station and the station downstream at different time points. Some of the most prominent variables are: Downstream Occupancy (DOCC), Spatial Difference in Occupancies (OCCD), Relative Spatial Difference in Occupancies (OCCRD), and Relative Temporal Difference in Downstream Occupancy (DOCCTD). These derived variables are evaluated at every time-step at each station in the concerned section of roadway and compared to thresholds at different points in a decision tree to determine whether an incident has occurred in the system. The thresholds are determined during calibration of the algorithm by minimizing the false alarm rate for a given level of detection rate. The algorithms in this set that used derived variables based on volume and volume-to-occupancy ratios were found to be inferior to algorithms based purely on occupancy based measures. Algorithm #7 uses a persistence requirement and replaces the variable DOCCTD in the last stage of the decision tree with the DOCC variable. This is done in order to account for two observations: 1 – non-incident-related compression waves traveling upstream cause false alarms; and 2 – drops in downstream occupancies are much greater in magnitude in cases of incidents than in normal compression waves generated by recurrent congestion. Algorithm #8, in addition to this, turns off incident detection for 5 minutes after the detection of a compression wave at the downstream detector (Payne & Tignor, 1978). This is supposed to give a better suppression of false alarms.

3.4.6 Bayesian-based algorithm

An incident detection algorithm based on Bayesian probability theory was developed by the Illinois DOT. This approach can be used on top of any algorithm to decrease the false alarm rate of the algorithm. The basic idea uses values of probability of occurrence of an incident for a given tracking signal. The signal can be any traffic variable or a variable derived from a traffic parameter, such as those used by the California algorithms. The requirement of the variable is its stability during the occurrence of the incident. The frequency distribution functions of the variable during incident and non-incident conditions are derived based on historical data during the algorithm calibration. These frequency distributions are used to derive values of Bayesian probability of the occurrence of an incident for strings of signals from the variable. The strings consist of a series of “ones” and “zeros,” depending on the presence and absence of the signals, respectively. A signal is generated when the value of the variable crosses a calibrated threshold (Levin & Krause, 1978). There can be several thresholds for operation under different traffic conditions and different geometric conditions. The requirement for the length of the string (string of consecutive “ones”) is determined from the probability values associated with the string of signals. It was found that a string length of four was sufficient for the section over which the algorithm was tested. In other words, a string of four consecutive “ones” indicated the occurrence of an incident. Determination of proper thresholds for the signal and the frequency distribution of the variables is critical to the proper functioning of the algorithm. The main drawback of this algorithm is its increased detection time. The logic ensures a reduction of false alarms, and if the base signal variable is stable enough, the detection ratio would not depreciate

with the use of this logic (Levin & Krause, 1978). Depending on the length required to obtain a high value of probability of the occurrence of an incident, the time required to detect the incident would increase. The tests conducted during the validation of the algorithm observed an increase of 2 to 2.5 minutes in detection time. This algorithm provides a statistical way of creating a persistence test. The persistence test can reduce the false alarm occurrence, but the detection ratio and the time to detect values depended primarily on the base signal or the base algorithm that feeds this logic (Levin & Krause, 1978).

3.4.7 Committee Decision logic units-based algorithm

Tsai and Case (1979) proposed two techniques designed to operate on top of the basic incident detection algorithm to improve detection performance. The first technique, the Incident Detection Persistence Test, proposed in their study is a methodology for reducing false alarms by distinguishing false alarms from true alarms. The logic is developed on top of a modified California Algorithm. It uses Bayes optimal decision rule to determine a duration threshold that maximizes the likelihood that an alarm with a duration less than the threshold duration turns out to be a false alarm. Alarm duration data for both false alarms and true alarms are used to determine such a threshold. The reduction of false alarms using this technique was observed to have an adverse effect on the detection ratio, which decreased (adversely) with a reduction in false alarms by the introduction of the persistence interval logic. The second technique uses a committee-machine approach to determine the lane of the multilane freeway on which the incident has occurred. The output of several detection algorithms in the form of the incident lane number is used in the first layer, in which the individual decision units are designated as committee decision logic units (CLDU). The second layer of the committee machine structure consists of a vote-taking logic unit (VTLU) that uses the decision outputs from the first layer and determines the lane where the incident has occurred, according to the majority decision principle (Tsai & Case, 1979).

3.4.8 HIOCC and PATREG Algorithms

The High Occupancy (HIOCC) and Pattern Recognition (PATREG) algorithms were developed at the Transport and Road Research Laboratory in Berkshire, UK. The HIOCC algorithm is primarily a congestion detection algorithm. Slow moving or stopped vehicles are detected by using the resulting high occupancy values. Instantaneous occupancy values, at a one tenth of a second sampling rate, are smoothed using an exponential filter before employing the algorithm. The threshold is so chosen that an alarm will be indicated when the passenger-car speed is less than 6 mph or the long-vehicle speed is less than 14 mph. To avoid multiple alarms resulting from fluctuations of the observations, the occupancy values are artificially raised to a 90% level at the beginning of the congestion so that the high is maintained until the occupancy comes back to the level before the congestion. Also, to account for stop-and-go traffic, an 8-second threshold of zero instantaneous occupancy is used to prevent the case of stopped traffic from triggering an end of congestion indication. The PATREG algorithm identifies incidents using patterns of significant speed changes. If the speed lies outside the pre-determined lower and upper thresholds specific to a lane for the duration of the pre-set persistence interval, an alarm is indicated. The PATREG algorithm works efficiently under low to medium volume conditions, whereas the HIOCC algorithm deals with the high volume conditions (Collins, Hopkins, & Martin, 1979; Collins, 1983).

3.4.9 ARIMA

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

3.4.10 DELOS

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

3.4.11 Principal Component Analysis-based algorithm

An incident detection algorithm based on the statistical technique of Novelty detection using Principal Component Analysis was developed at the University of Leeds. The flow, speed, and occupancy at two adjacent detectors form the 6-dimensional input vector. The principal components computed from this input data normally have a much lesser dimension than the input data, masking unwanted noise effects, and, at the same time, preserving the generality of the data. A calibrated threshold value is used to distinguish the novel input vectors from normal data. The novel input vectors, when identified, are indicative of incidents. Encouraging results were reported when using this detection scheme on simulated data sets (Chen, 1997).

3.4.12 Cumulative sum of occupancy-based algorithm

This detection algorithm, developed at the University of California, Berkeley, is based on a comparison of cumulative occupancy data for the two detectors on both sides of a hypothetical incident. Thereby, this is a two-detector algorithm, unlike most of the others, which are single detector algorithms. However, this scheme still relies on the road being more crowded upstream than downstream for an extended period of time – a situation which is also the case in recurrent congestion at bottlenecks. Consequently, this algorithm, like most other algorithms, is prone to generating false alarms under recurrent congestion.

Incidents are detected by tracking the fluctuation of the difference of the cumulative sum of occupancies at the two detectors. If the fluctuation is more than a time-variant threshold, which increases linearly with the passage of time, then an incident is indicated. Effects of variations in occupancy induced by individual driving patterns and faulty detector reporting can be absorbed by carefully choosing an appropriate threshold value (Lin & Daganzo, 1997).

3.4.13 Probabilistic Neural Network algorithm

In the Probabilistic Neural Network (PNN) algorithm (Abdulhai & Ritchie, 1999a; Abdulhai & Ritchie, 1999b; Jin, Cheu, & Srinivasan, 2002), the transfer function of the hidden layer is a radial-basis function, and that for the output layer is a competitive-transfer function. The PNN consists of four layers – the input layer, the pattern layer, the summation layer, and the output layer. The input layer distributes the input vector to the pattern layer. The neurons in the pattern layer are divided into two groups representing incident and incident-free conditions. The summation layer consists of two neurons, one for each class (i.e., incident and non-incident). Each of the summation neurons computes an average output signal for the associated pattern units and the scales it. The output neuron selects the higher value between the two and determines the class (i.e., incident or non-incident). Compared to MLF, PNN has been shown to have lower detection rates (95-100%) and higher false alarm rates (less than 0.33%). However, PNN has a better adaptation potential. Postprocessor feature extractors and postprocessor probabilistic output interpreters have been used successfully (Abdulhai & Ritchie, 1999b) to improve performance. The use of DWTs (Roy & Abdulhai, 2003) has also been explored for training the PNN, with encouraging results.

3.4.14 Fuzzy Wavelet Radial Function Neural Network algorithm

Adeli and Karim (2000) proposed an algorithm using a Discrete Wavelet Transform (DWT) for noise reduction and feature extraction, followed by a fuzzy c-mean clustering to reduce the dimensionality of the input vector, finally using a Radial Basis Function Neural Network (RBFNN) to classify the input pattern as an incident pattern or a non-incident pattern. Sixteen consecutive data-points for occupancy and speed from the immediate past are used to form the input signal. This signal is normalized and the DWT is computed using Daubechies wavelet system of length 8. The wavelet coefficients are filtered using soft-thresholding nonlinearity, followed by an inverse DWT to obtain the de-noised, normalized sequence. A fuzzy c-mean clustering is used to reduce the dimensionality of the pattern. The extracted eight elements (four for occupancy and four for speed) are fed into a trained RBFNN. The output is compared against a preset threshold to indicate either an incident condition or otherwise. This algorithm was compared with the California Algorithm #8 and was found to produce very low false alarms (on the order of 0.07%), as compared to the California algorithm (on the order of 3.82%) under the same detection rate scenarios when tested with simulated data. Limited tests with real data gave 0% false alarms at 95% detection ratio for this algorithm, whereas the California algorithm produced 0.63% false alarms at a 90% detection ratio (Adeli & Karim, 2000; Karim & Adeli, 2002a).

3.4.15 Adaptive conjugate gradient Neural Network-Wavelet algorithm

Another algorithm developed based on the DWT (Adeli & Samant, 2000; Samant & Adeli, 2000; Samant & Adeli, 2001) used an Adaptive Conjugate Gradient Neural Network

(ACGNN) and a Linear Discriminant Analysis (LDA). The DWT and LDA operations were used to filter and preprocess the data, and the ACGNN was used as the state classifier (i.e., incident or non-incident). High incident detection rates of 97.8% and low false alarm rates of around 1% were obtained based on simulated data.

3.4.16 Wavelet Energy with Radial Basis Function Neural Network algorithm

An algorithm using Wavelet Energy representation of traffic patterns was proposed (Karim & Adeli, 2002b, 2003) as an enhancement (in terms of the detection time) over the Fuzzy Wavelet RBFNN Incident Detection model proposed earlier by the same authors (Karim & Adeli, 2002a). The algorithm is based on an advanced energy representation of the time series pattern developed using Wavelet Theory. The desirable features of the traffic pattern are enhanced, and at the same time, a denoising of the traffic pattern is achieved by performing a DWT operation to break the input signal into several time-frequency components. This enables the extraction of features desirable for signal identification and recognition. A RBFNN is then used to classify the pattern as an incident-induced or a non-incident-induced traffic pattern. A sixteen data-point series of the occupancy data and a similar set with flow data are used to provide the input signal. Each signal is normalized to remove the effects of magnitude, followed by padding at both ends to extend the series size to 32 data-points. A two stage low pass filter (Daubechies filter) is applied. Next, the sequence is enhanced with the squared scaling coefficients – a measure of energy in the Wavelet domain which is subsequently extracted. The extracted four element sequences of the occupancy and flow data are then concatenated to form the input vector of the RBFNN with eight input vectors, twelve hidden nodes with Gaussian transfer functions, and one output node with a linear transfer function. If the output is greater than a pre-selected threshold (e.g., 0.2), then an incident is indicated. The algorithm was tested extensively with simulated data and, to a limited extent, with real data. The simulated data gave a 0% false alarm rate, and the real data performed well with false alarms rates going from a minimum of 0.13 % to a maximum of 1.04%.

3.4.17 Discrete Wavelet Transform algorithm

Another incident detection scheme based on the DWT technique involves a different approach to the problem using the same tool. Unlike the previous algorithms (Adeli & Karim, 2000; Adeli & Samant, 2000; Ghosh-Dastidar & Adeli, 2003; Karim & Adeli, 2002a, 2002b, 2003; Samant & Adeli, 2000, 2001), which use the DWT mostly as a tool for de-noising the dataset, this approach implies the direct use of the extracted features in the detection of changes in traffic flow. The difference of occupancies between two stations is used as the input signal. A search for large absolute values in the finest scale level (third stage) of the DWT of the signal comprises the first check. A subsequent check of the direction of change using the scale coefficients of the DWT is used to confirm the incident. This algorithm was compared with the MLF Neural Network algorithm, PNN algorithm, FRBFNN algorithm, Low Pass Filtering algorithm, and the California Algorithms (Teng & Qi, 2003b).

3.4.18 CUSUM-based algorithm

A detection delay-based optimization problem formulation approach to incident detection was proposed, along with a simplified procedure for its implementation. The algorithms

developed are based on the Cumulative Sum of Deviations of Subgroups statistic (the CUSUM statistic). Three algorithms, DCUSUM2, CUSUM1, and CUSUM2, involving different assumptions and different treatments of the problem, were developed in the process. The DCUSUM uses differences of occupancy in its analysis. CUSUM1 assumes that the correlation between individual observations (of occupancy) is zero, while CUSUM2 does not make such an assumption. A substantial change in the difference between the cumulative sum of the log-likelihood ratio for the existing time period and the minimum cumulative sum up to the existing time period is used to indicate a change in state of the process, and thereby, to indicate incident conditions. The DCUSUM algorithm was found to perform the best. A comparison with the Low Pass Filtering algorithm, the MLF algorithm, and California Algorithm #7 showed that the DCUSUM algorithm outperformed all of them (Teng & Qi, 2003a).

3.4.19 Support Vector Machine

An algorithm using the Support Vector Machine (SVM) pattern classifier was proposed by Chen, Kwon, Rice, Skabardonis, and Varaiya (2003). The SVM pattern classifier sorts out an input vector into one of two classes with a decision boundary developed based on the concept of structural risk minimization of classification error, using statistical learning theory. Three different SVM models were implemented with distinct embedded Kernel functions. A linear function, a polynomial function, and a radial basis function were the three Kernel functions used for this purpose. Comparative results of these three implementations, along with comparisons with the MLF algorithm and the PNN algorithm, were presented as applied to arterial data and freeway data. SVMs were shown to produce lower misclassification rates, higher detection ratios, lower false alarm rates, and in some cases, shorter detection times compared to the other algorithms (Yuan & Cheu, 2003).

4. Non-recurring congestion in hurricane evacuation preparedness

As it was previously explained, early detection and assessment of instances of non-recurring congestion 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 an area that is frequently evacuated due to recurring hurricane events. The Alabama's coastline is one of such areas.

Both the Atlantic and Gulf coasts of the United States are periodically subjected to severe tropical storms and hurricanes. Such storms are becoming more violent and destructive. The normal response to these occurrences is to evacuate inland from the coast. Normal traffic flows turn into congestion, frustration and gridlock. Such congestion and gridlock occur as the magnitude of traffic overwhelms the available road capacity, which is further impaired by instances of non-recurring congestion. The resulting stalled traffic reduces the number of vehicles that can leave an area subject to evacuation.

This was the situation in September of 1998 with Hurricane Floyd, when extensive unexpected traffic delays occurred along most inland evacuation routes. Subsequently, the United States Federal Emergency Management Administration conducted regional meetings to identify approaches for better traffic planning, management, and coordination. A variety of simulation tools were applied to project traffic flows during extreme events requiring

evacuation. For example, Pal et al. (2005) applied the Oak Ridge Evacuation Modeling System (OREMS) to evaluate traffic conditions resulting from evacuation from Baldwin and Mobile counties in Alabama.

As an initial step in this research, a comprehensive literature search was conducted. The purpose of this literature search was to identify and understand current theory regarding incident detection. The literature reviewed is identified in Section 3 of this paper, and provides a vast array of potential algorithmic models for use as the basis of non-recurrent traffic incident detection. As noted in Table 2, the corresponding detection and false alarm rates vary considerably, as reported in the literature (Fernandes, 2009).

Algorithms	Detection Rate	False Alarm Rate	Average Detection Time
Basic California Algorithm	82 %	1.73 %	0.85 min.
California Algorithm #7	67 %	0.134 %	2.91 min.
California Algorithm # 8	68 %	0.177 %	3.04 min.
Standard Normal Deviate	92 %	1.3 %	1.1 min.
Bayesian Algorithm	100 %	0 %	3.9 min.
Time-Series ARIMA	100 %	1.5 %	0.4 min.
Exponential Smoothing	92 %	1.87 %	0.7 min.
Low-Pass Filter	80 %	0.3 %	4.0 min.
Modified McMaster	68 %	0.0018 %	2.2 min.
Multi-layer Feedback Forward	89 %	0.01 %	0.96 min.
Probabilistic Neural Network	89 %	0.012 %	0.9 min.

Table 2. Comparison of Incident Detection Algorithms

Efforts were conducted to carry out a comprehensive review of the majority of these traffic incident algorithms identified, and determine a subset of the most effective for this problem domain. The authors have shown that the previously listed incident detection algorithms, in particular the California and Exponential Smoothing algorithms, can be successfully applied to assess and characterize instances of non-recurring congestions in highly transited urban areas (Fonseca, *at el.*, 2009).

As the progression of traffic incidents are quantified, and even predicted, the overall roadway capacity of the affected areas can be greatly increased by strategically choosing traffic evacuation measures oriented to the avoidance of travel routes that have been identified, through the detection algorithms, to have a high incidence of non-recurring congestion. Effective traffic management policies, as the ones suggested by the authors to

improve the overall evacuation process of the Alabama Gulf region during a hurricane situation (Moynihan, *at el.*, 2008) can then be devised by traffic officials around the negative impact that non-recurring congestion has on massive evacuation events.

5. Conclusion

In this paper, the authors have shown the importance of studying the negative effects of non-recurring congestion on massive evacuation events, as in the case of a hurricane evacuation. Non-recurring congestion can be detected by indentifying the presence of traffic incidents along the roadways of a transit network. Several incident detection algorithms have been successfully developed and implemented, throughout the years, to help traffic officials to assess and predict the occurrence of non-recurring congestion. These detection algorithms represent a formidable tool in the devising of effective planning strategies for massive hurricane-related evacuation events.

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This book represents recent research on tropical cyclones and their impact, and a wide range of topics are covered. An updated global climatology is presented, including the global occurrence of tropical cyclones and the terrestrial factors that may contribute to the variability and long-term trends in their occurrence. Research also examines long term trends in tropical cyclone occurrences and intensity as related to solar activity, while other research discusses the impact climate change may have on these storms. The dynamics and structure of tropical cyclones are studied, with traditional diagnostics employed to examine these as well as more modern approaches in examining their thermodynamics. The book aptly demonstrates how new research into short-range forecasting of tropical cyclone tracks and intensities using satellite information has led to significant improvements. In looking at societal and ecological risks, and damage assessment, authors investigate the use of technology for anticipating, and later evaluating, the amount of damage that is done to human society, watersheds, and forests by land-falling storms. The economic and ecological vulnerability of coastal regions are also studied and are supported by case studies which examine the potential hazards related to the evacuation of populated areas, including medical facilities. These studies provide decision makers with a potential basis for developing improved evacuation techniques.

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