Customisation of Automatic Incident Detection Algorithms for Signalised Urban Arterials

by

Bidisha Ghosh & Damien P. Smith

Civil, Structural and Environmental engineering Department
Trinity College, Dublin
Ireland

ABSTRACT

Non-recurrent congestion or incidents are detrimental to the operability and efficiency of busy urban transport networks. There exists multiple Automatic Incident Detection Algorithms (AIDA) to remotely detect the occurrence of an incident in highway or freeway scenarios, however very little research has been performed to automatically detect incidents in signalised urban arterials. This limited research attention has mostly been focussed on developing new urban arterial specific algorithms rather than identifying alternative methods to synthesize existing freeway based algorithms to urban conditions. The main hindrance to such synthesis is that the traffic patterns on the signalised urban arterials are significantly different from the same on highways/freeways due to the presence of traffic intersections. This paper introduces a new strategy of customising the existing AIDAs (freeway based or otherwise) to significantly improve their adaptability to signalised urban arterial transport networks. The new strategy focuses on preprocessing the traffic information before being used as input to a freeway/highway based AIDA to lessen the effect of traffic signals and to imitate the input patterns in highway/freeway based incident conditions. The effectiveness of this new strategy has been established with the help of four existing AIDAs. The proposed strategy is a simple solution to implement existing algorithms to signalised urban networks without any further instrumentation or operational cost.

1. Introduction

Travel-time delays, reduction in arterial capacity and air-pollution are some of the main detrimental effects of non-recurrent congestion or incidents on busy urban street networks. The implementation of efficient incident management systems in an urban transport network ensures early detection of operational problems like non-recurrent congestion and minimization of the associated detrimental effects. Practical and reliable Automatic Incident Detection Algorithms (AIDA) are essential to reduce and localize the effect of incidents.

Over the last few decades, multiple AIDAs have been developed and incorporated as part of the Incident Management Systems (IMS). Comparative algorithms, statistical algorithms, traffic theory based algorithms, time series algorithms, artificial intelligence algorithms, wavelet algorithms are the main categories of AIDA (Teng and Qi, 2003). Comparative algorithms compare traffic parameters against a certain threshold value or against one another. Popular comparative algorithms are California algorithm (Payne and Tignor, 1978), low-pass filtering algorithm (Chassiakos and Stephanedes, 1993) etc. Statistical algorithms such as standard normal deviate (Dudek et al., 1974) and Bayesian (Levin et al., 1978) algorithm use standard statistical techniques to identify abnormal behaviour in tracking variables. McMaster algorithm (Persaud et al., 1990) which depends on catastrophe theory is the most popular traffic theory based algorithm. Time series algorithms employ time-series analysis to predict the traffic parameters. Moving average (MA) algorithm (Whitson et al., 1969), double exponential MA algorithm (Cook and Cleveland, 1974) and autoregressive integrated MA algorithm (Ahmed, and Cook, 1982) are examples of time-series algorithms. In more recent years Artificial Intelligence (AI) based incident detection algorithms have been developed to tackle the problem of incident detection. The most well-known AI based algorithms are based on Artificial Neural Networks (ANN) (Cheu et al., 1991; Ritchie and Cheu, 1993; Cheu and Ritchie, 1995; Stephanedes and Liu, 1995; Dia and Rose, 1997; Abdulhai and Ritchie, 1999a; Abdulhai and Ritchie, 1999b; Jin et al., 2002; Srinivasan et al. 2008), fuzzy logic (Chang and Wang, 1994; Lin and Chang, 1998) and support vector machine (SVM) algorithms (Yuan and Cheu, 2003).

However, the majority of the research attention in incident detection algorithms has been generally focussed towards freeway incident management. But the applicability of the freeway based AIDA to an urban arterial situation is limited due to several reasons (Luk et al. 2001). Unlike freeway traffic, principle of conservation of flows does not always apply on urban arterials due to street parking and side streets etc. The traffic signals and intersections on arterials can also interrupt steady flows and can create incident like traffic patterns. As traffic volume increases on urban transportation networks, detecting incidents on urban arterials become more important mostly for traffic management purposes more than safety (Culip & Hall, 1997; Mak and Fan, 2006). Bell and Thancanamootoo (1988) were the first to develop an algorithm specific for arterial networks. The algorithm along with some other early AIDAs (Stephanedes and Vassilakis 1994; Culip & Hall, 1997) used raw traffic data to detect incidents on urban arterials. Time-series techniques (Bretherton and Bowen, 1991), image processing technologies (Hoose et al. 1992), discriminant techniques (Sethi et al, 1995), discriminant techniques combined with Kalman filtering (Chen and Chang, 1993) and Kalman filtering (Lee & Taylor, 1999) were developed to tackle the problem of incident detection on arterials. Data fusion techniques (Ivan et al. 1998 and Dia and Thomas 2011) used a fusion of data from separate sources: inductive loop detectors and travel time data collected by probe vehicles to detect incidents on urban arterials. Some more recent artificial intelligence based algorithms which were adopted for urban arterials are support vector machine (SVM) algorithms applied by (Yuan and Cheu, 2003), Bayesian network based algorithms (Zhang and Taylor, 2004, 2005, 2006) and a fuzzy-based system applied by Hawas (2007).

The focus of the research on detecting incidents on urban roads has mostly been on developing new urban arterial specific AIDA rather than identifying methods to improve transferability of the existing algorithms. This paper introduces a new strategy to implement the existing freeway AIDAs (freeway based or otherwise) to signalised urban arterials rather than developing new arterial specific algorithms. The research in the field of incident detection on freeways is much more improved and extensive compared to the same for urban arterials. The proposed strategy in this paper would provide an important tool in applying that knowledge to urban conditions. This approach would allow an ordinary AIDA to adapt to an urban arterial situation, and making it an effective urban arterial AIDA which can be easily incorporated into Incident Management System (IMS). Four existing AIDA algorithms were used to demonstrate the effectiveness of this new scheme; three algorithms based on Artificial Neural Networks (ANN) and a Support Vector Machine (SVM) based algorithm. ANN algorithms have proven to be one of the most effective methods of incident detection. Hence, a Multi-Layer Feed-forward (MLF) neural network, a Probabilistic Neural Network (PNN) and a Fuzzy-wavelet Radial Basis Function Neural Network (FWRBFNN) algorithms were chosen for this paper. SVM algorithms have only been used in incident detection in more recent years. However SVM algorithms have shown encouraging results in this area. Thus a SVM based AIDA was included in this paper (Yuan and Cheu, 2003).

Until now, all of these AIDAs have been evaluated utilising traffic information recorded/simulated at roadway sections distant from signalised traffic intersections and the effect of traffic signals on input patterns were not accounted for in the modelling. Hence, the most of these existing AIDAs cannot be implemented in urban transport networks where detectors are generally placed near the intersections and almost always a set of traffic signals or priority junctions are situated between any upstream-downstream detector pairs. To address this issue, this paper introduces a new approach in which the recorded traffic information from loop-detectors are preprocessed to reduce the effects of traffic signals before being used as input to AIDAs. Also, information from a different set of detector locations than the traditional approach is used to maximise the available information to the algorithms. This detector arrangement is similar to what exists in most real-world urban traffic management systems and includes information from all upstream approaches contributing to the downstream flow regarding a signal cycle. The proposed strategy proves effective in detecting incidents and can be considered as an excellent and cost-effective approach to implement existing AIDAs to signalised urban arterial networks.

2. Methodology

In this paper a new customisation scheme is proposed for existing AIDAs to improve their implementability to signalised urban transport networks. The effectiveness of the proposed scheme is tested by comparing the performances of four existing AIDAs when used in conjunction with the proposed scheme.

2.1 Customisation of Automatic Incident Detection Algorithms (CAIDA) Scheme

As discussed previously, the existing AIDAs are mainly used in detecting incidents in freeway/motorway/highway scenarios. In these scenarios, typically the detectors are placed approximately 30m to 120m from any signalised traffic intersection to ensure that the recorded traffic speed, volume or occupancy data are not influenced by the stop-and-go dynamics created by the presence of traffic signals at junctions. However, in urban transport networks due to shorter link lengths and high concentration of signalised traffic intersections, it is not possible to achieve similar detector arrangements. Also, in an urban transport network the traffic intersections are the most likely locations where incidents such as vehicle crashes and breakdowns can occur due to the presence of higher number of conflict zones and the stopping and starting of vehicles. For implementation of existing AIDAs in signalised urban transport networks to detect incidents on or near signalised traffic intersections, it is important to adapt/adjust/customise the existing highway based detection algorithms to identify and then to lessen the effects of traffic signals on measured traffic variables. To that effect, an innovative customisation scheme is proposed in the paper to alter the time domain response of upstream and downstream traffic variables which are the main elements of input information to an AIDA. This scheme thus preprocesses the input vectors to the algorithms, without altering the main structure of existing AIDAs.

Due to the presence of signalised intersections within the detection zone, the upstream and downstream traffic data inputted to the existing incident detection algorithms have different time-frequency content than the typical freeway/highway based inputs. Moreover, these inputs may not always provide an accurate description of the traffic conditions within the detection zone with regard to the occurrence of incidents. The urban traffic patterns are dominated by the presence of traffic signals, i.e. high occupancy and low volumes during red time and lower occupancy and higher volumes during green times. Similar changes in traffic occupancy and volume occurs due to the occurrence of incidents as well. Hence, observations recorded during red time can easily be misclassified as incidents. Also these input patterns, if used as the part of training dataset can lead to erroneous calibration of AIDAs which may lead to incidents going undetected due to their similarity with the traffic patterns observed during the red time. The key to improve the performance of any AIDA in a signalised urban setup is to reduce the effect of traffic signals on the input patterns. This can be achieved by altering the time and/or frequency content of the recorded upstream and downstream traffic information.

In this study this alteration has been achieved by scaling the upstream traffic occupancy and the traffic volume information using the following equations,

$$OCC_i^N = OCC_i \left(\frac{g_i}{C}\right)^2 \left(1 - \frac{(t_i - g_i)}{C}\right)^2 \tag{1}$$

$$\left.\begin{aligned} VOL_i > 0, \qquad & VOL_i^N = VOL_i \left(\frac{g_i}{C}\right)^2 \left(1 + \frac{(t_i - g_i)}{C}\right)^2 \\ VOL_i = 0, \qquad & VOL_i^N = a \left(\frac{g_i}{C}\right)^2 \left(1 + \frac{(t_i - g_i)}{C}\right)^2 \end{aligned}\right\} \text{ where, } 1 > a > 0 \tag{2}$$

$$\begin{cases} g_i = t_i & \text{when } t_i \le g_i \\ g_i = C & \text{when } t_i > g_i \end{cases} \tag{3}$$

where, OCC^N is the scaled upstream occupancy, OCC is the measured upstream occupancy, VOL^N is the scaled upstream volume, VOL is the measured upstream volume, g is the elapsed green time in seconds and t is the time in seconds from the initiation of a signal cycle at the i^{th} time interval. It is assumed that the cycle (of length *C*) starts with green indication and hence $g_i = t_i$ until the end of the green interval. Hence, the multiplicative factor operates in a binary regime.

In equation 1, during green indication the measured occupancy values are multiplied with a function similar to the probability of green indication; during red indication the measured occupancy values are multiplied with a function similar to the probability of non-occurrence of red indication. This preprocessing ensures the occupancy values are not unusually high during the red times as it is important to differentiate between the patterns during red time and during the occurrence of an incident. Fundamentally, the operation corresponds to a scaling of the traffic occupancy during red indication, which is proportional to a heuristic function of the percentage of elapsed red time during a cycle. For an incident, it is assumed that the time window of high occupancy would be significantly longer than the red time of the cycle. Consequently this scaling would negate the effects of traffic signals by decaying the high occupancy values during red time and by increasing the comparatively lower occupancy values during green time, allowing for a less variant transition between discontinuous zones of red and green indications but preserving the high occupancy due to incidents of time periods longer than cycle length.

In equation 2, during green indication the measured traffic flow values are multiplied with a function similar to the probability of green indication (but different from equation 1); during red indication the measured flow values are multiplied with a function similar to the probability of occurrence of red indication. Here, the multiplicative factor also operates in a binary regime and alters the pattern of measured traffic volume. In equation 2, a is an arbitrary constant used to remove zero values. This ensures that, during the red time the traffic volumes are artificially scaled up to differentiate between the patterns during red time and during the occurrence of an incident. Similar to equation 1, this operation corresponds to a scaling of the traffic volume during red indication, which is proportional to a heuristic function of the percentage of elapsed red time during a cycle. For an incident, it is assumed that the time window of low volume would be significantly longer than the red time of the cycle. Consequently this scaling would negate the effects of traffic signals by increasing the low flow values during red time and by decaying the saturation flow values during green time, allowing for a less variant transition between discontinuous zones of red and green indications as before.

To demonstrate the theoretical effect of this scaling, a brief illustrative example is presented here. During red time, the queue formation at an intersection ideally follows a Poisson process. It can be assumed that the occupancy during this time changes exponentially and during green time the dissipation of queue leading to decrease in occupancy follows a similar exponential pattern. Following this assumption, the occupancy values, OCC during four consecutive cycles are plotted in Fig. 1. On performing the scaling operation as described in equations 1 & 2 for 50:50 signal cycle, the OCC^N is plotted as a dashed line in Fig. 1. This shows limited effects of traffic light and tends to show a far more uniform occupancy level than measured originally.

However, this scheme poses some limitations and this scaling does not necessarily mean that the assumption of negating the effects of traffic signals holds true for all urban traffic flow conditions. In fact, for low flow volumes or for incidents lasting less than or equal to the cycle length cannot be detected. This is an inextricable condition and no AIDA will be able to separate the effects incident from the masking effects of the traffic signals. Such non-detection may not be important from a traffic management point of view but may be crucial for incident management purposes (such as notifying emergency services) and should be considered as a limitation of all AIDAs.

Before providing as an input to an AIDA, the measured volume and occupancy from all the upstream detectors are pre-processed following the equations 1 and 2. However, the downstream traffic volume and occupancy values are used as input without any alteration. The CAIDA scheme restricts the amount of useful traffic information from any approach when it receives red indication. Hence, it is advisable to include traffic information from other approaches in an intersection which are active (receives green indication) during the red time in the approach considered. This concept will be explored with further details in section 3.1.2.

2.2 The Four Chosen Automatic Incident Detection Algorithms

Three ANN based AIDAs and a SVM based AIDA have been identified as the chosen algorithms whose performance have been studied when used in conjunction with CAIDA scheme.

Artificial Neural Networks are mathematical models that have been developed from research into the workings of the human brain. Simple processing units or elements (PE) called “neurons” are arranged to form different layers and these layers are then interconnected to form the network structure. The network structure usually consists of an input layer, one or more hidden layers and an output layer. These layers are inter-connected, but the PEs are not usually interconnected within the same layer. The PEs receive input data at the input layer which is then weighted in relation the importance of the input and processed using pre-chosen function. The output of the processing is obtained at the output layer. The ANN algorithms are trained using a dataset consisting of input data and known output data.

The three ANN based AIDAs used in this study are described in the subsections 2.2.a to 2.2.c. In subsection 2.2.d the SVM based AIDA technique is described.

a. Multi-Layer Feed-Forward Neural Network

One of the most common ANN algorithm used for automatic incident detection is the Multi-Layer Feed-forward (MLF) networks used by Cheu et al. (1991), Ritchie and Cheu (1993) and Cheu and Ritchie (1995). An MLF network can consists of multiple layers however a three layered structure is usually most common, consisting of an input layer, a single hidden layer and an output layer. There is unidirectional connection between the neurons of adjacent layers. The input layer contains the same number of neurons (*n*) as there are inputs from the loop-detectors. The neurons in the hidden layer ($v_{1,} v_{2,\ldots\ldots} v_m$) receive the input vector from the input layer which is then multiplied by the weight vector (ω_{ji}) of the corresponding neuron. A bias vector (θ_j) is then added to the weighted input and the resulting vector is summated. This sum is passed through a sigmoid transfer function giving an output from the neuron in the hidden layer. For the j^{th} neuron in the hidden layer, the output will be

$$v_j = \frac{1}{1+e^{-h_j}}; \quad h_j = \sum_{i=1}^{n} \omega_{ji} x_i + \theta_j \tag{4}$$

The outputs of each neuron from the hidden layer are passed to the output layer in the same fashion as between the input layer and the hidden layer. The output from the output layer neuron is a binary value between 0 and 1 indicating non-occurrence and occurrence of incident respectively. The values of the weights and bias within the neural network are estimated by training the network using Levenberg-Marquardt method on a dataset containing traffic condition from both incident and incident-free scenarios.

b. The Probabilistic Neural Network

The other most well-known ANN algorithm used for detecting traffic incidents is the Probabilistic Neural Network (PNN) structures (Abdulhai and Ritchie, 1999a; Abdulhai and Ritchie, 1999b; Jin et al., 2002). The PNN structure consists of four layers, the input layer, pattern layer, summation layer, and the output layer. The sole purpose of the input layer is to pass the inputs from the loop-detectors to the neurons in the pattern layer ($v_{1,} v_{2,\ldots\ldots} v_m$). When an input vector $(\mathbf{X})$ is passed through the pattern layer, at each pattern neuron (say, the j^{th} neuron), the output is computed as,

$$v_j = e^{-h_j^2}; \quad h_j = \frac{\left\| \mathbf{X} - \boldsymbol{\omega}_j \right\|}{\sqrt{2}\sigma} \tag{5}$$

The output is a Gaussian function of the Euclidean distance between the input vector and the weight vector associated with each pattern neuron ($\boldsymbol{\omega}_j$) and a bias σ. The bias, σ, is used as a smoothing parameter, the larger the value of σ the more the function will behave like a nearest neighbour classifier and only input vectors very similar to a particular training vector will give a significant output value. The further σ is lowered the more other training vectors will begin to influence the networks decision. The value assigned to σ has a huge influence over the performance of the network algorithm.

The size of the pattern layer depends on the size of the training dataset used. There is the same number of neurons in the pattern layer as there are training patterns in the dataset. The neurons in the pattern layer are divided into two classes, one class representing incident and the other non-incident traffic scenarios. The summation layer consists of only two neurons, one for each class. At the summation layer, the output from each summation neuron is computed as a scaled sum of the outputs from the associated pattern neurons. In the last layer, the single output neuron selects the class which has the highest output value from the summation layer and generates that class number as the output. In many cases, weights are applied to the outputs from the summation layer in an attempt to minimise the Expected Cost of Misclassification (ECM). These weights can be assigned in accordance with Bayes' Decision rule.

In freeway based applications, PNN based AIDA has shown a lower detection rate, higher false alarm rate than MLF, but has a better adaptation potential (William and Guin, 2007).

c. Fuzzy-Wavelet Radial Basis Function Neural Network

The relatively new FWRBFNN based freeway incident detection algorithm was developed by Adeli & Karim (2000). The algorithm uses Radial Basis Function Neural Network (RBFNN) architecture in conjunction with wavelet-based denoising and fuzzy-logic based classification techniques. In the FWRBFNN algorithm, the input consists of the normalized upstream volume and occupancy over the last N time intervals, N=16 in this study. The normalized volume and occupancy datasets are then decomposed into low and high resolution components using Discrete Wavelet Transform (DWT). The high resolution component, represented as the wavelet coefficients (*d*) are then filtered using a soft-thresholding nonlinearity equation,

$$\eta(d) = \operatorname{sgn}(d)(|d| - t)^{+} \tag{6}$$

where t is the threshold, $(.)^{+}$ is equal to (.) if (.) is positive and equal to zero if negative. Sgn(*d*) will return the sign of the coefficient *d*. The volume and occupancy signals are then reconstructed by using inverse DWT. In the next step, the de-noised signal is clustered into 4 cluster centres using the fuzzy-C-mean (FCM) algorithm. This preprocessed data is then used as input into the RBFNN which classifies the input signal as either incident or non-incident condition.

The RBFNN architecture consists of three layers, input layer, hidden layer and output layer. The number of neurons in the input layer is same as the number of inputs (8 in this study) and the number of neurons in the hidden layer is equal to the number of clusters (say, m=4 as mentioned previously). The connection between the input layer and the hidden layer is very similar to the PNN structure as described in the previous section. The output from the hidden neurons is a function of the Euclidean distance between the input vector and the cluster centres (μ_j). The output from the only neuron at the output layer is computed as,

$$y = \sum_{j=1}^{m} \omega_j v_j ; \quad v_j = \exp\left(-\left\| \mathbf{X} - \boldsymbol{\mu}_j \right\|^2 \Big/ 2\sigma^2 \right) \tag{7}$$

If the output value, y , is greater than a pre-selected threshold (0.3 in this study) then the input pattern is classified as an incident, while any value less than the threshold is classified as non-incident. This algorithm was evaluated on real and simulated incident data from freeways and showed a high detection rate and low false alarm rate. The FWRBFNN algorithm performed superior to the California #8 algorithm (Karim and Adeli, 2002).

[To maintain comparability with other three algorithms, in this paper, the FWRBFNN algorithm uses upstream volume and occupancy as input instead of the upstream occupancy and speed as used by Adeli and Karim (2000).]

d. Support Vector Machine (SVM)

Support vector machine (SVM) is an efficient supervised learning algorithm which was developed by Vapnik (1995) for solving pattern recognition problems and was first applied in the field of automatic traffic incident detection by Yuan and Cheu (2003).

A SVM maps the data into a higher dimensional input space and then classifies the data by constructing an optimal separating decision boundary in this space. The construction of this decision boundary or optimal separating hyperplane (OSH) is optimised following the principle of structural risk minimisation. Given a set of training data $\{x_i, y_i\}_{i=1}^{N}$, $\mathbf{x} \in \mathbb{R}^n$ $\mathbf{y} \in \{+ \quad 1,\}$ where $\mathbf{x}$ is a input pattern vector and y_i is a binary output variable which indicates the class to which x_i belongs. In case of an AIDA, +1 denotes the incident class and -1 denotes the non-incident class. This classification is achieved using a SVM classifier which takes the following general form:

$$f(\mathbf{x}) = \operatorname{sgn}\left[\sum_{\forall i, \alpha_i > 0} \alpha_i y_i \psi\left(\mathbf{x}.\mathbf{x}_i\right) + b \right] \tag{8}$$

where, α_i is a positive real constant and *b* is a real constant. The input space formed using traffic parameter observations is a non-linearly separable space. Hence, a non-linear SVM classifier is required to be used to separate the incident and non-incident observations in this space. For non-linearly separable data, an OSH can be constructed using kernel functions which help to map the input vectors in a higher dimensional space where the OSH can be used for classifying the data. The kernel function used in this paper is radial basis function,

$$\psi(\mathbf{x}.\mathbf{x}_i) = \exp\left(-\left\| \mathbf{x} - \mathbf{x}_i \right\|^2 \Big/ 2\sigma^2 \right) \tag{9}$$

Further details on the construction of OSH can be found in Vapnik (1995). To prevent overtraining of the SVM a cost parameter χ is used. This parameter controls whether the SVM will have strict boundaries or to accept some misclassification in the training. This is called a soft margin SVM. The higher the cost of a misclassification the more rigid the margin and thus less error in the training is accepted.

The SVM based AIDA is developed for both freeway/expressway and urban arterials (Yuan and Cheu 2003). However, the algorithm is not tested for near intersection detection scenarios. This algorithm is included in this study to emphasise the potential of the CAIDA scheme in improving the performance of such urban arterial based AIDA algorithms when applied to detect incidents near traffic intersections.

2.3 Performance Evaluation Measures

In this paper, the performance of an AIDA is evaluated using the following five criteria:

Detection Rate (DR)

DR is the percentage of successfully detected incidents against the total number of incidents that have occurred. DR is an indicator of the accuracy of an AIDA.

$$\text{DR} = \frac{\text{Number of Incidents Detected}}{\text{Total Number of recorded Incidents}} \text{X}100\% \tag{10}$$

False Alarm Rate (FAR)

A false detection or a false alarm is defined as the detection of an incident during an incident free interval. FAR is the ratio of total number of false detections to the total number of possible incident intervals expressed as a percentage. Usefulness or implementability of an AIDA can be governed by the low FAR values.

$$\text{FAR} = \frac{\text{Total Number of False Incidents}}{\text{Total Number of Applications of the Algorithm}} \text{X}100\% \tag{11}$$

Mean Time to Detect (MTTD)

MTTD is the average time taken from the initiation of an incident to the detection of the incident by the algorithm.

$$\text{MTTD} = \frac{1}{n}\sum_{i=1}^{n}(t_{id} - t_{i0}) \tag{12}$$

where, *n* is the total number of incidents detected, t_{i0} initiation time of incident *i* and t_{id} is the time of detection of the incident *i*.

Misclassification Rate (MCR)

MCR is the ratio of the total number of incorrect decisions to the total number of decisions made by the algorithm. The incorrect decisions include both non-detections of incidents as well as the false alarms.

$$\text{MCR}=\frac{\text{Total Number of Misclassified Applications of Algorithm}}{\text{Total Number of Applications of the Algorithm}} \text{X}100\% \tag{13}$$

Receiver Operating Characteristics (ROC) Plots

A high DR and a minimal FAR are the desired performance values for an AIDA. However there is a trade-off relationship between the FAR and DR. It is possible to reduce the FAR by decreasing the sensitivity of an algorithm, however that in turn will result in poor DR as many incidents will remain undetected due to the low sensitivity of the algorithm. On the other hand, the attempts to increase the DR will also increase the FAR decreasing the implementability or specificity of the algorithm. Hence, another criterion called the Receiver Operating Characteristic (ROC) space is utilised. The ROC space allows for a convenient means for characterising and comparing the performance of algorithms in non-destructive structural damage detection, image processing (Pakrashi et al., 2011) etc. and can be used as a useful evaluator for comparing the performance of AIDAs. This is typically a plot of DR versus MCR, which are alternatively known as Probability of Detection (PoD) and Probability of False Alarm (PFA) respectively in the field of probability space and decision theory. Each (MCR,DR) pair form a coordinate in the ROC space. In this paper, ROC has been used for graphical comparison.

However, ROC space can be further utilized for quantitatively comparing the algorithm performances using the α-δ method (Schoefs et al., 2012). This method relies on calculating the angle, α, and the Euclidean distance, δ, between the best performance point, and the considered point to give a measure of the performance of the considered performance point. The best performance point is defined as an ideal AIDA with 100% detection and 0% misclassification rates and represented in the ROC space with coordinates (0,1). The angle, α, denotes the shape of the ROC curve which is important to analyze the reliability of the algorithms and is not the focus of this study. Hence, only the delta, δ, parameter is discussed. A low value for δ is indicative of strong performance accuracy.

3. Evaluation of Case Study

In this section, the usefulness of the CAIDA scheme when used in conjunction with existing AIDAs has been evaluated through a case study of detecting arterial incidents on signalised urban transport network. Due to lack of availability of real incident data on urban arterials, a simulated dataset has been used in this paper. The details of the simulation are discussed in the next sub-section. The implementation of the CAIDA scheme is described in the two subsequent sub-sections.

3.1 Incident Data

3.1.1 Incident Simulation

The incident dataset used in this study is simulated using the microsimulation software package VISSIM. A section of the urban arterial transport network at the city-centre of Dublin has been modelled using VISSIM (Fig. 2 & Fig. 3) and the incidents were simulated in this congested network during evening peak hours. The main thoroughfare in the network stretches roughly about 700m from Inns Quay to Ormond Quay Lower and contains two signalised intersections. It is a three-lane road with one-way traffic flow. Each of the intersecting roads also contains three lanes with the exception of Chancery Place which is a two-lane road. All of the minor roads are one-way with the traffic moving northbound in Rossa Bridge and Chancery Place and the traffic on Capel Street and Grattan Bridge moves southbound. Capel Street and Rossa Bridge each have a lane for traffic turning onto Ormond Quay. The traffic signal cycles at each of the modelled junctions consist of two phases. At the first junction the first phase is for the main traffic flow on Inns Quay moving straight to Ormond Quay Upper. The second phase is to accommodate straight and right turning vehicles from Rossa Bridge merging into Ormond Quay Upper. The first phase of the second junction is for traffic going from Ormond Quay Upper to Ormond Quay Lower and also accommodates for traffic turning right onto Gratten Bridge. The second phase is for traffic from Capel Street moving straight onto Gratten Bridge and also left turning traffic to Ormond Quay Lower.

The model uses real-time traffic information as obtained as a part of the SCATS (Sydney Coordinated Adaptive Traffic System) system which is the existing Urban Traffic Control System (UTCS) in Dublin. As a part of the SCATS system, inductive loop-detectors are placed near the stop-line at signalised road intersections and collect traffic volume and occupancy data at regular intervals. Real-time traffic volume and occupancy information collected over a period of 25 days have been used as travel demand input to the VISSIM model. In Fig. 4, a distribution of the observed and modelled traffic demand levels are plotted. The modelling and simulation have been performed at high and medium levels of traffic demand. This was done to eliminate any possibilities of masking of incident patterns due to the presence of traffic signals at intersections (as discussed in detail in section 2.1).

Incidents were simulated at three different locations as shown in Fig. 2. At each location, incidents were simulated at four different times within the evening peak hours. Each of these incidents was simulated as blocking two lanes out of three for durations of either five or ten minutes. Each of the incident simulations was run on three different traffic signal cycle times of 60, 90 and 120 seconds to estimate the effect of signal time on arterial incident detection. 1800 incidents were simulated in total. During each simulation, at four detector locations (As shown in Fig. 3) within the modelled urban transport network, traffic occupancy and volume data were recorded at 30 second intervals. Out of these four detector positions, detectors at position 1, 2 and 4 are real inductive loop-detector locations as exists within the chosen network in Dublin. The other detector at position 3 was simulated to facilitate the evaluation of the proposed CAIDA scheme. Traffic volume and occupancy data are the only traffic variables that are recorded using the real loop-detectors in Dublin and hence, these were the only two variables that were used for evaluation purposes in this study.

3.1.2 The Detector Arrangement Schemes

To illustrate the potential of the proposed CAIDA scheme in improving the performance of existing AIDAs while applied to an urban transport network, each of the four chosen algorithms was tested under three different detector arrangement scenarios as described below:

Scenario 1: Freeway like Scenario

The first scenario is the traditional dual-station setup for detecting incidents; the upstream and downstream detector stations are positioned on the same link. Upstream and downstream traffic volume, occupancy and speed information are collected by the detectors and algorithms are applied to detect the existence of any incidents in between the two detector stations. This detector arrangement is most commonly used in freeway scenarios and typically traffic signals or traffic junctions do not exist in between the two detector stations. In this paper, this detector arrangement is referred to as ‘Freeway-like Scenario’.

In the Fig. 3, the detector locations 2 & 3 can be considered as the upstream and the downstream stations for a freeway like scenario. The simulated values of upstream and downstream traffic volume and occupancy from these detector stations were used as input parameters to the four chosen AIDAs. The MLF, PNN and SVM each used the same 16 inputs which consist of upstream volume and occupancy for the last five time intervals and downstream volume and occupancy for the last three time intervals. The FWRBFNN used only upstream volume and occupancy over the last 16 time intervals.

Scenario 2: Original Urban Network Scenario

This scenario replicates a traffic situation where traffic signals or traffic intersections are present in between the upstream and downstream detector stations. This scenario is representative of an urban transport network situation where traffic intersections are ubiquitous and cannot be avoided in a dual station setup in an incident management system. In this scenario the detectors are assumed to be located just upstream to traffic intersections similar to the real-life SCATS traffic control system. The dual station set-up constitutes of two detectors placed in two consecutive links; the upstream detector station located upstream of the connecting traffic intersection between the two links and the downstream detector station is located upstream to the next downstream intersection at the downstream end of the second link. The measured traffic information (such as, volume, occupancy and speed) obtained from the detectors are expected to be greatly affected by the presence of traffic signals.

In the Fig. 2, the detector locations 1 & 2 can be considered as the upstream and the downstream stations for an original urban network scenario. The simulated values of upstream and downstream traffic volume and occupancy from these detector stations were used as input parameters to the four chosen AIDAs. The inputs to MLF, PNN, SVM and FWRBFNN are the same as those in freeway like scenario.

Scenario 3: CAIDA Urban Network Scenario

The detector arrangement in third scenario is conceptually a departure from the traditional single-station or dual-station setup. The detector arrangement in this scenario is very similar to the scenario 2, 'Original Urban Network Scenario', with the addition of extra upstream detectors on all upstream turning approaches which contribute to the flow recorded on the downstream detector. This detector arrangement ensures that traffic information is received from all the upstream approaches that contribute to the link.

In the Fig. 2, the detector locations 1 & 3 can be considered as the upstream stations and the detector location 2 can be considered as the downstream stations for the CAIDA urban network scenario. This arrangement allows for a more constant flow of relative information to be inputted into the incident detection algorithms. The simulated values of upstream and downstream traffic volume and occupancy from these detector stations were used as input parameters to the four chosen AIDAs. In this scheme, the number of inputs to the detection algorithms increases, however the traffic parameters used for the inputs remain the same. The MLF, PNN and SVM each had 26 inputs consisting of the upstream volume and occupancy of both the upstream detector stations for the last five time intervals and downstream volume and occupancy for the last three time intervals. The number of inputs to the FWRBFNN doubled due to the inclusion of extra detector station taking the upstream volume and occupancy from each of the two upstream detector stations over the last 16 time intervals.

3.2 Application of CAIDA

The CAIDA scheme along with the four chosen AIDAs were developed and evaluated in MATLAB environment. In the following the subsections the steps of development and application of the same are described in detail.

3.2.1 Preprocessing using CAIDA

In this paper, the customisation of the existing AIDAs for application to signalized urban networks was achieved by preprocessing the inputs from all upstream detector stations as described in the aforementioned CAIDA scheme. In Fig. 5 & Fig. 6, the original and preprocessed simulated traffic occupancy and volume data from detector location 1 have been plotted to show the effectiveness of preprocessing in amplifying the effect of an incident on the signal pattern. In Fig. 5, the original occupancy time-series dataset (Fig. 5(A)) and the preprocessed occupancy time-series signal (Fig. 5(B)) are plotted along with the Continuous Wavelet Transform (CWT) plots of the two signals (Mallat, 1989). A 'Coiflet 4' wavelet has been used up to scale 128 to achieve the plots. In the CWT plots the scale is indicative of frequencies in the data, where time signifies the temporal nature and comparing Fig. 5(C) and Fig. 5(D) it is apparent that there is a shift in the temporal signature between the two datasets. It is important to note that the frequency contents of the two datasets are largely similar.

In Fig. 6, the original traffic volume time-series dataset (Fig. 6(A)) and the preprocessed volume time-series signal (Fig. 6(B)) are plotted along with the Autocorrelation Function (ACF) plots of the two signals (Mallat, 1989). ACF values up to lag 100 are plotted. The plots show both the datasets are non-stationary and by comparing Fig. 6(C) and Fig. 6(D) it is apparent that the time-domain responses of the two datasets are significantly different. For illustrative purposes, the CWT plots for the occupancy values and ACF plots for volume counts are shown in Fig. 5 and Fig. 6 respectively. Overall, from the preprocessed traffic time-series plots shown in both figures, it is observed that the volume and occupancy counts during the occurrence of an incident are significantly different from values under non-incident conditions. However, in the original traffic information dataset (Fig. 5(A) and Fig. 6(A)), the incident situations are not so distinctively different from red-light situations. It is also important to note that the preprocessing is more effective in altering the occupancy time-series compared to traffic volume.

3.2.2 Application of AIDAs

The preprocessed traffic volume and occupancy datasets were then used as inputs to each of the four chosen AIDAs to subsequently detect incidents on the modelled urban arterial section. The traffic dataset was divided into a training dataset and an evaluation dataset. Each algorithm was trained on a training dataset consisting of preprocessed simulation data of 15 days and then its performance was evaluated on the remaining 720 incidents. For the training and evaluation purposes, the inputs used to the MLF, PNN, SVM and FWRBFNN were as described in section 3.1.2. Each of the chosen AIDAs were trained separately for each different scenario.

A ROC based optimization framework was chosen to arrive at the best model for each different AIDA for each scenario. In the MLF network, the best network architecture was achieved by adjusting the number of hidden neurons to arrive at the minimum δ value. The MLF network consisted of 25 hidden neurons and one output neuron for all three scenarios. In PNN and FWRBFNN networks, the smoothing parameter σ was adjusted to arrive at the optimised network structure. In PNN networks the value of σ was taken as 1.2, 1.4 and 0.7 in the order of the scenarios. In FWRBFNN networks, the value of σ was taken as 3 for scenarios 1 & 3 and 2 for scenario 2. For PNN and FWRBFNN networks the training dataset consisted of 1080 incident patterns and 7008 non-incident patterns. In SVM classification the penalty parameter of the error term, χ, and the kernel parameter which defines the decision boundary were optimised for the minimum δ value. The RBF kernel parameter was taken as 0.4 and χ was varied between 0.2 to 0.5 for the different scenarios. For all AIDAs the parameter values and network structure were specific to the traffic volume and sites chosen and for future implementation in other locations with different traffic demands training, calibration and validation of the AIDAs are essential.

3.3 Comparison of Performances

The CAIDA scheme was evaluated based on the performance of the four chosen detection algorithms when applied under the three aforementioned detector arrangement scenarios.

The traffic signal cycle length is one of the most important factors that influence the values of the traffic parameters (such as, traffic volume or density) near a signalised road intersection in an urban transport network and in turn this factor interfere considerably with the useful implementation of AIDA in urban networks. The algorithms were evaluated using simulated accident information from the modelled network operating under three different traffic cycle times, 60, 90 and 120 seconds (Table 1). As observed from the results, all four algorithms perform very well with high DR, low FAR and MCR values under scenario 1(freeway like scenario) as the existence of the traffic signals do not largely influence the consistency of the traffic information available from the detectors in this case. However, the upstream detector used in this scenario is generally not available in real-life networks. The real-life representation of possible detector arrangements in urban transport networks are seen in scenario 2 and 3. In scenario 2 the algorithms perform the worst and in scenario 3 the performances have been observed to improve significantly across the board with the application of CAIDA scheme. A particularly important observation is that in majority of the cases in scenario 2, the algorithms produce high false alarm rates indicating the fundamental problem behind the implementation of existing freeway based algorithms to urban scenarios. The FAR values reduce with the application of the proposed CAIDA scheme. Performance indexes improve with the increase in cycle length. It is also observed that the MLF and SVM algorithms perform better than the rest.

The incidents were simulated in three positions on the Ormond Quay Upper. The incident positions are shown in Fig. 2. The performances of the algorithms vary with the change of incident positions and it has been tabulated in Table 2. The proximity of an incident location to an upstream or downstream intersection affects the detectability of the incident. In this study, it has been observed that all four algorithms are least effective for incident position 1 which is furthest from the upstream intersection. The effect of the existence of an intersection most significantly affects the performances of AIDAs in scenario 2. The performance of the algorithms in scenario 1 and 3 are largely comparable. There is little difference between the performance of the algorithms on positions 2 and 3 when considering the DR and FAR. However, the MTTD is smaller for position 3 as the effect of queue built up is realised the quickest at the upstream detector for this incident position. Similar to the case of varied cycle lengths, the MLF and SVM algorithms perform better than the rest.

Intuitively, the longer the incident duration, the more is the severity and easier it is to detect the incident. This pattern is noticed for all four algorithms under all three detector arrangements in this paper (Table 3). Incidents were simulated over two time intervals, 5 min and 10 min. The detection rates are much higher for 10min long incidents, however the FAR values are quite similar for both cases. The MTTD values are lower for 5min long incidents. The performance of MLF and SVM algorithms are much more consistent under variable durations of incidents. Overall, the algorithms perform the worst under scenario 2 (Table 4). The FAR, MCR and MTTD all increase significantly for this scenario, proving that the existing algorithms are unsuitable when applied in signalised traffic networks. Scenario 3 provides a significant improvement from this and even with the presence of intersections the algorithms provide high DR, low FAR, MCR and MTTD values.

The ROC curves for all four algorithms under all three scenarios were plotted and the δ values were calculated. As an illustrative example, the ROC plots for PNN algorithm has been shown in Fig. 7. This graphically establishes the superiority of algorithm performance under scenario 3 in comparison to scenario 2. According to the δ values as shown in Table 4, SVM algorithm provides the best performance under scenario 1 and 3. The performances of all four algorithms improve under the proposed CAIDA scheme.

4. Discussion

In this section a brief discussion on the usefulness and applicability of the proposed CAIDA strategy is provided. The proposed CAIDA scheme is the first attempt to adapt existing incident detection algorithms for implementation in signalised urban transport networks. This CAIDA scheme is a simple way of dealing with the presence of signalized intersections within the detection zone without developing new algorithms to deal with the issue. The main difficulty with implementation of existing incident detection algorithms in signalised urban transport networks is that the traffic dynamics during the red time is very similar to the traffic dynamics during incident conditions. Consequently the application of existing highway based AIDAs often result in high FAR, MCR and MTTD values indicating inferior performance as seen in scenario 2. The proposed CAIDA strategy tackles this key problem and improves the performance of the algorithms resulting in reasonably good DR, low FAR, MCR and MTTD values as seen in scenario 3. The main focus of CAIDA scheme is pre-processing the traffic variable observations to imitate the traffic pattern in highways as closely as possible before they are used as input to the existing highway based detection algorithms.

Also, CAIDA scheme utilises information from all upstream detectors unlike most existing detection algorithms. In well-known and popular UTCS (such as, SCATS in Dublin) majority of the detectors are located upstream and near to the traffic intersections. The existence of detectors both at the upstream and downstream end of a road as seen in scenario 1 is quite rare in real-life urban transport networks. Hence, implementation of existing AIDAs utilising the detector arrangement as for scenario 1 will involve installation of new detectors at the end of roadway sections. However, the performance of the algorithms matches well between scenario 1 and scenario 3. The CAIDA scheme can be considered as a simple and effective way for implementing existing incident detection algorithms to signalised urban transport networks without incurring additional infrastructural or operational costs.

The study in this paper utilises four algorithms to show the effectiveness of the proposed CAIDA strategy. Though the research is not meant to compare the performance of the algorithms, it is possible to draw conclusions on their applicability in urban scenarios. All of the four chosen algorithms, MLF, PNN, FWRBFNN and SVM have been evaluated for their effectiveness under freeway conditions. The SVM based AIDA has been previously tested for urban arterials (Yuan and Cheu 2003). This is the first instance of testing these algorithms on signalised urban transport networks including traffic intersections. The PNN and FWRBFNN based algorithms in general provided less consistent and accurate results compared to the other two algorithms. This is largely due to the fact that the training of these two algorithms were computationally expensive and due to resource constraint the sizes of the training datasets used for these algorithms were smaller than the other two algorithms. FWRBFNN was developed for freeways and hence the DWT part of the algorithm utilises a denoising technique to remove the high frequency parts of the traffic time-series datasets. In an urban signalised network, the frequency content of the traffic time-series datasets are considerably different from those of the freeways and removing the high frequency parts which are generated due to the presence of traffic signals on city streets may negatively impact on the detectibility of an incident. In addition, in this paper a different set of input variables were used for FWRBFNN than the original ones and that might have also contributed to the poor performance of the algorithm. The two remaining MLF and SVM based algorithms perform very well in detecting incidents under varied conditions. SVM provides the best performance, however at the training phase this algorithm can be much more computationally intensive and expensive than MLF based algorithm. Considering precision, ease of implementation and computational cost, the MLF based AIDA in conjunction with CAIDA scheme appears to be the most suitable choice for implementation in urban signalised transport networks.

The AIDAs were trained using incidents simulated from a VISSIM model of the network developed using real traffic demand levels. The algorithms were also evaluated using simulated incidents. For real life implementation of these algorithms along with CAIDA strategy, similar steps can be followed, as it is quite implausible to have a comprehensive set of real incident data (Yuan & Cheu, 2003) in a signalised urban transport network. However, in the case of real world implementation attention must be paid in calibration and validation of the developed microsimulation model. Under these circumstances, all four AIDAs are adaptable and transferable to any transport network. The only limitation of these algorithms in conjunction with CAIDA scheme lies in the fact that for low flow volumes or for incidents lasting only a couple of minutes, the proposed scheme will not be effective due to the masking effects of traffic signals on incident patterns.

5. Conclusion

A new strategy, CAIDA scheme, has been proposed in this paper to improve the adaptability of existing AIDAs in signalised urban transport networks. The proposed CAIDA scheme is an excellent solution to implement existing algorithms to signalised urban networks without further instrumentation or operational cost. The effectiveness of this new strategy has been established with the help of four existing AIDAs. All of these four algorithms have been evaluated for their effectiveness under freeway like conditions (i.e. without involving signalised traffic intersections) and in actual urban traffic conditions with and without applying the proposed CAIDA strategy. The performances of these algorithms are expectedly worst under actual urban conditions. However, the performances improve and compare very well with the same in freeway like conditions when used in conjunction with CAIDA scheme. This establishes that the CAIDA scheme is a simple solution in improving the adaptability and portability of existing freeway based incident detection algorithms for implementation in signalised urban networks.

The CAIDA scheme is essentially a heuristic scheme for scaling the traffic volume and occupancy data to minimise the effect of traffic signals with the aim of improving incident detection on signalised urban arterials. Further studies of the fundamental diagram on urban arterials may help in developing more appropriate multiplicative functions which may help to completely eliminate the effect of traffic signals from traffic variables.

The CAIDA scheme effectively diminishes the need for implementation of expensive urban arterial based AIDAs for detecting incidents in signalised urban transport networks. The simplicity of this methodology makes it an extremely attractive solution for urban traffic management authorities. With the help of this simple customisation strategy existing incident management systems such as MIDAS (Motorway Incident Detection and Automatic Signalling) can now be tested for implementation in urban transport networks.

REFERENCES

Abdulhai, B. and Ritchie, S. G. (1999a). "Enhancing the Universality and Transferability of Freeway Incident Detection Using a Bayesian-Based Neural Network". *Transportation Research. Part C: Emerging Technologies*, Vol.7 No.5, pp.261-280.

Abdulhai, B. and Ritchie, S. G. (1999b). "Preprocessor Feature Extractor and Post Processor Probabilistic Output Interpreter for Improved Freeway Incident Detection". *Transportation Research Record*, No.1678, pp.277-286.

Adeli, H. and Karim, A. (2000). “Fuzzy-Wavelet RBFNN Model for Freeway Incident Detection”. *Journal of Transportation Engineering*, ASCE, Vol. 126, No.6, pp. 464-471.

Ahmed, S. A. and Cook, A. R. (1982). "Application of Time-Series Analysis Techniques to Freeway Incident Detection". *Transportation Research Record*, No.841, pp. 19-21.

Bell, M.G.H., Thancanamootoo, B. (1988). “Automatic incident detection within urban traffic control systems”. *Proceedings of the Roads and Traffic 2000 Conference*, Berlin, Vol. 4, No. 2.

Bretherton, R.D., Bowen, G.T. (1991). “Incident detection and traffic monitoring in urban areas”. *Proceedings of DRIVE Conference on Advanced Telematics in Road Transport.*

Chang, E. P. and Wang, S. H. (1994). "Improved Freeway Incident Detection Using Fuzzy Set Theory". *Transportation Research Record*, No.1453, pp. 75-82.

Chassiakos, A. P. and Stephanedes, Y. J. (1993). "Smoothing Algorithms for Incident Detection". *Transportation Research Record*, No.1394, 8-16.

Chen, C. and Chang, G. (1993). “A dynamic real-time incident detection System for urban arterials - system architecture and preliminary results”. *Proceedings of the ASCE Third International Conference on Applications of Advanced Technologies in Transportation Engineering*, Seattle, Washington.

Cheu, R. L., Ritchie, S. G., Recker, W. W. and Bavarian, B. (1991). "Investigation of a Neural Network for Freeway Incident Detection". *UCI-ITS-WP*, Vol.91 No.6, 20.

Cheu, R. L. and Ritchie, S. G. (1995). "Automated Detection of Lane-Blocking Freeway Incidents Using Artificial Neural Networks". *Transportation Research. Part C: Emerging Technologies*, Vol.3 No.6, 371-388.

Cook, A. R. and Cleveland, D. E. (1974). "Detection of Freeway Capacity-Reducing Incidents by Traffic-Stream Measurements". *Transportation Research Record*, No.495, 1-11.

Cullip, M. and Hall, F. (1997). “Incident detection on an arterial roadway”. *Transportation Research Record,* No. 1603, pp. 112-118.

Dia, H. and Rose, G. (1997). "Development and Evaluation of Neural Network Freeway Incident Detection Models Using Field Data". *Transportation Research. Part C: Emerging Technologies*, Vol.5 No.5, 313-331.

Dia, H. and Tomas, K. (2011). “Development and evaluation of arterial incident detection models using fusion of simulated probe vehicle and loop detector data”. *Information Fusion*, Vol. 12, No. 1, pp. 20–27.

Dudek, C. L., Messer, C. J. and Nuckles, N. B. (1974). "Incident Detection on Urban Freeway". *Transportation Research Record*, No.495, pp. 12-24.

Hawas, Yaser E. (2007). “A fuzzy-based system for incident detection in urban street networks”. *Transportation Research Part C,* Vol. 15, pp. 69–95.

Hoose, N., Vicencio, M. A., and Zhang, X. (1992). “Incident detection in urban roads using computer image processing”. *Traffic Engineering and Control*, Vol. 33, pp. 236-244.

Ivan, J.N., Sethi, V., (1998). “Data fusion of fixed detection and probe vehicle data for incident detection”. *Computer-Aided Civil & Infrastructure Engineering*, Vol. 13 (5), pp. 329–337.

Jin, X., Cheu, R. L. and Srinivasan, D. (2002). "Development and Adaptation of Constructive Probabilistic Neural Network in Freeway Incident Detection". Transportation Research. Part C: Emerging Technologies, Vol.10 No.2, 121-147.

Karim, A. and Adeli, H. (2002). “Comparison of the Fuzzy–Wavelet RBFNN Freeway Incident Detection Model with the California Algorithm”. *Journal of Transportation Engineering*, ASCE, No. 1, 128, pp. 21-30.

Lee, J-T. and Taylor, W. C. (1999) “Application of a Dynamic Model for Arterial Street Incident Detection”, Intelligent Transportation Systems Journal, Vol. 5, No. 1, pp. 53-70.

Levin, M. and Krause, G. M. (1978). "Incident Detection: A Bayesian Approach". *Transportation Research Record*, No.682, pp. 52-58.

Lin, C. K. and Chang, G. L. (1998). "Development of a Fuzzy-Expert System for Incident Detection and Classification". *Mathematical and computer modelling*, Vol.27 No.9-11, pp. 9-25.

Luk, J. Y. K. and Chung, E. C. S. (2001). “Characterization of incidents on an urban arterial road”. *Journal of Advanced Transportation,* Vol. 35, No. 1,pp. 67–92.

Mak, C. L. and Fan, H. S. L. (2006) “Heavy Flow-Based Incident Detection Algorithm Using Information From Two Adjacent Detector Stations”, *Intelligent Transportation Systems Journal*, Vol. 10, No. 1, pp. 23-31.

Mallat, S. G. (1989). “A theory for multiresolution signal decomposition: the wavelet representation”. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 11, No. 7, pp. 674-693.

Pakrashi, V. Schoefs, F. Memet, J.B. O'Connor, A. (2010). “ROC Dependent Event Isolation Method for Image Processing Based Assessment of Corroded Harbour Structures”. *Structure and Infrastructure Engineering*, Vol. 6 (3), pp. 365-378.

Payne, H. J. and Tignor, S. C. (1978). "Freeway Incident-Detection Algorithms Based on Decision Trees with States". *Transportation Research Record*, No.682, 30-37.

Persaud, B. N., Hall, F. L. and Hall, L. M. (1990). "Congestion Identification Aspects of the Mcmaster Incident Detection Algorithm". *Transportation Research Record*, No.1287, 167-175.

Ritchie, S. G. and Cheu, R. L. (1993). "Simulation of Freeway Incident Detection Using Artificial Neural Networks". *Transportation Research. Part C: Emerging Technologies*, Vol.1 No.3, 203-217.

Schoefs F, Boéro J, Clément A, Capra B. (2012) “The α-δ method for modelling expert Judgment and combination of NDT tools in RBI context: application to Marine Structures, Structure and Infrastructure Engineering: Maintenance, Management, Life-Cycle Design and performance (NSIE)”. *Monitoring, Modeling and Assessment of Structural Deterioration in Marine Environments.* Vol. 8, pp. 531-43.

Sethi, V., Bhandari, F. S., Koppelman, Schoffer, J. L. (1995). “Arterial incident detection using fixed detector and probe vehicle data”. *Transportation Research. Part C: Emerging Technologies*, Vol.3 No.2, pp. 99-112.

Srinivasan, D. and Sharma, V., (2008). “A Reduced Multivariate Polynomial Based Neural Network Model Pattern Classifier for Freeway Incident Detection”. IJCNN 2007, pp. 2366-2372.

Stephanedes, Y. J., and Vassilakis, G. (1994) “Intersection incident detection for IVHS”. *Transportation Research Board, Proceedings 74th Annual Meeting,* Washington DC.

Stephanedes, Y. J. and Liu, X. (1995). "Artificial Neural Networks for Freeway Incident Detection". *Transportation Research Record*, No.1494, pp. 91-97.

Teng, H. and Y. Qi (2003) “Application of Wavelet Technique to Freeway Incident Detection”, *Transportation Research. Part C: Emerging Technologies,* Vol. 11, Issues 3-4, pp. *289-308.*

Vladimir N. Vapnik, *The Nature of Statistical Learning Theory*. Springer, 1995.

Whitson, R.H., Burr, J.H., Drew, D.R., McCasland, W.R. (1969). “Real-time evaluation of freeway quality of traffic service”. *Highway Research Record,* Vol. 289, 38–50.

William, B. M., Guin, A. (2007). “Traffic Management Center Use of Incident Detection Algorithms: Findings of a Nationwide Survey.” *IEEE Transactions on Intelligent Transportation Systems*. Short papers, vol. 8, no.2, pp. 351-358.

Yuan, F. and Cheu, R. L. (2003). “Incident detection using support vector machines.” *Transportation Research Part C: Emerging Technologies* , Vol.11, No.3, pp. 309–328.

Zhang, K. and Taylor, M. A. P. (2005). “Simulation of freeway incident detection using Bayesian networks.” *Proc IVRI’05: Intelligent Vehicles and Road Infrastructure Conference*. February, Melbourne. CD-ROM, paper no IVRI16. (Society of Automotive Engineers – Australasia: Melbourne).

Zhang, K. and Taylor, M. A. P. (2006). “Effective arterial road incident detection: A Bayesian network based algorithm.” *Transportation Research Part C*, Vol. 14, pp. 403–417

Zhang, K. and Taylor, M. A. P. (2004). "A New method for incident detection on urban arterial roads." *11th World Congress on ITS*, Nagoya, Japan.

List of Figures

List of Tables

Table 1: Performance Matrix under Variable Cycle Lengths

	DR (%)	FAR (%)	MCR (%)	MTTD (sec)	DR (%)	FAR (%)	MCR (%)	MTTD (sec)	DR (%)	FAR (%)	MCR (%)	MTTD (sec)
60 sec Cycle												
	Scenario1				Scenario2				Scenario3			
MLF	83.33	0.45	1.80	98.85	63.72	0.30	2.31	189.88	82.42	0.34	2.02	120.12
PNN	78.43	1.92	9.81	152.28	58.82	1.71	19.03	218.15	62.74	1.26	15.76	158.73
SVM	83.33	0.99	2.02	101.91	78.43	1.14	2.84	156.81	82.35	0.84	2.30	128.82
FWRBFNN	62.78	0.89	4.86	223.44	44.36	5.90	8.31	200.26	52.63	4.76	7.10	185.43
90 sec Cycle												
	Scenario1				Scenario2				Scenario3			
MLF	91.00	0.34	1.40	77.94	88.66	0.23	1.77	106.03	89.30	0.32	1.71	101.51
PNN	90.07	1.99	9.18	98.51	87.30	3.67	14.80	124.84	87.30	1.41	6.06	134.15
SVM	91.25	0.89	1.58	71.04	90.42	1.12	2.24	87.18	90.42	0.96	1.94	83.30
FWRBFNN	64.03	0.79	5.16	206.13	51.54	6.54	27.87	205.67	68.01	4.82	6.98	162.55
120 sec Cycle												
	Scenario1				Scenario2				Scenario3			
MLF	89.83	0.48	1.46	63.31	87.99	0.29	1.62	76.27	91.26	0.31	1.55	75.59
PNN	93.18	1.54	7.72	109.18	92.10	2.57	12.25	107.38	93.18	0.83	3.44	108.65
SVM	92.29	1.04	1.73	75.37	90.81	0.78	1.86	71.45	92.06	0.47	1.77	76.42
FWRBFNN	71.46	3.95	16.32	162.71	53.88	5.47	24.22	259.13	84.73	4.30	6.42	134.39

Table 2: Performance Matrix under Variable Incident Positions

	DR (%)	FAR (%)	MCR (%)	MTTD (sec)	DR (%)	FAR (%)	MCR (%)	MTTD (sec)	DR (%)	FAR (%)	MCR (%)	MTTD (sec)
Position 1												
	Scenario1				Scenario2				Scenario3			
MLF	62.85	0.61	2.13	61.52	54.45	0.34	2.37	118.60	62.32	0.35	2.20	102.12
PNN	72.75	2.05	9.41	113.88	62.44	2.70	15.91	157.21	68.27	1.86	7.93	133.01
SVM	63.23	1.17	2.31	56.68	62.19	1.09	2.87	107.97	64.13	1.04	2.62	102.65
FWRBFNN	54.03	1.47	3.60	187.07	38.97	4.78	18.97	193.25	54.60	3.93	6.16	181.60
Position 2												
	Scenario1				Scenario2				Scenario3			
MLF	100.00	0.39	1.40	93.78	92.00	0.27	1.81	128.87	98.92	0.28	1.59	100.55
PNN	93.68	1.68	8.83	129.56	92.87	3.69	15.03	137.20	94.74	2.20	9.84	138.28
SVM	100.00	0.79	1.60	86.08	99.00	0.86	1.99	106.59	99.29	0.27	1.39	92.34
FWRBFNN	71.50	0.69	4.34	170.53	48.81	4.94	18.92	250.82	67.65	3.68	5.91	163.82
Position 3												
	Scenario1				Scenario2				Scenario3			
MLF	100.00	0.31	1.16	83.71	95.45	0.28	1.69	120.37	99.29	0.27	1.39	92.34
PNN	94.64	1.74	8.60	124.24	95.60	3.88	15.59	131.53	96.30	1.51	6.40	127.41
SVM	100.00	0.88	1.41	93.60	96.50	0.88	1.96	100.12	97.05	0.89	1.77	93.53
FWRBFNN	68.04	2.39	4.33	105.85	43.48	4.55	18.40	239.98	62.50	3.56	5.82	160.74

Table 3: Performance Matrix under Variable Incident Duration Lengths

	DR (%)	FAR (%)	MCR (%)	MTTD (sec)	DR (%)	FAR (%)	MCR (%)	MTTD (sec)	DR (%)	FAR (%)	MCR (%)	MTTD (sec)
10 min												
	Scenario1				Scenario2				Scenario3			
MLF	89.30	0.40	1.92	84.83	86.03	0.27	2.45	136.45	89.57	0.28	2.23	98.33
PNN	94.12	1.79	8.93	137.96	94.12	3.84	15.88	145.14	94.34	2.04	8.99	139.85
SVM	88.02	0.86	2.03	87.76	86.06	0.53	2.50	123.91	88.16	0.97	2.45	97.99
FWRBFNN	78.18	2.35	4.84	151.91	57.17	4.71	19.20	292.25	77.82	3.69	6.64	208.66
5 min												
	Scenario1				Scenario2				Scenario3			
MLF	87.51	0.46	1.16	74.91	76.89	0.33	1.44	108.73	85.04	0.28	1.28	92.66
PNN	81.54	1.79	8.85	111.69	80.83	3.85	15.18	123.16	84.72	2.01	8.24	124.58
SVM	87.70	0.80	1.43	87.51	79.24	0.50	1.49	108.84	86.46	0.84	1.67	99.33
FWRBFNN	53.71	0.75	4.27	151.45	30.68	4.83	18.35	164.96	45.93	3.75	5.28	128.12

Table 4: Overall Performance Matrix

Overall															
	Scenario1					Scenario2					Scenario3				
	DR	**FAR**	**MCR**	**MTTD**	**δ**	**DR**	**FAR**	**MCR**	**MTTD**	**δ**	**DR**	**FAR**	**MCR**	**MTTD**	**δ**
MLF	88.35	0.43	1.54	80.04	0.10	81.46	0.30	1.95	122.59	0.17	87.57	0.30	1.71	98.09	0.09
PNN	87.55	1.82	8.93	122.99	0.15	87.84	3.85	15.51	136.03	0.24	88.82	2.96	13.16	134.67	0.14
SVM	88.46	0.94	1.75	79.56	0.08	86.55	0.94	2.26	104.70	0.12	87.31	0.90	2.06	98.61	0.08
FWRBFNN	63.40	0.84	5.01	214.79	0.35	43.92	4.77	18.77	228.61	0.57	61.88	3.72	5.96	168.39	0.34

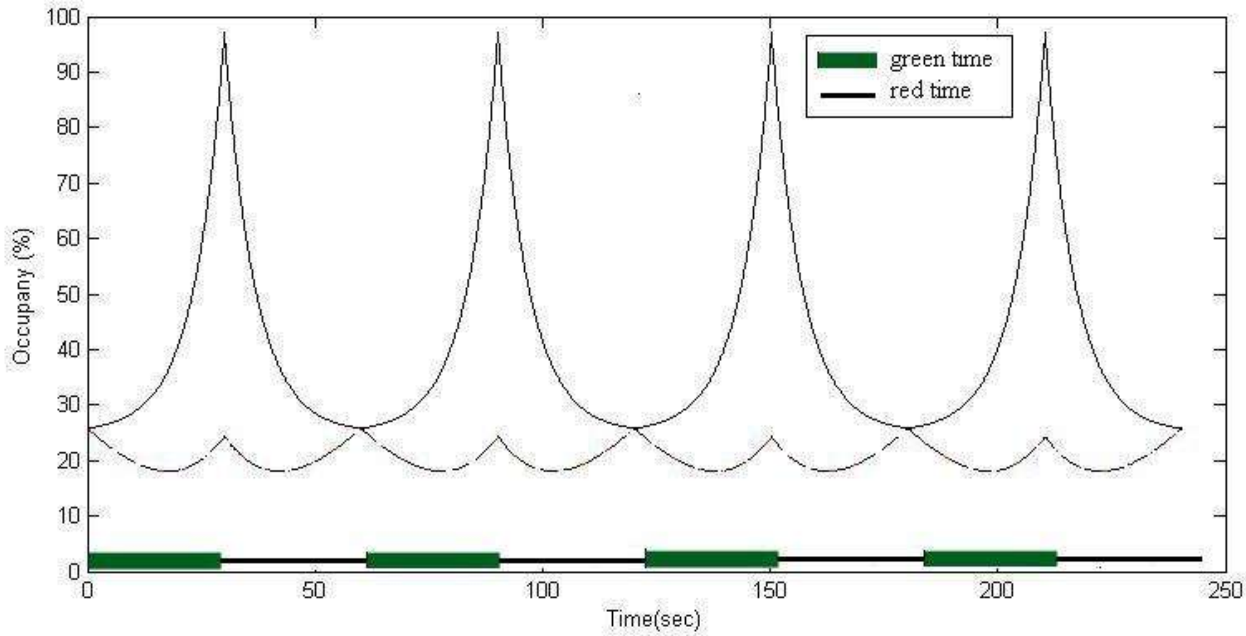

Figure 1: Measured and Scaled Occupancy using Proposed CAIDA Scheme

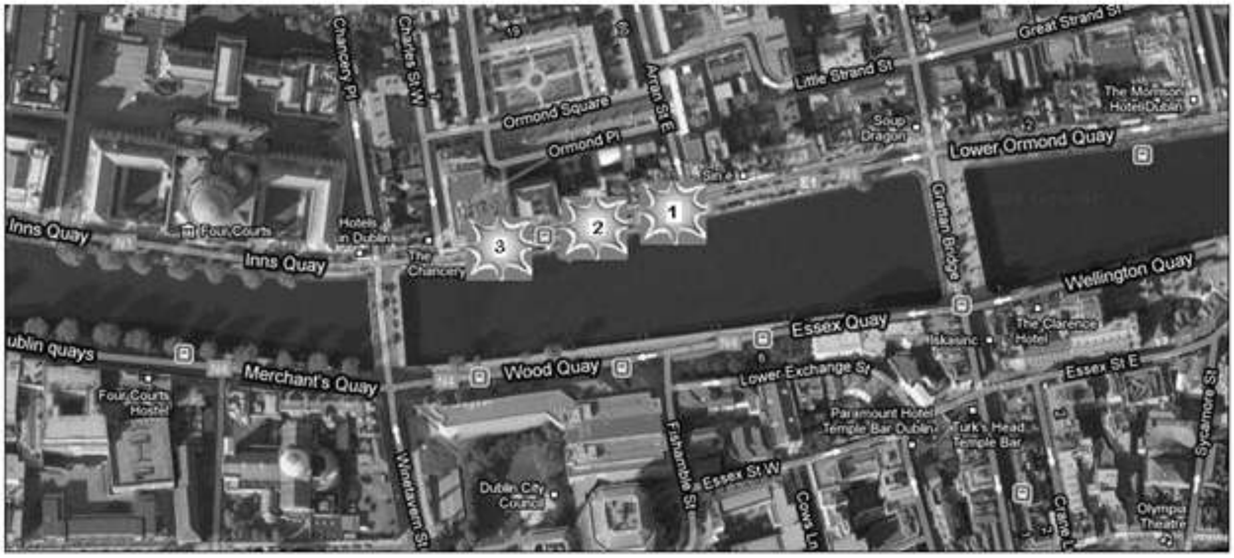

Figure 2: Chosen Urban Transport Network and Incident Positions

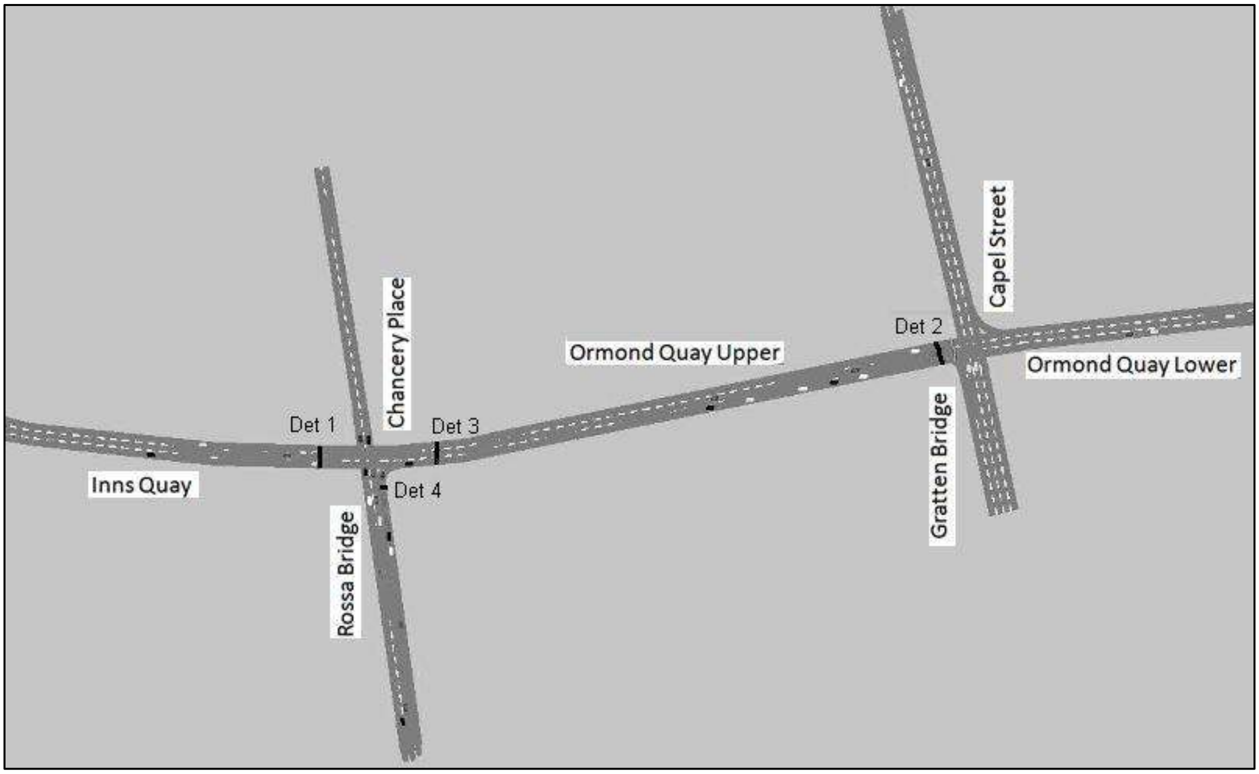

Figure 3: The Micro-simulation Network Representation

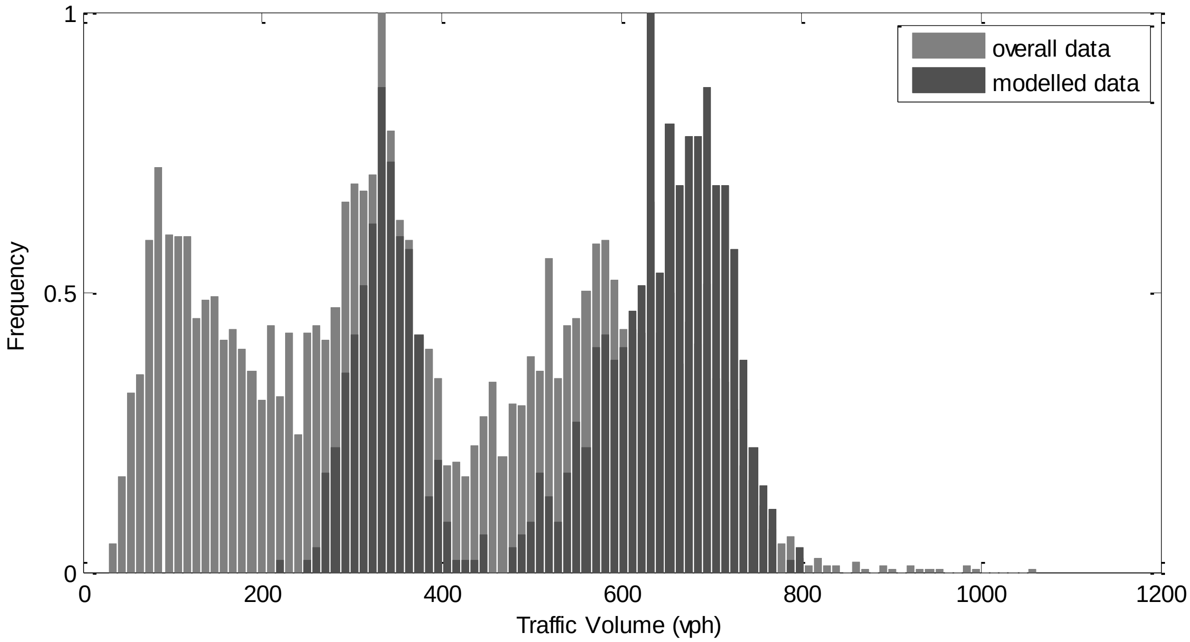

Figure 4: The Observed and Modeled Traffic Volume Distribution

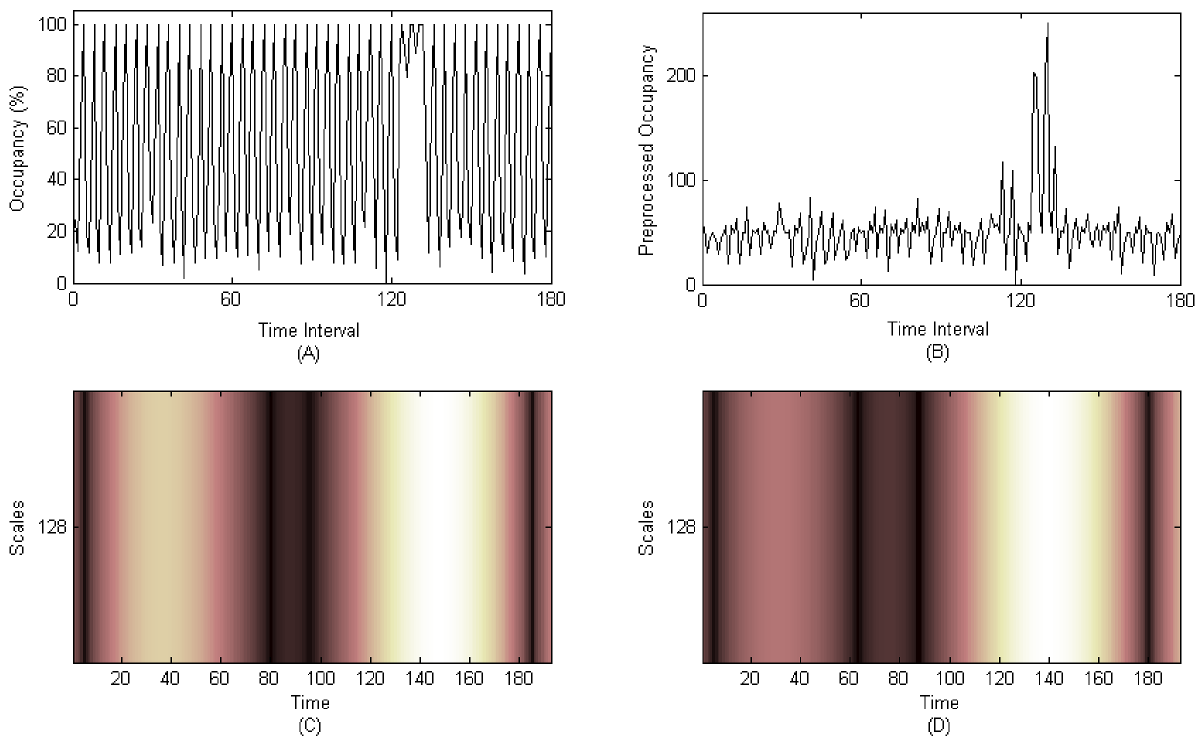

Figure 5: Original and Preprocessd Traffic Occupancy

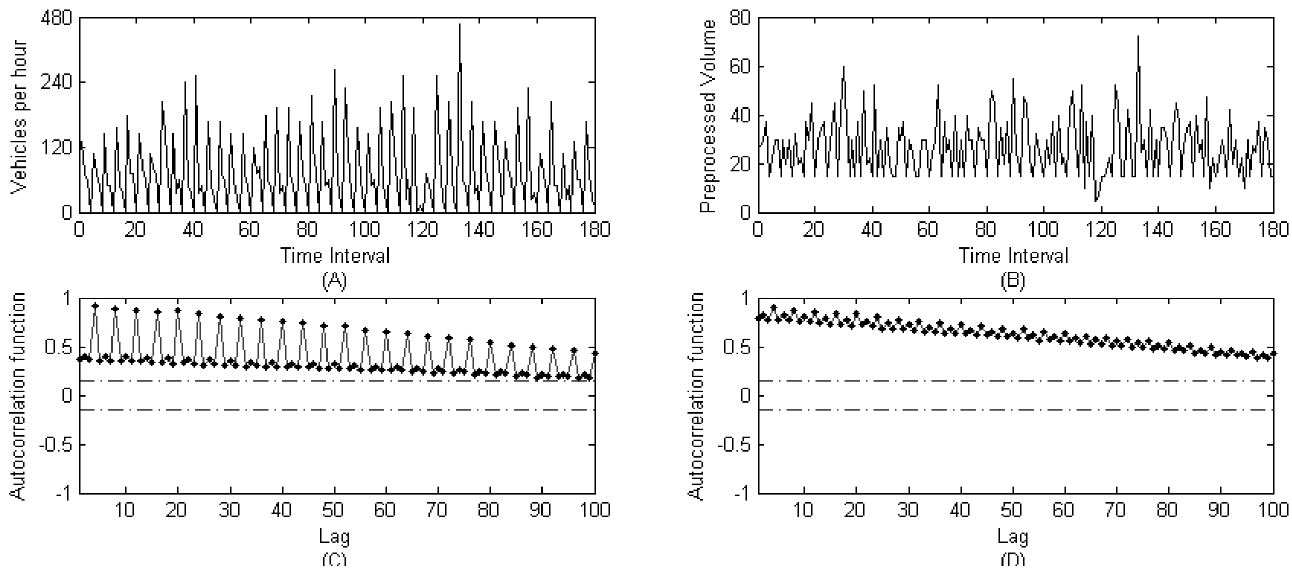

Figure 6: Original and Preprocessd Traffic Volume

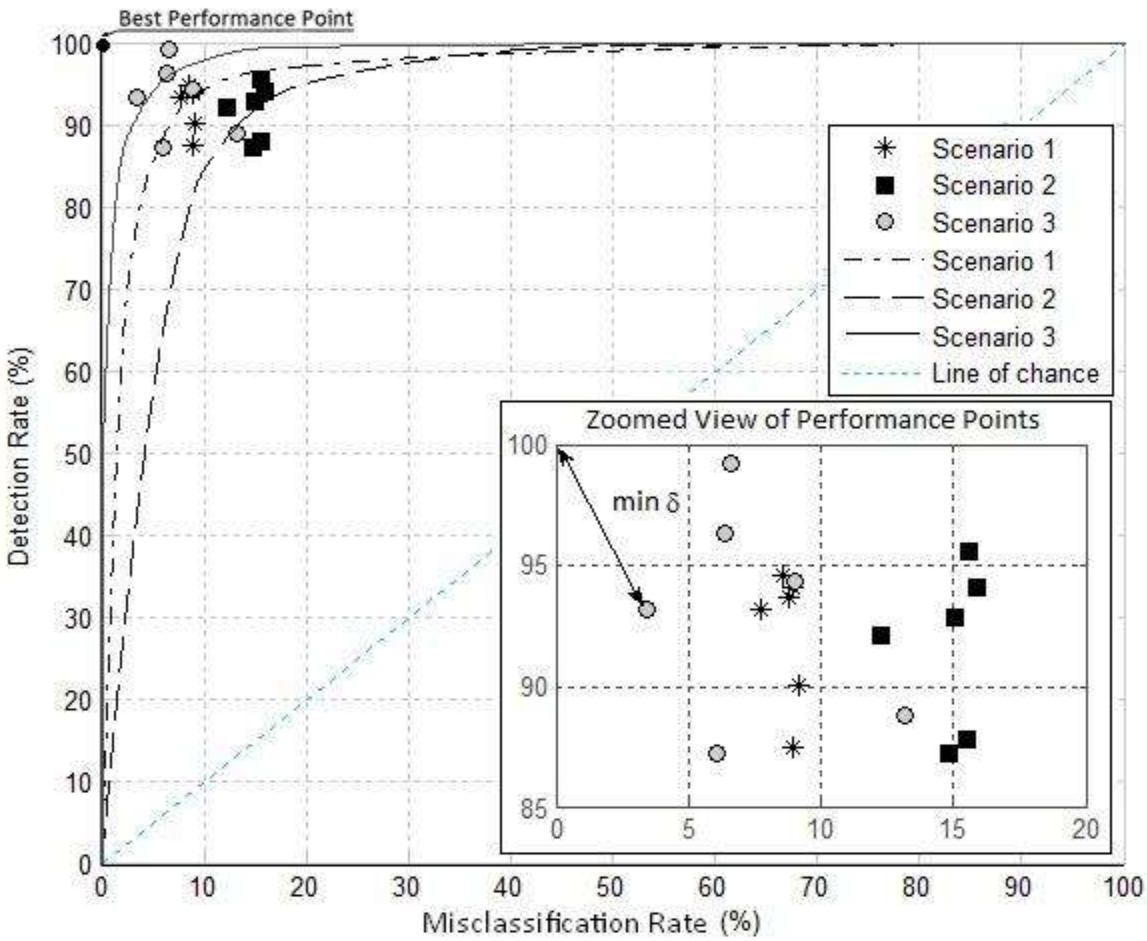

Figure 7: ROC Space for PNN