Comparative study of freeway incident detection algorithms using real-life incident data

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ABSTRACT

This paper compares the performance of three rule based algorithms and one artificial neural network (ANN) model. The selected algorithms are calibrated and evaluated using real-life incident data observed on Tokyo Metropolitan Expressway (MEX). The results show that the California algorithm has the highest detection rate and the MEX algorithm has the lowest false alarm rate. Relative to the California algorithm, the ANN model has lower detection rate and higher false alarm rate.

1. INTRODUCTION

Freeway incident management system often relies on incident detection algorithms to detect incident. Early detection of incident reduces the time to execute an incident management plan and as a result reduces the delay to traffic and increases safety. However, there is little comparative study on the performance of freeway incident detection algorithms by fully calibrating and evaluating algorithms using real life data. Hence it is not possible to compare the performance of individual algorithms.

The objective of this paper is to compare the performance of three rule based algorithms (California algorithm (Payne et al.1976), University of California, Berkeley (UCB) algorithm (Lin and Daganzo 1997) and Tokyo Metropolitan Expressways (MEX) algorithm (MEX et al. 1993)) and an artificial neural network (ANN) model (Ritchie and Cheu 1993; Dia et al. 1996) using real life incident data collected on the Tokyo Metropolitan Expressways. The selected algorithms and ANN model are calibrated and evaluated on separate field data.

2. AUTOMATIC INCIDENT DETECTION ALGORITHMS

Four incident detection algorithms were selected for this study and are briefly discussed.

California algorithm,

The California algorithms developed in the late 1960s for use in Los Angeles freeway surveillance control centre is perhaps the mostly widely known AID algorithm (West 1971; Payne et al 1976). Along with the McMaster algorithm (Hall et al. 1993)., they are often used as a standard for measuring the performance of other algorithms. There are more than 10 versions of the California algorithm and algorithm 8 is the version currently used in California. In addition to the variations to the classic California algorithm (algorithm 1 to 7), algorithm 8 has an additional element that detects compression wave at the downstream station. Only algorithm 8 is selected for this study.

University of California, Berkeley (UCB) algorithm

Recently developed at University of California, Berkeley (Lin and Daganzo 1997), this algorithm analyses the difference in upstream and downstream cumulative occupancies for significant disturbances. Cumulative sums allow the past observations to be automatically remembered and robust results to be obtained despite random fluctuations in data. Under normal traffic conditions the cumulative difference typically dwells around zero. Sustained deviations suggest the presence of an incident.

Tokyo Metropolitan Expressway (MEX) algorithm

In 1993 MEX commissioned a study to develop a rule based freeway incident detection algorithm. One of MEX specification for developing the freeway incident detection algorithm was to minimise false alarm rate. The objective was to develop an algorithm that will assist the operator at the traffic control centre detect incidents without increasing the operators workload due to false alarms. Everyday operators in the traffic control centre have to manage about 90 incidents (45 vehicles breaking down and 45 accidents) that occurs on MEX freeways. A relatively high false alarm rate would add a significant workload to the operators. MEX algorithm analysis compares the flow and speed between upstream and downstream detector stations and starting from the upstream detector station.

Artificial Neural Network (ANN) model

Neural networks are used to simulate the thought process of the human brain, and different paths can be taken to reach a final decision. A neural network consists of many simple processing elements (PEs) having densely parallel interconnections. A single PE can receive inputs, weighted by the strength of associated connection values, from many other PEs, and can rapidly communicate its outputs to many other PEs. The PE layers that receive input from external sources and the layer that communicates its output to external sources are known as the input and output layers respectively. Processing elements found in between the input and output layers are referred to as hidden layers. The hidden layer is invisible to the external sources and only interacts with the input and output layers of the network.

Automatic incident detection neural networks typically use a multi-layer, feed forward (MLF) structure. Inputs to the MLF include speed, flow and occupancies at both upstream and downstream detectors.

The network requires substantial training to establish appropriate weights on the PE links, but has the ability to learn from past trial-and-error processes.

3. DATA AND PERFORMANCE INDICATORS

3.1. Data

The incident data used for this study was collected on the Tokyo Metropolitan Expressway. A total of 170 incidents data set were collected in March, May and October of 1995. However only the May and October data were available for this study.

Incident data set collected from MEX freeways are divided into two groups. The March data set was used for calibrating the algorithms and the May data set was used for evaluating the performance of the algorithms. The calibration data set has a total of 24 incidents with 20 incidents due to vehicle accidents and the remaining incidents are caused by vehicle break down. Five full day data were used for calibrating the rule base algorithms whilst only selected data (for example all incidents and selected non incident data) were used for training the ANN models.

3.2. Performance Indicators

The performance of an incident detection algorithm are characterised by:

- *Detection rate (DR)*

The number of detected incidents to the recorded number of incident in the data set. Detection rate is given as a percentage.

- *False alarm rate (FAR)*

  The number of incorrect detection interval to the total number of intervals the algorithm was applied. This paper expresses FAR in percentage per section per day because different traffic systems have different sampling rate. Using time period of one day allows comparison of FAR over different traffic system independent of the traffic sensors sampling period.

$$FAR = \frac{N_f N_h}{N_t} * 24 * 100$$

  where

  N_f is the number of incorrect detection interval,

  N_t is the total number of intervals the algorithm was applied, and

  N_h is the number of intervals per hour.

- *Mean time to detection (MTTD)*

  The time to detection is the time difference between the time the incident was detected by the algorithm and the actual time the incident occurred. The mean time to detection (MTTD) is the average time to detection over *n* incidents.

Detection rate and false alarm rate measure the effectiveness of an algorithm while the mean time to detection reflects the efficiency of the algorithm. These performance measurements are positively correlated. Algorithms set to detect large number of incidents are highly sensitive and also tend to generate a large number of false alarms. On the other hand less sensitive algorithms detect fewer incidents and produce fewer false alarms.

4. CALIBRATION

Calibration of the rule-based algorithms involved testing different parameter values until the optimal value is determined. It is often difficult to select the best parameter values as the detection rate (DR), false alarm rate (FAR) and mean time to detection (MTTD) are inter-related. One parameter value may give the highest detection rate whilst another parameter value may give the lowest false alarm rate.

A performance index, PI was used in the calibration process to assist in selecting the optimal parameter values.

$$\mathrm{PI} = \left[\frac{100 - \mathrm{DR}}{100}\right]^{\mathrm{m}} * \mathrm{FAR}^{\mathrm{n}} * \mathrm{MTTD} \qquad \text{for DR} < 100\% \text{ and FAR} > 0\%$$

where coefficients m>0 and n>0.

A lower PI value indicates better performance. The PI equation also considers MTTD, a performance indicator not reflected on the FAR versus DR performance. Other constraints such as maximum acceptable MTTD and FAR can be added to the PI equation. This is to ensure that performance outside the constraints would not be accepted. The coefficients m and n in the PI equation is used to emphasise the importance of DR and FAR respectively. Typical values for the two coefficients are m=1 and n=1.

Calibration results of the four incident detection algorithms are shown in **Table 1**. The California algorithm has the highest detection rate and the MEX algorithm has the lowest false alarm rate. Note that all the algorithms are capable of detecting greater number of incidents than the numbers shown in **Table 1**. However more sensitive algorithms ie higher detection rates than the calibration results generate much higher false alarm rate.

Figure 1 shows the performance curves of the four incident detection algorithms. Performance curves of the California, ANN and UCB have similar shape. That is in the beginning the detection rate increases at a higher rate than the false alarm rate. This is followed by a higher rate of increase for the false alarm than the detection the detection rate. The performance curve of the MEX algorithm start of with the detection rate increasing at a higher rate than the false alarm rate. Unlike the other three algorithms, the MEX algorithm performance curve reaches its maximum detection rate quickly. This means that the maximum detection rate for MEX algorithm is low. Of the four algorithms, the California algorithm has the highest detection rate at any false alarm rate.

Table 1
Calibration Results

Algorithm	Number of incident detected	DR (%)	FAR per section per day (%)	MTTD (min)
California algorithm	15	62.5	7.2	3.9
UCB algorithm	9	37.5	16.4	12.8
MEX algorithm	10	41.7	8.6	5.0
ANN	12	50	9.6	7.1

5. EVALUATION

The data set used for evaluation of the calibrated algorithms were collected on the 17th October 1995. Whole day data for the 5 routes shown in **Table 2** were used. The data set contained a total of 10 incidents. Traffic conditions after 4 of the 10 incidents were noted as *no change*. This meant that the 4 incidents would be very difficult to detect.

Table 2
Evaluation data set

Route	Accident	Vehicle break down	Vehicle overturn
Route 6 Mukoujima	3		
Route 6 Misato		1	
Route 7		1	
Middle Loop	1	1	1
Kawaguchi line	1		1
Total	5	3	2

Evaluation results of the 4 algorithms are shown in **Table 3**. The results showed that California algorithm has the highest detection rate of 40% and MEX algorithm has the lowest false alarm rate of 0.3% per section per day. There are approximately 1600 detectors on MEX freeways. If an algorithm with a false alarm rate of 50% were to be used on MEX freeways, there would be approximately 33 alarms per hour. This is quite high for MEX traffic control centre's operators. For practical purposes, a false alarm rate of less than 10 alarm per hour per operator would be a more acceptable. The mean time to detection for the four algorithms ranges from 4 to 9.5 minutes and MEX algorithm has the lowest mean time to detection.

Table 3
Evaluation Results of Four Calibrated Algorithms

Algorithm	Number of incident detected	DR (%)	FAR per section per day (%)	MTTD (min)
California algorithm	4	40.0	17.4	5.5
UCB algorithm	2	20.0	141.0	9.5
MEX algorithm	3	30.0	0.3	4.0
ANN	2	20.0	7.2	7.0

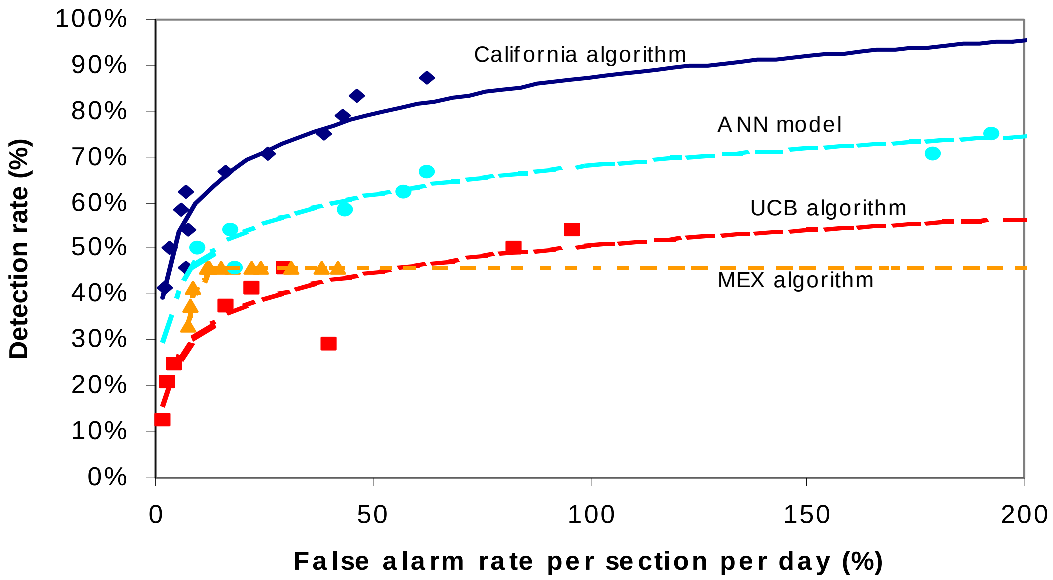

Fig. 1 - Performance curves of the four incident detection algorithms

6. CONCLUSION AND COMMENTS

This study has shown the different performances of the four incident detection algorithms calibrated and evaluated using real life incident and non incident data. A performance index equation was introduced to assist in selecting optimal parameter values.

The results showed that the California algorithm has the highest detection rate and the MEX algorithm has the lowest false alarm rate. Relative to the California algorithm, the ANN model has lower detection rate and higher false alarm rate.

There are no optimal parameter values for each algorithm. The best algorithm and optimal parameter values depend on the freeway system the algorithm is applied and the sampling rate of the traffic data. A higher false alarm rate is acceptable in a freeway system with less detector stations than MEX freeways. Hence a higher detection rate could be achieved. Also a short sampling rate would allow longer persistency test for example over 5 interval to reduce false alarm rate. Furthermore short sampling rate reduces the mean time to detection.

MEX algorithm

Different speed thresholds are used for freeway with 2 and 3 lane configurations. The current version of MEX algorithm did not address which threshold should be use at freeway section that are in the transition between 2 to 3 lanes and vice versa. From the MEX report (MEX et al. 1993), it was not clear how the algorithm handles missing or corrupt data. The freeways selected for this study has no sections that change in the lane configuration from 2 to 3 lanes. This study omitted the analysis of detector stations at time interval when the stations have invalid or missing data.

Another incident detection issue not addressed in the MEX report is how the algorithm detects incident at the start or the end of a freeway section. At present incidents are confirmed only when 2 upstream detector stations are congested and 2 downstream detector stations are free. For example incidents that occurred between detector stations 1 (upstream) and 2 (downstream) would mean that it is not possible to find a detector station upstream of detector station 1. In this study when an incident is classified as tentative and when no further upstream or downstream stations are available to confirm an incident, only valid traffic data from available detector stations are used. In other words when no traffic data are available, the data are assumed to satisfy the criteria of an incident.

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