Comparative study of freeway incident detection algorithms

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Abstract

This paper compares the performance of California, University of California, Berkeley, and Tokyo Metropolitan Expressways (MEX) freeway incident detection algorithms and artificial neural network model. The selected algorithms are calibrated and evaluated using MEX real-life incident data. Results of the fully calibrated algorithms are presented.

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.

Since 1970s a variety of freeway incident detection algorithms have been developed based on traffic flow theory, pattern recognition and statistical techniques. Some of the widely known algorithms are California algorithm (Payne et al.1976), McMaster algorithm (Hall et al. 1993), ARIMA algorithm (Ahmed and Cook 1982), HIOCC (Collins 1983; Steed and Clowes 1989), ARRB-VicRoads (Luk and Sin 1992), University of California, Berkeley (UCB) algorithm (Lin and Daganzo 1997) and Tokyo Metropolitan Expressways (MEX) algorithm (MEX et al. 1993). In this paper, this group of algorithms will be referred to as rule based algorithms. Recent development of freeway incident detection algorithms involves using Artificial Neural Network (ANN) (Ritchie and Cheu 1993; Dia et al. 1996).

Many incident detection algorithms have been developed but 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, UCB and MEX algorithms) and an ANN model 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.

This paper discusses the performance indicators used to evaluate the performance of incident detection algorithms. Descriptions of each selected algorithm and of the incident data used in this study are introduced. The calibration process of rule based algorithms, training of ANN model, the calibration and evaluation results are presented.

PERFORMANCE INDICATORS

Before comparing the performance of incident detection algorithms, the performance indicators used to evaluate the algorithms performance are discussed. 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. False alarm rate is usually expressed as percentage per section (ie between upstream and downstream detector stations) over time period. The time period commonly used is the data sampling period of the traffic sensors. 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.

Since false alarms are generally caused by random fluctuation of traffic flow, persistence test is applied by raising an incident alarm only when multiple incidents are detected in consecutive intervals. The trade off is longer detection time and results in a greater impact on traffic.

The three performance measures are inter-related and it is not necessary to seek one optimal setting. The incident detection calibration must balance the DR, FAR and MTTD combinations for a specific application.

INCIDENT DETECTION ALGORITHMS

The following incident detection algorithms are selected for this study and are discussed in details:

- California algorithm,
- University of California, Berkeley (UCB) algorithm,
- Tokyo Metropolitan Expressway (MEX) algorithm, and
- Artificial Neural Network (ANN) model.

Further details regarding the wide range of incident detection algorithms can be found in Chang et al (1993) and Black (1996).

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.

The California algorithm analysis is based on loop occupancy variables and is given by:

(i) the average occupancy at the downstream detector

$$\left| O_u(t) - O_d(t) \right| > k_1$$

symbol 0 \f "Tiiithe difference in occupancy between the upstream and downstream detectors

$$\left| O_u(t) - O_d(t) \right| > k_1$$

symbol 0 \f "Tiiiithe difference in the occupancy between the upstream and downstream detectors relative to the upstream occupancy

$$\frac{\left[O_u(t) - O_d(t) \right]}{O_d(t)} > k_2$$

symbol 0 \f "Tiivthe rate of change in the downstream occupancy at a given time interval

$$\frac{\left[O_d(t - \Delta) - O_d(t) \right]}{O_d(t - \Delta)} > k_3$$

where

$O_u(t)$ is the upstream occupancy at time t,

$O_d(t)$ is the downstream occupancy at time t,

Δ is the time interval offset (s), and

T_1, T_2, T_3, T_4, T_5 are the pre-determined threshold values.

There are more than 10 versions of the California algorithm and algorithm 8 (see Fig. 1) is the version currently used in California. This algorithm has an element in addition to the variations to the classic California algorithm (algorithm 1 to 7), that detects compression wave at the downstream station. Only algorithm 8 is selected for this study.

The structure of algorithm 8 (see Fig. 1) can be broadly divided into two branches. One branch is for cases when compression waves are detected and the other is for cases when there are no incidents, incidents are tentative, confirmed or continuing. The first occurrence of a compression wave at the downstream detector is when $O_d(t) \geq T_5$ and $O_d(t-\Delta\tau)-O_d(t)/O_d(t-\Delta\tau) < T_2$. After the detection of compression waves at the downstream station, the incident detection element of the algorithm is suppressed for 5 minutes. The compression wave element in algorithm 8 lowers the false alarm rate and slightly increases the mean time to detection.

The detection status changes from incident free to tentative incident when conditions (i), (ii) and (iii) are satisfied. If condition (iii) persisted, the status of the incident is upgraded from tentative to confirmed and from confirmed to continuing.

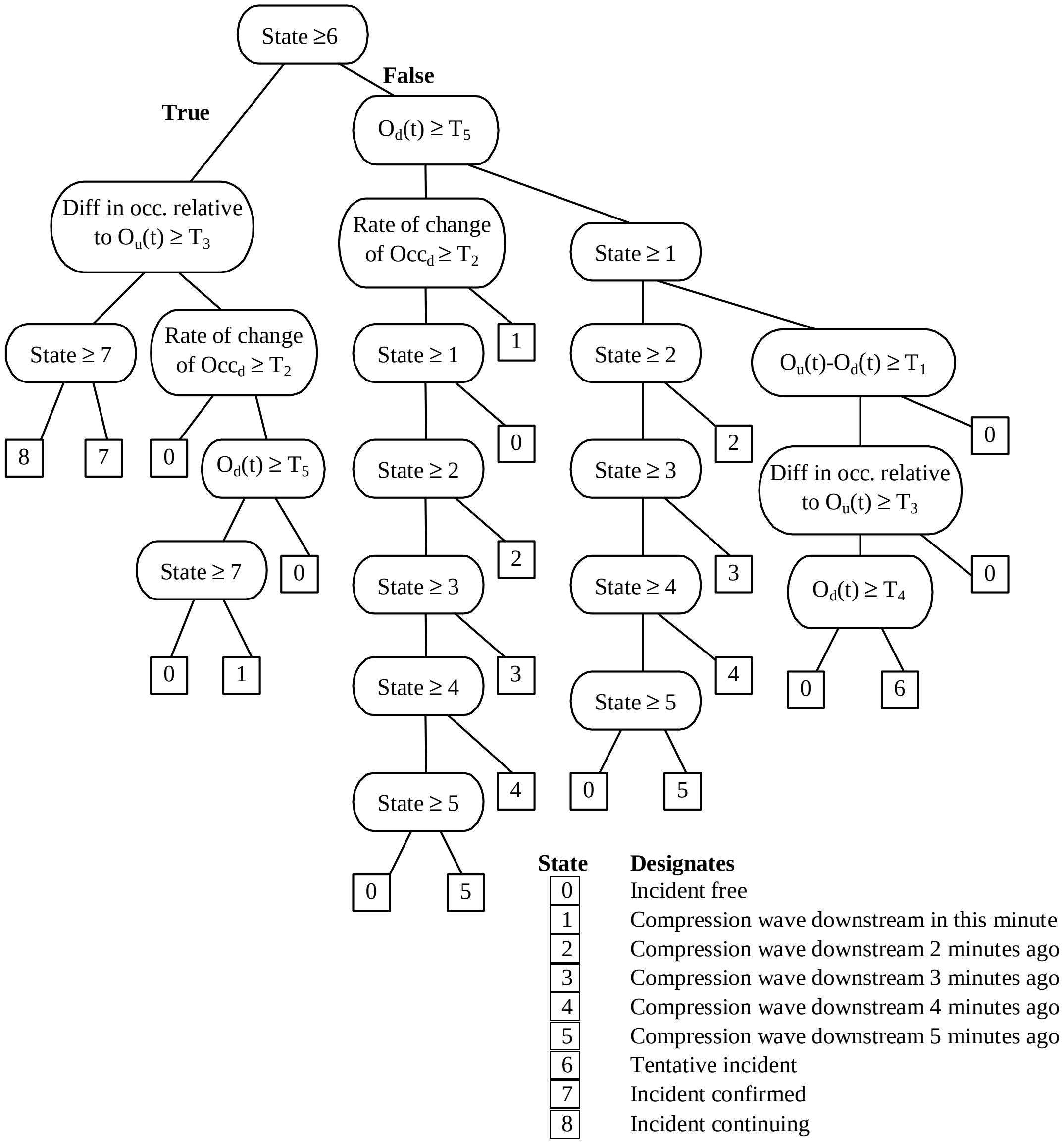

Fig. 1 - California algorithm #8 flow chart (Source: ???)

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. An incident alarm is triggered whenever $Y(t_{j+1})$ exceeds the detection threshold, $\tau\xi_0$.

The UCB algorithm analysis can be expressed by:

$$Z(t_j) = \sum_{i=1}^{j} O_u(t_i) - \sum_{i=1}^{j} O_d(t_i) \qquad (j = 1,2,.....)$$

$$Y(t_{j+1}) = \begin{cases} 0 & (j = 0) \\ \max\{0, Y(t_j) + Z(t_{j+1}) - Z(t_j) - \tau\} & (j = 1,2,....) \end{cases}$$

where

$O_u(t)$ is the upstream occupancy at time t,

$O_d(t)$ is the downstream occupancy at time t, and

τβ is the critical occupancy difference beyond which incidents can be detected.

The use of cumulative occupancies in the UCB algorithm means that when there are missing or corrupt data due to communication error at a detector station, the UCB algorithm analysis may show this situation as an incident. The comparison of cumulative occupancy also means that conservation of flow needs to be preserved for example at a pair of detector stations between on-ramp and off-ramp. In order to overcome the two shortcomings of the UCB algorithm the following measures were introduced:

- when there is missing or corrupt data during a particular interval, the traffic data of the pervious interval is used
- no detection would be carried out at detector stations between an on-ramp or an off-ramp. A better approach would be to use the on-ramp or off-ramp traffic data. Unfortunately the on-ramp and off-ramp traffic data were not available.

  In Tokyo Metropolitan Expressway ramps spacing are very close together. For example in the inbound direction of Route 4 there are 7 ramps approximately 7km from downtown Tokyo. Therefore at locations close to downtown Tokyo it can be difficult to find a pair of detector station that does not have a ramp. The ramp configuration of the Tokyo Metropolitan Expressway would reduce the usefulness of UCB algorithm unless the ramp information is used.

Tokyo Metropolitan Expressway (MEX) Algorithm

The Tokyo Metropolitan Expressway (MEX) has 250 km of freeway under its jurisdiction. About 1600 sensors are installed on the freeways. At present there are two control centres monitoring the Tokyo metropolitan freeway systems. One control centre monitors the eastern section and the other control centre monitors the western section. In future all the traffic surveillance will be carried out from one control centre.

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. The traffic parameter sampling rate for the MEX system is at 1 minute interval. The MEX algorithm (see Fig. 2) is divided into free flow and congested flow based on the current speed v(t). The detector station is considered as free if the current speed $v(t) > v_f$.

For upstream detector station with free flow condition at time t, three criteria have to be satisfied before an incident can be classified as a tentative incident:

(i) average traffic flow rate at the detector station must be $\leq q_2$ and $\leq q_3$ for 2 and 3 lanes respectively,

(ii) speed change at the detector station $\bar{v}(t-2) - v(t) \geq \#\#\#_f$ where $\bar{v}(t-2)$ is the 3 minutes moving average at time t-2 minutes,

(iii) speed difference b etween the upstream and downstream stations $\geq \delta_f$.

When all the above criteria are satisfied, persistency check using only criterion (iii) is applied at time t+1 and t+2. In the case where criterion (iii) persisted, an incident is confirmed only when criterion (vi) is satisfied. Criterion (vi) states that the flow condition at two upstream detector stations are $\leq v_f$ (ie. congested) and the flow condition at two downstream detector stations are $> v_f$ (ie. free). If the traffic condition failed the persistency test, the whole process is repeated from the start at the next time interval. A confirmed incident is verified as continuing when the third and fourth criteria are satisfied.

The criteria for congested flow condition differ slightly from the free flow condition. At time t, two criteria have to be satisfied before an incident can be classified as a tentative incident:

(iv) speed change at the detector station $\left|\bar{v}(t-2) - v(t)\right| \geq \#\#\#_{c2}$ and $\geq \#\#\#_{c3}$ for 2 and 3 lanes respectively, where $\bar{v}(t-2)$ is the 3 minutes moving average at time t-2 minutes,

- if $\bar{v}(t-2) - v(t) < 0$ the current detector station is considered as an downstream station, and

- if $\overline{v}$(t-2) - v(t) > 0, the current detector station is considered as a upstream station.

(v) the speed difference between the upstream and downstream detector stations $v_u(t) - v_d(t) \geq \delta_{c2}$ and $\geq \delta_{c3}$ for 2 and 3 lanes respectively.

When both criteria above are satisfied, persistency check using criterion (v) only is applied at time t+1, t+2, t+3 and t+4. In the case where criterion (v) persisted, an incident is confirmed only when the criterion (vi) is satisfied. Criterion (vi) states that the flow condition at two upstream detector stations are $\leq v_f$ (ie. congested) and the flow condition at two downstream detector stations are > v_f (ie. free). If the traffic condition failed the persistency test, the whole process is repeated from the start at the next time interval. A confirmed incident is verified as continuing when criteria (v) and (vi) are satisfied.

The comparison of speed change at detector stations (see criteria ii and iv) with threshold values in the range of 20-30 km/h is only applicable when the incident happens. This means that MEX algorithm has only one chance to detect incidents. This is fine provided that the algorithm can detect all the incidents when they occurred. However perfect detection rate is not possible in real life application.

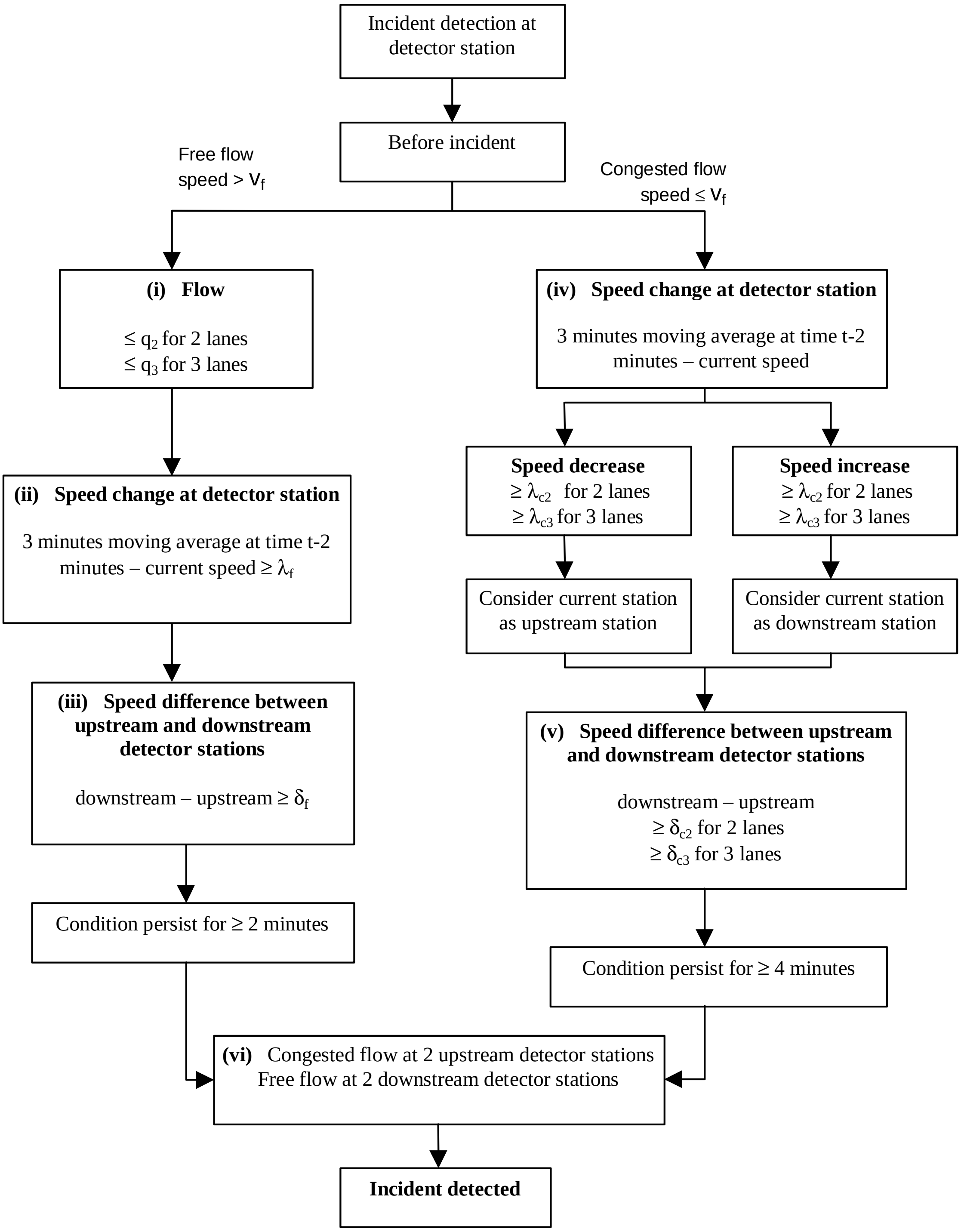

Fig. 2 – MEX incident detection algorithm flow chart

Different speed thresholds are used for freeway with 2 and 3 lane configurations (see criteria i, iv and v). 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 (see criteria iv and vii), 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.

ARTIFICIAL NEURAL NETWORK

Neural networks are used to simulate the thought process of the human brain, and different paths can be taken to reach a final decision (Black 1996). 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 receives 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 (see Fig. 3). 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.

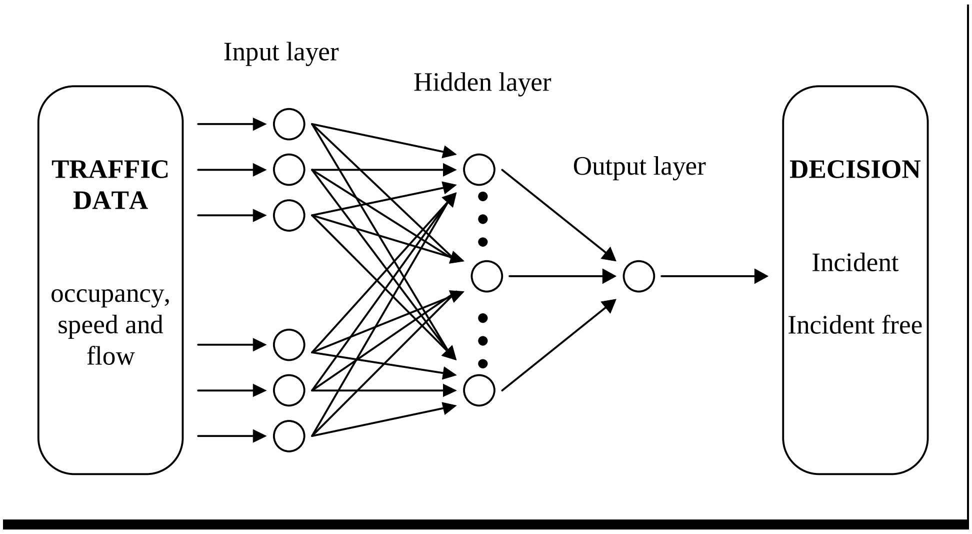

Fig. 3 - Artificial neural network modelling framework

Dia (1996) developed a MLF ANN model by training the model with 60 real life incident data that occurred on Tullamarine Freeway in Melbourne, Australia. The performance of the trained ANN model was evaluated using independent data set of 40 incidents collected from the Tullamarine and South Eastern freeways in Melbourne. The data sets were collected at 20 seconds cycle from inductive loop sensors at 500 m spacing.

Dia's ANN model framework structure was a result of some 500 models with different number of:

- hidden processing elements ranging from 2 to 99;
- time interval: t; t and t-1; t, t-1 and t-2; t, t-1, t-2 and t-3; t, t-1, t-2, t-3 and t-4;
- stations: upstream and downstream, upstream only and downstream only; and
- station input data: station average, fast lane and all lanes.

The best MLF ANN model from Dia's research has the following structure:

- 6 inputs: upstream and downstream speed, flow and occupancy,
- 1 hidden layer with 14 processing elements, and
- 1 output: incident state {0,1}.

The MLF ANN model structure above was used for this study.

Data requirements

Table 1 provides the data requirements of each algorithms described above. All algorithms except MEX algorithm use occupancy. In fact occupancy is the common traffic parameter used by all published algorithms such as McMaster, ARIMA and HIOCC. Therefore it is interesting to note that occupancy is not used in the MEX algorithm.

Table 1

Data Requirements for Incident Detection Algorithms

Algorithm	Occupancy	Volume	Speed
California	symbol 252 ¥f "Wingdings " ¥s 10✓❝		
Tokyo Metropolitan Expressway (MEX)		symbol 252 ¥f "Wingdings " ¥s 10✓❝	symbol 252 ¥f "Wingdings " ¥s 10✓❝
University of California, Berkeley	symbol 252 ¥f "Wingdings " ¥s 10✓❝		
Artificial Neural Network	symbol 252 ¥f "Wingdings " ¥s 10✓❝	symbol 252 ¥f "Wingdings " ¥s 10✓❝	symbol 252 ¥f "Wingdings " ¥s 10✓❝

INCIDENT DATA

The incident data used for this study was collected on the Tokyo Metropolitan Expressway. The Tokyo Metropolitan Expressway covers 250 km of 2 lane expressway in each direction with the exception of Bayshore route, which is a 3 lane expressway (see ref _Ref418323256 ¥h Fig. 4). Ultra sonic sensors are installed at 300m spacing on the expressway to collect a weighted average occupancy, flow and speed across all lanes at 1 min interval. The detection length of the sensors and different firing positions employed (ie. overhead and side firing) were different. As a result the occupancy values collected by MEX were not used. Instead normalised occupancy values using the speed collected and assumed detection length of 1 m and average vehicle length of 5.5 m were used. The normalised occupancy values enable the occupancy data along all routes to be analysed together.

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. Details of the incident data used for this study are shown in ref _Ref408048339 ¥h
Table 2.

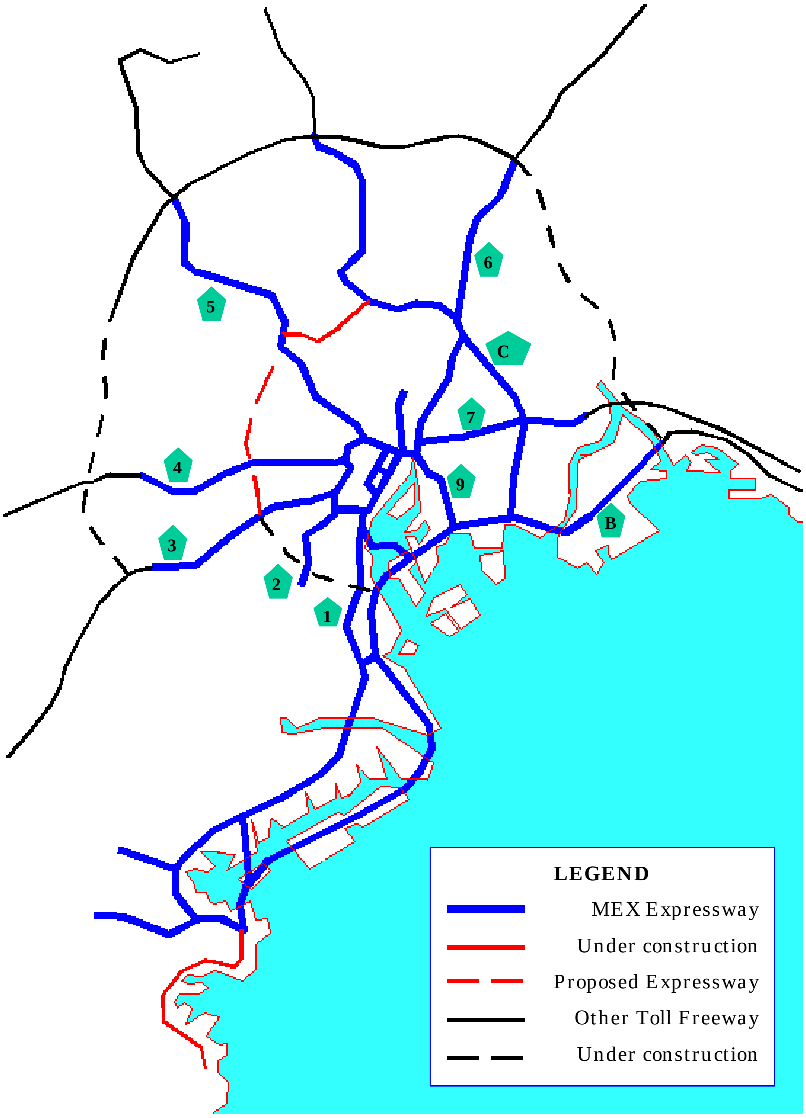

Fig. seq Fig. ¥ Arabic 4 – Tokyo Metropolitan Expressway (MEX) Network Configuration*

Table seq Table ¥* Arabic 2

Incident Data Used for this Study

Route	Date of data collection	Number of incidents
3	12th-16th May 1995	9
4	12th-16th May 1995	8
5	12th-16th May 1995	7

6	17th October 1995	4
7	17th October 1995	1
Middle loop	17th October 1995	3
Kawaguchi line	17th October 1995	2

Although 34 incidents data set were used, only 20 incidents showed notable changes in traffic condition after the incidents have occurred. These were due to the following reasons:

- Tokyo freeways are often very congested. When an incident occurs upstream of a bottleneck where the reduced in capacity caused by the incident is still greater than the bottleneck capacity, there would be very little changes in the traffic data.
- Incidents that occurred during off peak periods when flow rates are very low would not cause much disruption to other traffic.
- Only aggregate traffic data across all lanes are collected. This would make it difficult to detect incidents that occurred during the two periods described above. With a lane by lane traffic information, incidents at positions closed to traffic sensors would show some changes in traffic information for example a reduction of traffic flow across one lane.

CALIBRATION PROCESS AND RESULTS

Incident data set collected from MEX freeways are divided into two groups. The May data set from 12^{th} to 16^{th} was used for calibrating the algorithms and the October data set was used for evaluating the performance of the algorithms. The calibration data set (see ref _Ref408153960 ¥h Table 3) has a total of 24 incidents with 20 incidents due to vehicle accidents and the remaining incidents is 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.

Table seq Table ¥* Arabic 3

Calibration data set

Route	**Accident**	**Vehicle break down**
Route 3	5	4
Route 4	8	
Route 5	7	
Total	20	4

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

A typical performance curve of an incident detection algorithm is shown in ref _Ref408135174 ¥h Fig. 5. The optimal parameter value is usually at the point where the increase in detection rate does not lead to a large increase in false alarm rate. While plotting the DR and FAR data points on a curve may help in selecting the optimal parameter value, this approach alone is not very useful when an optimisation routine is employed to search for the best parameter values. An optimisation routine is necessary when there are more than two parameters to be calibrated.

An optimisation routine usually needs an index to guide the search process. A performance index, PI can be used in the calibration process. A lower PI value indicates better performance.

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

where coefficients m>0 and n>0.

The PI equation also considers MTTD, a performance indicator not reflected on the FAR versus DR performance curve (see ref _Ref408135174 ¥h Fig. 5). Other constraints such as maximum acceptable MTTD and FAR, for example 5 minutes and 0.5% respectively could 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. Larger value denotes a greater importance of the particular performance indicator.

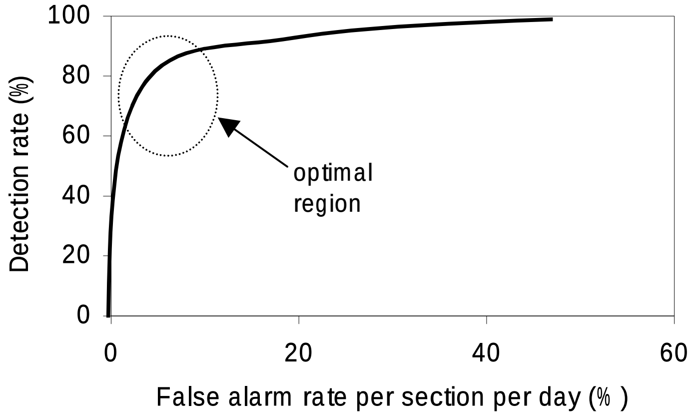

Fig. seq Fig. ¥ Arabic 5 – Typical performance curve of an incident detection algorithm*

California algorithm

California algorithm 8 has five parameters T_1, T_2, T_3, T_4 and T_5 (see ref _Ref407606015 ¥h Fig. 1). Values ranging from 0.03 to 0.7 were tested for the five parameters. The performance curve for the calibration of California algorithm is shown in ref _Ref408158830 ¥h Fig. 6. The best parameter values for the California algorithm are T_1=0.3, T_2=0.2, T_3=0.5, T_4=0.13 and T_5=0.13.

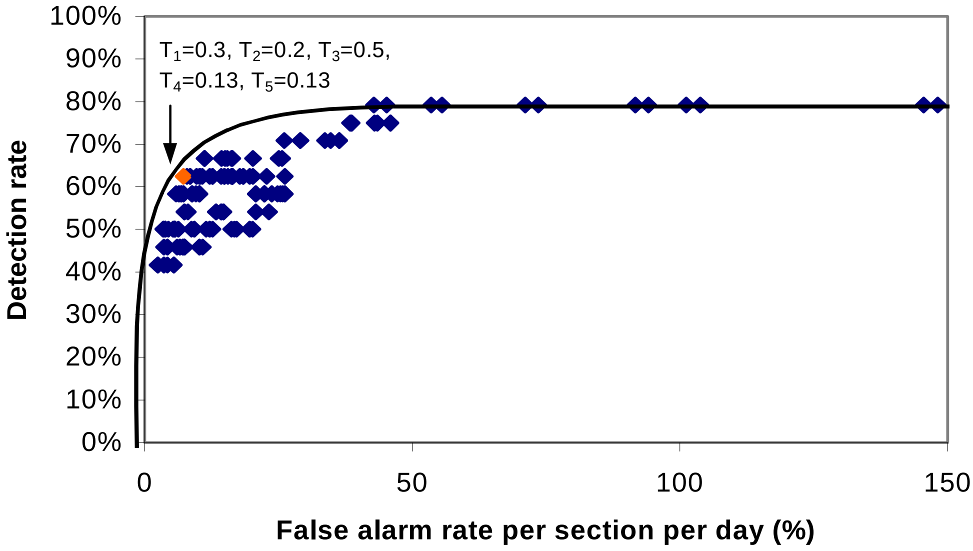

Fig. seq Fig. ¥ Arabic 6 – Performance curve of California algorithm 8*

University of California, Berkeley (UCB) Algorithm

UCB algorithm has only 2 parameters symbol 116 ¥f "Symbol" ¥s 11τ and symbol 116 ¥f "Symbol" ¥s 11τ_0 to calibrate. Values ranging from 0.1 to 0.6 and 0.1 to 2.5 were tested for symbol 116 ¥f "Symbol" ¥s 11τ and symbol 116 ¥f "Symbol" ¥s 11τ_0 respectively. The performance curve for the calibration of UCB algorithm is shown in ref _Ref408159126 ¥h Fig. 7. The best parameter values for the UCB algorithm are symbol 116 ¥f "Symbol" ¥s 11τ=0.3 and symbol 116 ¥f "Symbol" ¥s 11τ_0=0.6.

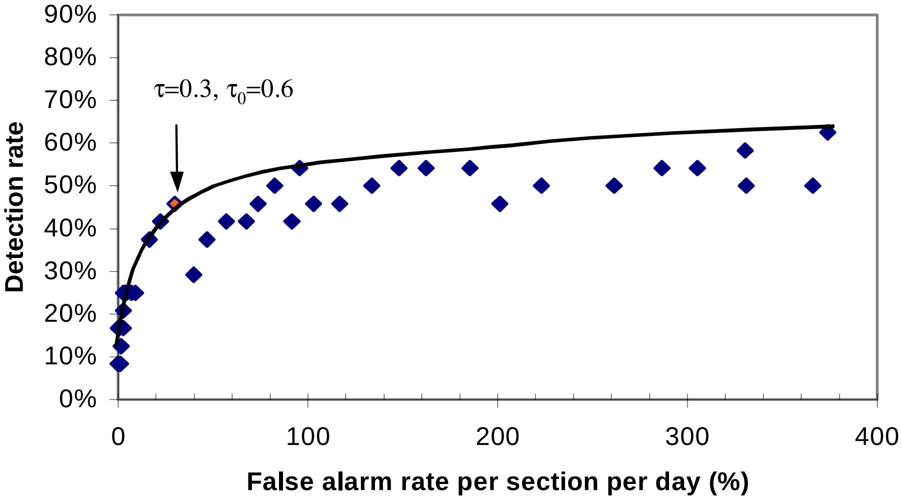

Fig. seq Fig. ¥ Arabic 7 – Performance curve of University of California, Berkeley algorithm*

Tokyo Metropolitan Expressway (MEX) Algorithm

The MEX algorithm was developed from the full set of incident data collected on MEX freeways in 1995. Parameter values for the algorithm was given in the MEX report (???? 1996). Few assumptions addressing the handling of situations such as missing data and detection at the start and end of a freeway were made in this study. As a result it was necessary to recalibrate the algorithm based on these new assumptions. There are six parameters v_f, q_2, symbol 115 ¥f "Symbol" ¥s 11σ_f, σψμβολ 108 ∴φ ∀Σψμβολ∀ ∴σ 11$\lambda_{f,}$ symbol 115 ¥f "Symbol" ¥s 11σ_{c2}, σψμβολ 108 ∴φ ∀Σψμβολ∀ ∴σ 11λ_{c2} that are pertinent to 2 lane freeways. The performance curve for the calibration of MEX algorithm is shown in ref _Ref408225818 ¥h Fig. 8. The best parameter values for the algorithm are v_f=41 km/h, q_2=30 veh/min, symbol 115 ¥f "Symbol" ¥s 11σ_f=30 km/h, σψμβολ 108 ∴φ ∀Σψμβολ∀ ∴σ 11λ_f=36 km/h, symbol 115 ¥f "Symbol" ¥s 11σ_{c2}=22 km/h, σψμβολ 108 ∴φ ∀Σψμβολ∀ ∴σ 11λ_{c2}=36 km/h.

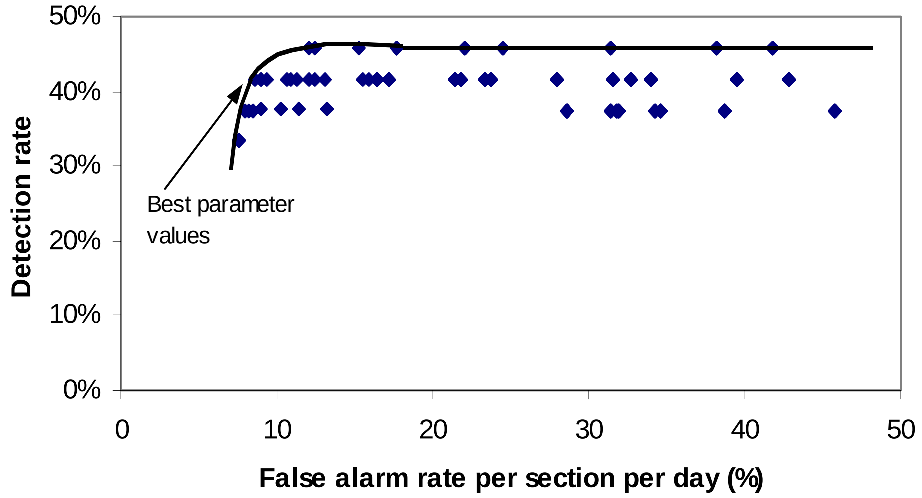

Fig. seq Fig. ¥ Arabic 8 – Performance curve of Tokyo Metropolitan Expressway algorithm*

Artificial Neural Network (ANN)

Data set that comprises of incident and non incident data were used to train ANN models. A number of training data set using:

- data from all incidents,
- only data from incidents that caused significant change in traffic flow condition, and
- different amount of non incident data.

Non incident data were sampled from all hours of the day to give a full representation of the traffic conditions. ref _Ref408226228 ¥h Table 4 shows the different combination of training data set.

Table seq Table ¥* Arabic 4

Training Data Set for ANN Models

ANN Model	Number of incident data (minutes)	Number of non incident data (minutes)	Ratio of incident: non incident
All incident data			
Model 7	1237	7440	1:6.0
Model 8	1237	5880	1:4.8
Model 9	1237	2940	1:2.4
Selected incident data			

Model 11	865	2340	1:2.7
Model 12	865	7440	1:8.6
Model 13	865	4680	1:5.4
Model 14	865	8820	1:10.2
Model 15	865	5580	1:6.3
Model 16	865	2940	1:3.4

ANN models trained with data containing all incident (Model 7-9) showed high false alarm rate compared with ANN models trained with selected incident data only (Model 11-16). The results showed that ANN models trained with all incident data have difficulty distinguishing between incident and non incident data. Hence it is important to use training data that are representative of an incident.

The ratio of incident to non incident data also showed some affect on the performance of the ANN model. Test results showed that ratio of incident to non incident less than 1:5, for example 1:6, is required to train ANN model that produces reasonable false alarm rate. However the performance of Model 13 to 15 are very similar.

The output from ANN models ranges from 0 to 1. It is necessary to determine a detection threshold (DT) to decide whether the output from an ANN model is an incident or a non incident. For example an ANN model with DT=0.9 would classify any output value of less than 0.9 as non incidents. Detection threshold ranging from 0.6 to 0.99 were used to calibrate 9 of the trained ANN models.

Persistency test was applied to the ANN model to reduce the false alarm rate. Three options were tested:

- no persistency test,
- persistency test of symbol 179 ¥f "Symbol" ¥s 11≥1 time interval, and
- persistency test of symbol 179 ¥f "Symbol" ¥s 11≥2 time intervals.

The performance curve of Model 12 to 15 with different persistency tests and detection threshold values is shown in ref _Ref408238761 ¥h Fig. 9. The best ANN model is Model 15 with persistency test of 2 interval and DT=0.95.

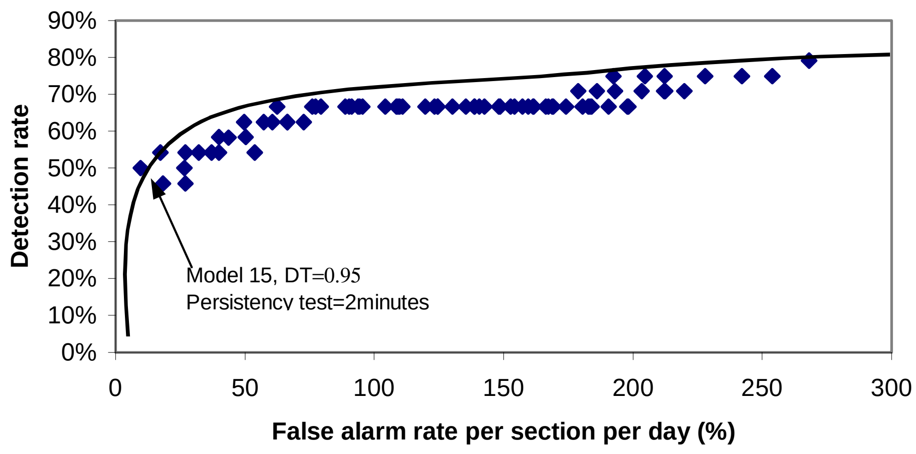

Fig. seq Fig. ¥ Arabic 9 – Performance curve of trained Artificial Neural Network models*

Calibration Results

Calibration results of the four incident detection algorithms are shown in ref _Ref408238984 ¥h Table 5. 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 (see Figs. 5 to 8) than the numbers shown in ref _Ref408238984 ¥h Table 5. However more sensitive algorithms ie higher detection rates than the calibration results generate much higher false alarm rate.

Figure ref _Ref408656598 ¥h Fig. 10 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. 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 seq Table ¥* Arabic 5

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

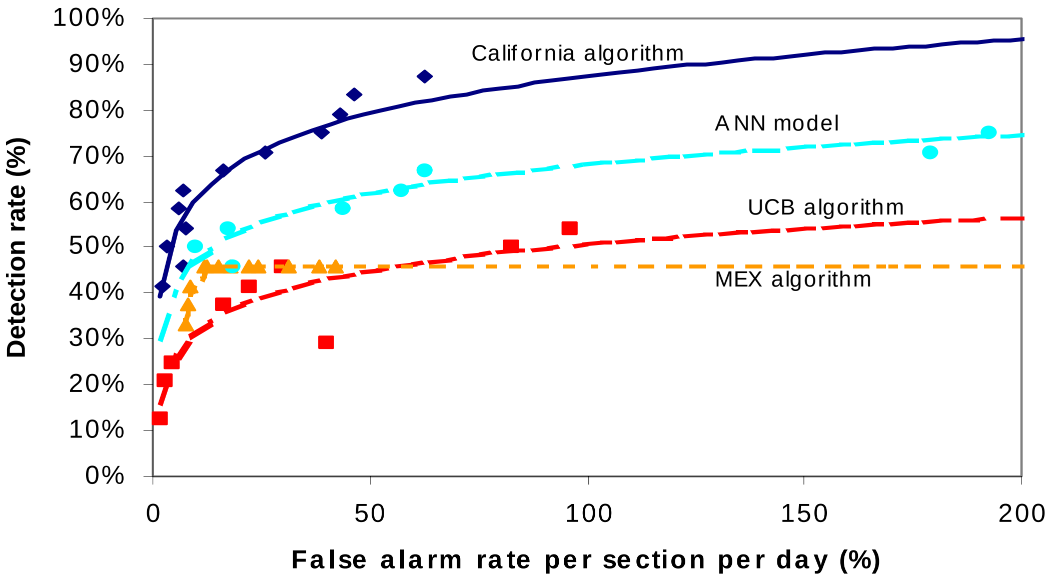

Fig. seq Fig. ¥ Arabic 10 - Performance curves of the four incident detection algorithms*

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 ref _Ref408411545 ¥h Table 6 were used. The data set contained a total of 10 incidents. Traffic condition after 4 of the 10 incidents were noted as *no change*. This meant that the 4 incidents would be very difficult to detect.

Table seq Table ¥* Arabic 6

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 ref _Ref408411742 ¥h Table 7. 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 algorithm ranges from 4 to 9.5 minutes and MEX algorithm has the lowest mean time to detection.

Table seq Table ¥* Arabic 7

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

CONCLUSION

This paper 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 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. The false alarm rate of the ANN model may be reduced if variable detection threshold were introduced (Dia and Rose 1997). Dia and Rose (1997) found that the false alarm could be improved without sacrificing the detection rate performance.

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.

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